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Bank Lending Standards, Loan Demand, and the Macroeconomy: Evidence from the Korean Bank Loan Officer Survey*

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A typical sign-restriction approach imposes restrictions on the bank lending rate (price) and the volume of loans (quantity) to identify a loan supply shock under the implicit assumption that the observed interest rate equates supply and demand for loans. Using the bank loan officer surveys from 12 countries, we document a novel cyclical pattern found in bank lending standards and loan demand, which differs between market-based and bank-based economies. In particular, the lending rate does not necessarily reflect the credit market conditions in bank-based economies, suggesting the presence of excess demand for credit. Using the Korean economy as an example, we demonstrate the failure of identification of loan supply shocks when relying on the lending rate and propose novel

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identifying schemes by exploiting the information from the bank loan officer survey. Our findings suggest that disentangling the supply and demand factors of credit shocks is crucial in understanding their macroeconomic effects.

E32, E44, E51.

1. Introduction

Are credit shocks an important driver of the macroeconomy? Various theoretical models have been proposed to understand the mechanism through which an exogenous shock to credit markets drives fluctuations in output (Holmstrom and Tirole 1997; Kiyotaki and Moore 1997). Indeed, the recent episodes of widespread credit crunches and recessions following the collapse of Lehman Brothers have spurred renewed interest in understanding the link between credit markets and the macroeconomy using a quantitative framework (Gertler and Karadi 2011; Gilchrist and Zakrajšek 2012; Perri and Quadrini 2018).

As earlier studies emphasized, however, identifying a causal link from credit market disturbances to the macroeconomy is challenging because of apparent reverse causality. While declines in credit growth often coincide with recessions, one cannot rule out potential credit demand effects in addition to credit supply effects (Bernanke and Lown 1991; Bernanke and Gertler 1995; Peek, Rosengren, and Tootell 2003; Jiménez et al. 2014; Amiti and Weinstein 2018).[1] Although the sign-restriction approach of Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005) has been widely used to identify credit supply shocks, most applications of this approach impose restrictions on the price of credit—the interest

[1]Another stream of the literature has focused on how exogenous events affect bank credit supply to establish causality between credit markets and economic activity. For example, see Peek and Rosengren (2000) on the Japanese banking crisis in the early 1990s, Leary (2009) on the introduction of certificates of deposits in the early 1960s, and Chava and Purnanandam (2011) on the Russian crisis in 1998. However, these exogenous events provide only limited implications on the effect of credit supply shocks over business cycles because of their one-off nature.

rates on bank loans or corporate bonds—under the implicit assumption that the observed price reflects the underlying credit market conditions.

Whether this assumption holds in the data depends on the degree of credit market imperfection in the economy. If nonprice lending terms are widely used to alleviate information asymmetry or moral hazard, especially during economic downturns (Weinstein and Yafeh 1998; Bae, Kang, and Lim 2002), the observed interest rate may fail to equate supply and demand factors for bank loans. In extreme circumstances, this may result in credit rationing in which the allocation of credit to borrowers is independent of the interest rate (Laffont and Garcia 1977; Stiglitz and Weiss 1981). This issue is more likely to be problematic in bank-based economies, where firms' access to corporate bond markets is rather limited, than in market-based economies (Gyntelberg, Ma, and Remolona 2006; Khwaja and Mian 2008; Gambacorta, Yang, and Tsatsaronis 2014).

We address the identification issue by controlling for loan demand over business cycles using novel bank loan officer survey data. Among the various types of credit, we exclusively focus on bank lending to the business sector because household credit often behaves differently from firm credit (Den Haan and Sterk 2011; Bahadir and Gumus 2016). We aim to disentangle the demand and supply factors in bank lending and evaluate their macroeconomic effects using a Bayesian sign-restriction vector autoregression (VAR) model à la Uhlig (2005). To the best of our knowledge, this is the first attempt to apply a sign-restriction approach to the information from bank loan officer surveys. We are motivated to use this identification strategy by the novel stylized facts about cyclicality in bank lending standards and loan demand across both advanced and emerging market economies (EMEs).

Bank loan officer surveys provide important information about bank lending standards and demand for business loans that is not necessarily captured by the bank lending rate. The U.S. Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS) and the euro-area Bank Lending Survey (BLS) are the best-known bank loan officer surveys. They have been used to identify credit supply shocks in the United States (Lown and Morgan 2006; Bassett et al. 2014; Becker and Ivashina 2014) and more recently in the euro area (Del Giovane, Eramo, and Nobili

2011; Ciccarelli, Maddaloni, and Peydro 2015; van der Veer and Hoeberichts 2016) because tightened lending standards are associated with an adverse shock to credit supply.[2]

However, we cannot identify changes in bank loan supply just using changes in lending standards because of the obvious demand-side interpretation. Tighter standards could signal another negative disturbance to economic activity that reduces demand for loans simultaneously. To overcome this problem, Bassett et al. (2014) adjusted lending standards for macroeconomic and bank-specific factors affecting loan demand using bank-level data and obtained a cleaner measure of loan supply factors. Similarly, Becker and Ivashina (2014) used firm-level information on substitution from bank loans to corporate bonds and commercial papers to control for bank loan demand. Alternatively, Del Giovane, Eramo, and Nobili (2011), Ciccarelli, Maddaloni, and Peydro (2015), and van der Veer and Hoeberichts (2016) exploited bank-level information on the factors behind tightened standards and reduced loan demand from the BLS data to identify a credit supply shock.[3]

Unfortunately, such micro-level information is not readily available in the bank loan officer survey from the rest of the world. Instead, we use a sign-restriction approach to separate the loan supply from the loan demand factors reflected in the aggregate data.[4] We impose sign restrictions on lending standards, loan demand, and the volume of bank loans to jointly identify bank loan demand and supply shocks and estimate their macroeconomic effects. Imposing restrictions on the demand and supply factors proxied by the survey data directly, we obtain a cleaner measure of a loan supply shock that is less subject to the criticism raised by Musso, Neri, and Stracca

[2]For example, Gilchrist and Zakrajšek (2012) found a high correlation between changes in bank lending standards and the excess bond premium—their measure of credit market conditions. See, among others, Dell'Ariccia and Marquez (2006) and Ravn (2016) for the structural interpretation of changes in bank lending standards as an outcome of the information asymmetry between lenders and borrowers.

[3]In the BLS, banks also respond to more detailed questions about the factors affecting their decisions on credit standards, the specific terms and conditions for approving loans, and their assessment of the determinants of loan demand.

[4]Using micro-level data is not a panacea when identifying loan supply shocks, as they typically do not allow us to estimate macroeconomic effects (with the notable exception of Amiti and Weinstein 2018), which is our ultimate interest.

(2011), who noted that "while there is consensus on how to identify monetary policy and housing demand shocks, it is somewhat harder to come up with restrictions for identifying credit supply shocks." Although the sign-restriction approach has been widely used to identify credit supply shocks in advanced economies (Busch, Scharnagh, and Scheithauer 2010; De Nicolò and Lucchetta 2011; Helbling et al. 2011; Hristov, Hülsewig, and Wollmershäuser 2012; Meeks 2012; Finlay and Jääskelä 2014; Halvorsen and Jacobsen 2014; Gambetti and Musso 2017), applications to other countries, especially EMEs, are limited.[5]

This paper has two parts. In the first part, we establish novel stylized facts about bank lending that have not been exploited in the existing literature using the bank loan officer surveys from 12 countries. Although both lending standards and loan demand are strongly procyclical in the SLOOS and BLS data,[6] when extending to the similarly constructed bank loan officer surveys from the 10 additional countries where survey data are available (Chile, Estonia, Hungary, Japan, Korea, Poland, the Philippines, Russia, Thailand, and Turkey), loan demand is acyclical or even countercyclical in many of these countries, which suggests increased bank loan demand during turbulent times.

We further discover that the cyclicality of loan demand is strongly associated with the banking-sector dependence of each economy. In a country where firms rely more on indirect financing via banks, demand for bank loans appears less procyclical. Moreover, using a panel estimation with fixed effects, we find that the bank loan rate does not reflect the demand conditions in bank-based economies only. These stylized facts illustrate why conventional identifying assumptions using the bank lending rate are unsuitable in a bank-based economy where direct financing does not readily substitute bank loans.

[5]To the best of our knowledge, Tamási and Világi (2011) (Hungary) and Houssa, Mohimont, and Otrok (2013) (South Africa) are the only existing studies of EMEs using the sign-restriction approach. However, these studies impose a restriction on output, which prevents them from studying the short-term impact of a loan supply shock on output, or use corporate bond spreads to identify a bank loan supply shock, probably because of limited data availability.

[6]In other words, bank lending standards tighten (loosen) and loan demand decreases (increases) during recessions (expansions).

In the second part, using the Korean economy as a benchmark unit of the Bayesian VAR analysis, we demonstrate the failure of the conventional assumptions used to identify a bank loan supply shock (i.e., standard sign restrictions relying on the price-quantity framework) and provide alternative identification schemes using the bank loan officer survey. Once correctly identified, we find that an adverse loan supply shock has a substantial negative effect on output, while a negative loan demand shock does not have any recessionary effect. Depending on the VAR model specifications, loan supply shocks account for 10–15 percent of output fluctuations in the Korean economy, which is in line with previous studies of other countries using a sign-restriction approach (e.g., Meeks 2012 in the United States; Hristov, Hülsewig, and Wollmershäuser 2012 and Bijsterbosch and Falagiarda 2015 in the euro area; Halvorsen and Jacobsen 2014 in the United Kingdom and Norway; and Helbling et al. 2011 in G-7 countries). During the peak of the global financial crisis, this shock contributes to more than 40 percent of the output decline, suggesting its particular importance under extreme financial conditions.

We then discuss the interpretation of our findings. Using data from the Korean corporate bond market, we explain the contrasting effects on output between a loan supply shock and a loan demand shock. We find that the identified negative loan supply shock acts as a tightening in economy-wide credit supply, reflected in a sharp increase in credit spreads. The identified negative loan demand shock, however, is associated with an improvement in corporate bond market conditions. The substitution of bank loans by corporate bonds that is driven by improved bond market conditions appears the reason why a negative loan demand shock is not recessionary in the Korean economy. Extending the baseline model to jointly identify other structural shocks (monetary policy, aggregate supply, and aggregate demand shocks) embedded in a standard small-scale New Keynesian framework, we confirm the main results of the baseline model. If anything, loan demand and supply shocks have qualitatively different effects on the macroeconomic variables, further suggesting the importance of disentangling supply and demand factors. The additional exercise using Japanese data to validate our findings arrives at similar results.

The rest of this paper is organized as follows. Section 2 documents novel stylized facts about the cyclicality in lending standards and loan demand across 12 countries and provides the panel estimation results for the determinants of the bank lending rate. Section 3 illustrates the issues with the conventional identification of a loan supply shock using a sign-restriction approach and proposes an alternative approach using the survey data. Section 4 presents the key findings by estimating a baseline model with the Korean data and discusses the mechanism at work. Section 5 provides a battery of robustness checks, including an extension to the small-scale New Keynesian model and using Japanese data. Section 6 concludes the paper.

2. Stylized Facts from the Bank Loan Officer Surveys

This section provides a set of new empirical stylized facts by exploiting the bank loan officer surveys from 12 countries, including four advanced economies (the United States, the euro area, Korea, and Japan) and eight EMEs (Chile, Estonia, Hungary, the Philippines, Poland, Russia, Thailand, and Turkey), in which the relevant data are available for more than 30 quarters. Although such data have been available in the current format for the United States since 1991:Q4, they are available for much shorter periods in most countries. As a result, bank loan officer surveys have been largely unexploited, especially in the EME context. We bridge this gap in the literature by providing a novel systematic analysis that uncovers interesting heterogeneity in the determinants of the interest rate as well as its link to the corporate financing structure.

2.1 Cyclicality of Bank Lending Standards and Loan Demand

We first document the cyclical pattern of bank lending standards and loan demand in the United States and the euro area as benchmarks. U.S. data are taken from the SLOOS, and euro-area data are from the BLS. See online appendix C (at http://www.ijcb.org) for further details on the U.S. and euro-area survey data. Figure A.1 in online appendix A shows lending standards and demand for business loans in the United States from 1991:Q4 to 2019:Q2 (left) and the euro area from 2003:Q1 to 2019:Q1 (right), together with the recession dates defined by the OECD. An increase in the index of lending standards denotes relaxed lending standards for new loans.[7] Over business cycles, lending standards move closely with loan demand in both economies and both fall sharply during recessions, indicating that both lending standards and loan demand are procyclical in these economies.

We further document the cyclical pattern of lending standards and loan demand in the eight EMEs as well as Korea and Japan to assess whether the pattern found in the United States and euro area can be generalized to the rest of the world. We check the main questionnaires across countries, carefully using their central bank websites. We focus only on questions on lending to the business sector, not the household sector, to ensure consistency with the U.S. and euro-area data. Compared with figure A.1 in online appendix A, the EME data in figure 1 show an interesting cyclical pattern. In general, there is much weaker co-movement between lending standards and loan demand over business cycles.[8]

We argue that such a difference is not simply driven by the difference in income level or the (potentially) poor quality of the bank loan officer surveys in EMEs, as a similar pattern from the two additional advanced economies (Korea and Japan) is found (figure 2). Among the countries in which relevant survey data are available, Korea and Japan are characterized by firms' heavy reliance on bank financing via lending relationships over direct financing (Weinstein and Yafeh 1998; Bae, Kang, and Lim 2002).[9] Indeed, loan demand does not appear to be procyclical in these two countries, and it increased shortly after the collapse of Lehman Brothers, while banks tightened their lending standards.[10]

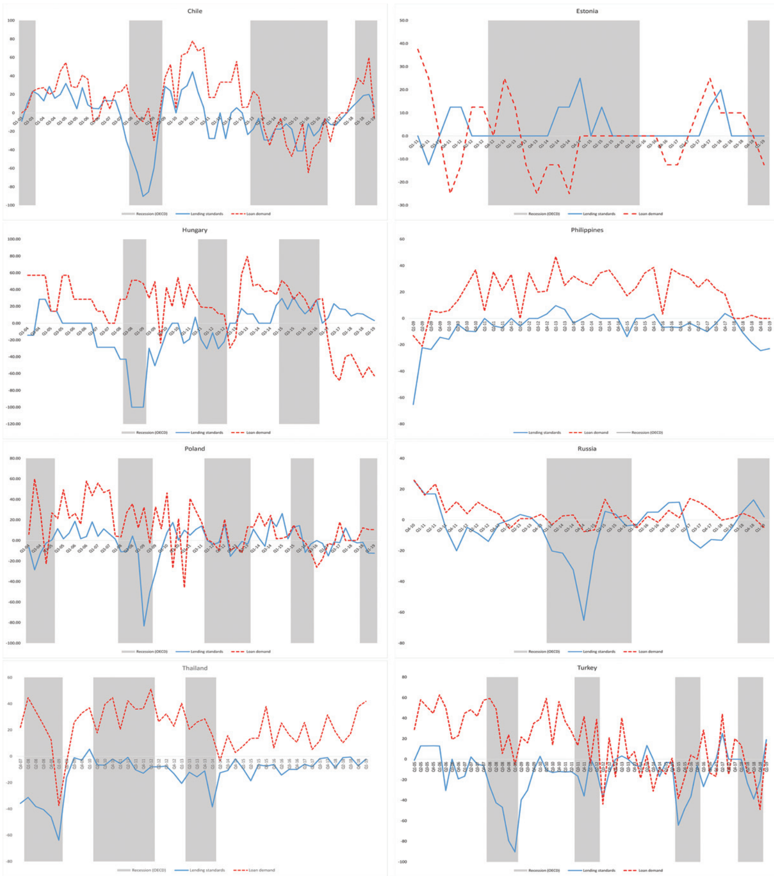
[7] For consistency across countries, we reverse the sign of the lending standards in the original data if an increase denotes tightening.

[8] Discrepancies in the questionnaires do not explain this difference, because the EME bank loan officer survey takes the SLOOS as a benchmark and essentially asks the same questions (see online appendix C for the sources and coverage of surveys as well as examples of the main questionnaires). Thus, the compatibility of the survey is not the primary concern here.

[9] As shown in figure A.2 in online appendix A, banks are still the primary source of corporate financing in the two countries.

[10] The sharp increase in the loan demand of Japanese firms during the global financial crisis is particularly helpful for understanding the factors underlying the cyclical behavior of bank loan demand. The Financial Systems and Bank Examination Department of the Bank of Japan provides detailed information about the

Figure 1. Lending Standards and Loan Demand: Emerging Market Economies



Notes: This figure shows changes in lending standards towards new business loans (solid) and demand for business loans (dashed) in EMEs. Shaded areas denote the recession dates defined by the OECD. Recession dates for the Philippines are not available. The signs of the lending standards in the original data are reversed so that a decrease denotes tightening. See online appendix C for further details on the construction of indexes.

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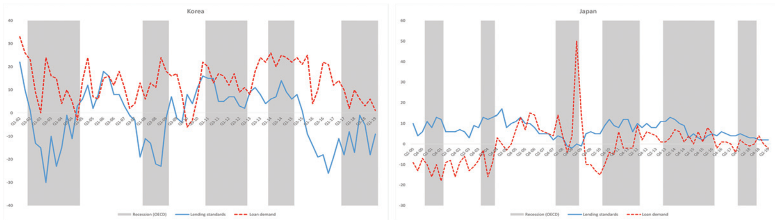
survey results. In 2008:Q4, 22 percent and 44 percent of banks report substantially and modestly stronger loan demand from firms, respectively, whereas only 2 percent report weaker loan demand. Among banks experiencing stronger loan demand, the most important factor attributable to this increase is "customers'

Figure 2. Lending Standards and Loan Demand: Korea (left) and Japan (right)



Notes: This figure shows changes in lending standards towards new business loans (solid) and demand for business loans (dashed) in Korea (left) and Japan (right). Shaded areas denote the recession dates defined by the OECD. The signs of the lending standards in the original data are reversed so that a decrease indicates tightening. See online appendix C for further details on the construction of indexes.

Table 1 summarizes the cyclical pattern shown in the previous graphs as well as the country-level bank dependency ratio to provide a greater structural interpretation. The cyclicality of bank lending standards and loan demand is computed as their correlation with (quarter-over-quarter) real GDP growth. The bank dependency ratio is the ratio of bank credit to the private sector expressed as a percentage of the sum of bank credit plus bond and equity market capitalization averaged from 2001 to 2011. A higher value of the indicator suggests a more bank-oriented financial structure (Gambacorta, Yang, and Tsatsaronis 2014). These data, which provide the relative importance of the banking sector in corporate financing, contain information beyond the absolute importance of the banking sector—often measured by the ratio of bank credit to GDP.[11]

On average, both bank lending standards and loan demand are procyclical, consistent with the well-known "simultaneity problem" when identifying a bank loan supply shock (Jiménez et al. 2014;

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borrowing shifted from other sources to your bank," followed by "customers' internally generated funds decreased" and "customers' funding from other sources became difficult to obtain." Hence, an increase in bank loan demand is clearly a consequence of credit market imperfections rather than an increase in investment opportunities.

[11]No aggregate data on the euro area exist.

Table 1. Banking-Sector Dependency and the Cyclicality of Lending Standards and Loan Demand

Country	**Period**	**Bank Dependence**	$Corr(\Delta y,\Delta s_t)$	$Corr(\Delta y,\Delta d_t)$
Advanced Economies				
United States	1991:Q1–2019:Q2	0.19	0.48*	0.30*
Euro Area	2003:Q1–2019:Q2	N/A	0.69*	0.55*
Japan	2000:Q2–2019:Q2	0.42	0.13	−0.05
Korea	2002:Q1–2019:Q1	0.41	0.24*	0.03
Emerging Market Economies				
Chile	2003:Q1–2019:Q1	0.33	0.48*	0.46*
Estonia	2011:Q1–2019:Q1	0.61	0.01	0.18
Hungary	2002:Q3–2019:Q1	0.63	0.63*	−0.18
Philippines	2009:Q1–2019:Q1	0.37	0.61*	0.27
Poland	2004:Q1–2019:Q1	0.56	0.03	0.10
Russia	2010:Q4–2019:Q1	0.33	0.49*	0.46*
Thailand	2007:Q4–2019:Q1	0.52	0.16	0.25
Turkey	2005:Q1–2019:Q1	0.46	0.38*	0.16
Average		0.43	0.37	0.21

Notes: Bank dependence is measured by the ratio of bank credit to the private sector to the sum of bank credit plus bond and equity market capitalization. A higher value of the indicator suggests a financial structure that is more bank oriented (Gambacorta, Yang, and Tsatsaronis 2014). $Corr(\Delta y,\Delta s_t)$ denotes the correlation between real GDP growth rate and changes in lending standards, whereas $Corr(\Delta y,\Delta d_t)$ denotes the correlation between real GDP growth rate and changes in loan demand. Countries with bank loan officer surveys that are available for more than 30 quarters are included. The bank loan officer survey for Hungary is at a semi-annual frequency before 2009:Q1. * denotes that the correlation is statistically significant at the 5 percent level.

Amiti and Weinstein 2018). However, the substantial heterogeneity across countries masks the average cyclicality, especially in loan demand. In many economies, bank loan demand is acyclical or even countercyclical, which is in sharp contrast to the United States and euro area. The imperfect substitutability between direct and indirect financing and higher dependence on the banking sector as a source of corporate borrowing could explain the distinct pattern.

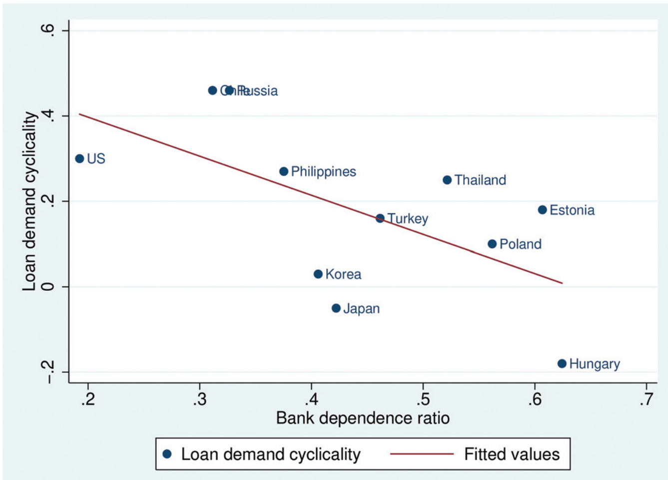
First, bank loan demand may increase during turbulent times if firms have limited access to market finance, as they look to finance countercyclical liquidity needs to manage inventories and trade payables and working capital (e.g., Gertler and Gilchrist 1993). The detailed information from the Japanese bank loan survey about the factors driving the increase in bank loan demand during the global financial crisis is fully consistent with this case. Second, banks also treat firms differently in times of financial distress because they are long-term players in the debt market, whereas bondholders or equity holders are not. Acquiring information about firms, banks attract firms that are likely to face temporary financial distress (e.g., Chemmanur and Fulghieri 1994 and De Fiore and Uhlig 2011). A firm's preference for bank debt over public debt during turbulent times due to credit market imperfections is, therefore, compatible with higher bank dependence in the steady state.

We provide suggestive evidence for this hypothesis by plotting the cyclicality of bank loan demand against the bank dependency ratio. As shown in figure 3, there is a robust negative relationship between the two factors: loan demand is less procyclical in a country with higher banking-sector dependence.[12] Interestingly, Chile and Russia, which have the largest procyclicality of loan demand comparable to the United States, also have the lowest banking-sector dependence. Figure A.3 in online appendix A confirms that this pattern hardly changes when we include offshore bank lending.

Taken together, this empirical regularity implies that economic development does not necessarily translate into the development of public debt markets, and thus banks could still play a unique role

[12]Despite the small sample, the relationship between the two is strong: while the correlation is -0.62 and the associated p-value is 0.04, Spearman's rank correlation coefficient is -0.71, and the associated p-value is 0.02.

Figure 3. Correlation between the Banking-Sector Dependency and the Cyclicality of Loan Demand



Notes: Bank dependence ratio is the ratio of bank credit to the private sector that is expressed as a percentage of the sum of bank credit plus bond and equity market capitalization. A higher value of the indicator suggests a financial structure that is more bank oriented (Gambacorta, Yang, and Tsatsaronis 2014). Bank loan officer surveys of emerging economies available for more than 30 quarters are included. The bank loan officer survey for Hungary is at a semi-annual frequency before 2009:Q1. The cyclicality of loan demand is taken from table 1.

in providing credit even in advanced economies.[13] Although a small sample prevents us drawing a clear-cut conclusion, the decline in the volume of bank lending during recessions in countries with higher bank dependency is likely to be driven by a supply-side disruption in contrast to the United States and euro area, where both supply and demand factors contribute to the reduction in the volume of bank lending. Thus, ignoring confounding factors is likely to underestimate the adverse effect of a loan supply shock in bank-based economies.

[13]For example, Demirguc-Kunt and Levine (2001) found that legal origin is an important determinant of the bank- and market-based financial structure across a large group of countries.

2.2 Determinants of the Bank Lending Rate

Motivated by the distinct pattern in the cyclicality of loan demand in bank-based economies, we ask whether the bank lending rate in these countries truly reflects credit market conditions. If not, the observed bank lending rate could fail to equate supply and demand for bank loans, which implies the possibility of a credit market disequilibrium; therefore, the failure of the conventional sign restriction applied to the price (lending rate) and quantity (volume) of bank loans to identify a loan supply shock in the literature.

To test this possibility, we estimate the following panel regression with country and time fixed effects:

$$\begin{aligned} \Delta i^L_{i,t} = \alpha_i + \alpha_t + (\beta_0 + \beta_1 \times high_i)\Delta S_{i,t} \\ + (\gamma_0 + \gamma_1 \times high_i)\Delta D_{i,t} + X_{i,t} + u_{i,t}, \\ u_{i,t} \sim N(0, \Sigma), \end{aligned} \quad (1)$$

where $i^L_{i,t}$ is the bank loan rate in country i at time t, $S_{i,t}$ is a supply factor proxied by bank lending standards (an increase indicates easing), and $D_{i,t}$ is a demand factor proxied by bank loan demand. α_i and α_t capture the country and time fixed effects, respectively. $high_i$ denotes a dummy variable indicating that country i has a high (i.e., above median) bank dependency ratio, and $X_{i,t}$ includes additional time-varying country-level variables.

Because we cannot reject the null hypothesis that the bank lending rate is nonstationary, we take the first difference and use it as a dependent variable.[14] The country fixed effects capture any time-invariant factors specific to each country, and the time fixed effects control for any movements at the global level that affect the bank lending rate in every country, such as global financial cycles and U.S. monetary policy. If the bank loan officer survey captures both the supply and the demand factors of bank lending correctly, the bank loan rate must be negatively (positively) associated with an increase in lending standards (loan demand), other things being constant.

[14]The Dickey–Fuller unit-root test for individual countries cannot reject the I(1) process of the bank lending rate except for Turkey, Chile, and Poland. After taking the first difference, the null of the existence of a unit root is rejected in every country.

Any deviation from this theoretical relationship suggests that the observed volume of bank loans does not necessarily equate demand and supply, which casts doubt on the ability of conventional sign restrictions to identify a loan supply shock using the bank loan rate.

Table 2 shows the estimation results, which highlight the problem of using the bank lending rate for the identification. Column 1 shows the baseline result. The estimated coefficients on lending standards and loan demand are statistically significant, and their signs are consistent with the textbook theory of interest rates. However, the interaction term of loan demand and the dummy variable is negative and statistically significant, indicating that the theoretical relationship between loan demand and the interest rate does not hold in a bank-based economy. The interaction term of lending standards and the dummy variable is close to zero and statistically insignificant, suggesting no difference between the two groups in this case.

Columns 2–7 confirm the robustness of our findings. In column 2, we control for changes in CPI inflation (quarter-over-quarter) since lending standards and loan demand are real factors, whereas the dependent variable is nominal. Although changes in the inflation rate enter the expected sign with statistical significance, controlling for the inflation rate does not affect the main results. We further control for real GDP growth, which is associated with both lending standards and loan demand. While we must take caution in interpreting the results because of multicollinearity, controlling for real GDP growth hardly changes the main result (column 3). We also take the lagged values of the independent variables in robustness checks (column 4). Although the statistical significance of the interaction term of loan demand and the dummy variable weakens, the results are qualitatively similar to the baseline results. Column 5 shows the results from limiting the sample from 2010:Q1 to rule out the possibility that the main finding is driven by the global financial crisis.

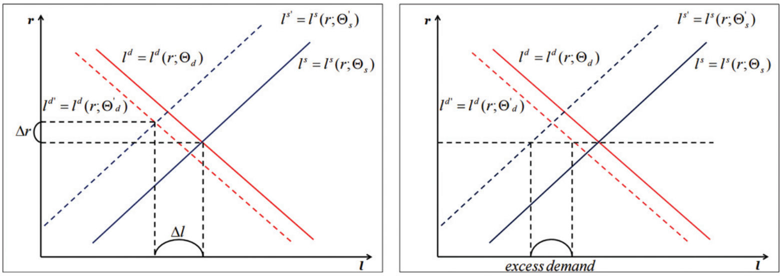
Instead of the estimation using the interaction terms, columns 6 and 7 show the results from the subsample estimation of countries with high and low bank dependency, respectively. Despite the weak power of the test due to the reduced sample size, our main finding is preserved. An increase in loan demand, if anything, is followed by a decline in the bank loan rate in bank-based economies. Taken

Table 2. Determinants of the Bank Loan Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lending Standards	−0.015**	−0.012**	−0.012**	−0.006	−0.017*	−0.005	−0.017**
	(0.006)	(0.004)	(0.004)	(0.007)	(0.009)	(0.003)	(0.005)
Loan Demand	0.010*	0.010*	0.011**	0.007*	0.008*	−0.005	0.012**
	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.005)	(0.005)
High × Lending Standards	0.000	0.002	0.005	−0.001	−0.003		
	(0.008)	(0.007)	(0.006)	(0.007)	(0.015)		
High × Loan Demand	−0.016**	−0.016**	−0.017**	−0.005	−0.014***		
	(0.006)	(0.006)	(0.006)	(0.003)	(0.004)		
Changes in Inflation		0.099***	0.098***			0.088**	0.117**
		(0.018)	(0.017)			(0.032)	(0.036)
Real GDP Growth			−0.012			−0.031***	0.001
			(0.009)			(0.007)	(0.006)
Country Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	625	625	616	615	410	330	284
R-squared	0.252	0.356	0.375	0.210	0.266	0.412	0.480

Notes: Heteroskedasticity-robust standard errors are in parentheses. Standard errors are clustered at the country level. ***, **, and * denote significance at the 1 percent, 5 percent, and 10 percent levels, respectively. Standard errors are in parentheses.

Figure 4. Identifying a Loan Supply Shock under Credit Market Equilibrium (left) and Disequilibrium (right)



Notes: The left panel illustrates a negative loan supply shock when the bank lending rate equates the supply and demand for bank loans, whereas the right panel illustrates the case when the bank lending rate does not equate the two.

together, we find robust evidence that the bank loan rate fails to reflect a loan demand factor in a country in which firms heavily rely on the banking sector. This finding motivates the use of bank loan officer surveys to identify structural shocks.

3. Empirical Framework

3.1 Illustration of the Credit Market Disequilibrium

The left panel in figure 4 highlights the empirical difficulty of identifying a loan supply shock from demand-side factors when using aggregate data. Both the supply of (l^s) and demand for (l^d) bank loans depend on the bank lending rate (r) and other factors (Θ_s and Θ_d), which shift the supply and demand curves. For the supply curve, such factors include the bank deposit rate, the cost of evaluating the creditworthiness of borrowers, and the minimum reserve ratio. The need for working capital, cost of direct financing, and availability of trade credit are examples of factors that shift bank loan demand.

In addition, factors simultaneously shift the supply and demand curves in the same direction (i.e., $\Theta_s \cap \Theta_d \neq \emptyset$), as illustrated in figure 4. Such factors include the expectation about the prospects of the economy and uncertainty surrounding the course of monetary policy. Therefore, the aggregate data are likely to show a combination of loan supply and demand shocks, which corresponds to the "simultaneity problem" when identifying a bank loan supply shock (Jiménez et al. 2014; Amiti and Weinstein 2018). To resolve this issue using aggregate data, the sign-restriction approach of Uhlig (2005) has been applied to the credit market (Busch, Scharnagl, and Scheithauer 2010; De Nicolò and Lucchetta 2011; Helbling et al. 2011; Hristov, Hülsewig, and Wollmershäuser 2012; Meeks 2012; Finlay and Jääskelä 2014; Halvorsen and Jacobsen 2014; Gambetti and Musso 2017). The intuition is simple; a loan supply shock must move the interest rate and volume of loans in opposite directions.

However, this identification approach is only valid when the bank lending rate reflects credit market conditions. If r observed from the data cannot equate the demand for—and the supply of—bank loans, the equilibrium condition ($l^* = l^s = l^d$) may not hold, and either excess supply or excess demand can exist ($l^* = \min\{l^s, l^d\}$), as illustrated by Laffont and Garcia (1977). If this were true, the real effect of loan supply shocks could be considerably larger than any model using the lending rate would predict. The right panel in figure 4 demonstrates the case of credit rationing as a result of excess loan demand.[15]

In this regard, the bank loan officer surveys can improve the identification of structural shocks by providing information beyond the bank lending rate. For example, Lown and Morgan (2006) and Ravn (2016) showed theoretically and empirically that bank lending standards obtained from the bank loan officer surveys adequately summarize various nonprice lending terms in typical bank business loans, thereby capturing the supply factors of bank credit. Imposing a non-negative sign restriction on the loan demand proxy directly, we can further eliminate the contribution of a simultaneous drop in loan demand to a negative loan supply shock, which is not feasible in the identification scheme using the interest rate.

3.2 Sign-Restriction Approach

We briefly summarize the sign-restriction approach here (refer to Uhlig 2005 for more details). Instead of relying on restrictions based

[15] Without loss of generality, we focus on excess demand for bank loans in the example.

on the timing of shocks, this identification approach can produce impulse responses consistent with the theoretical predictions. Consider a reduced-form VAR model:

$$Y_t = \sum_{p=1}^{P} B_p Y_{t-p} + u_t, \tag{2}$$
$$u_t \sim N(0, \Sigma),$$

where Y_t is an $n \times 1$ vector of the observed economic variables, B_p are $n \times n$ matrices of autoregressive coefficients, and u_t are an $n \times 1$ vector of reduced-form residuals with a variance-covariance matrix Σ. We estimate the VAR using Bayesian techniques, with the prior and posterior distributions of the reduced-form VAR following an n-dimensional normal-Wishart distribution.

Because the reduced-form residuals u_t bear no structural interpretation, we incorporate additional restrictions to identify the structural shocks. As in Faust (1998), Canova and De Nicolo (2002), and Uhlig (2005), we identify shocks by imposing sign restrictions. Consider an $n \times n$ matrix A, which relates reduced-form residuals u_t to structural shocks ϵ_t:

$$u_t = A\epsilon_t, \tag{3}$$
$$\Sigma = E[u_t u_t'] = AE[\epsilon_t \epsilon_t']A' = AA'.$$

For any orthogonal matrix Q such that $QQ' = I_n$ and $\Sigma = AQQ'A$, there is also an admissible decomposition for which $u_t = AQ\tilde{\epsilon_t}$ and $\tilde{\epsilon_t}\tilde{\epsilon_t}' = I_n$, where $\tilde{\epsilon_t}$ denotes the (many) different structural shocks implied by the alternative identification. Although different orthogonal matrices Q produce different signs and magnitudes of the impulse responses, discriminating among them from the data is not possible, as they imply identical VAR representations. Therefore, for any decomposition $\Sigma = AA'$, there exist infinitely many identification schemes $AQ^{(k)}$ for $k = 1, 2, \ldots, \infty$, such that $\Sigma = AQ^{(k)}Q^{(k)'}A'$. Following Rubio-Ramirez, Waggoner, and Zha (2010), an orthogonal matrix $QQ' = I$ is generated from a QR decomposition of some random matrix W, which is drawn from an $N(0, I_n)$ distribution.

Unlike Uhlig (2005), who identified only one (monetary policy) shock, we attempt to identify multiple structural shocks simultaneously:

(i) Draw $d = 1, \ldots, m$ models from the posterior distribution of the VAR (model d consists of VAR parameters $B_j^{(d)}$ and a covariance matrix $\Sigma^{(d)}$).

(ii) For $j = 1, 2, \ldots,$ draw randomly from the m models.

(iii) Choose $A = \tilde{A}^{(j)}$, where $\tilde{A}^{(j)}$ is any Cholesky decomposition of $\Sigma^{(j)}$, such that $\Sigma^{(j)} = \tilde{A}^{(j)}\tilde{A}^{(j)\prime}$.

(iv) For each j, draw random matrices $Q^{(k(j))}$, $k(j) = 1, \ldots, K$ until the impulse response functions implied by B_p^j and identification schemes $\tilde{A}^{(j)}Q^{(k(j))}$ satisfy the sign restrictions. If all the sign restrictions are satisfied, we define the combination of model j and identification scheme $\tilde{A}^{(j)}Q^{(k(j))}$ as an accepted model.

(v) Iterate over (ii)–(iv) until 200 models are accepted. We assign an equal positive weight to the accepted draws and a zero weight to those that violate the restrictions.

3.3 Identification Strategy

We do not attempt to identify every structural shock in the system because imposing further sign restrictions is not necessarily desirable for our purpose (Uhlig 2005). The approach taken in this study identifies loan supply and demand shocks by imposing sign restrictions on three variables—namely, d_t, s_t, and l_t—and remains agnostic about the response of r_t and y_t. This identifying scheme is in sharp contrast to those in the empirical literature imposing restrictions on the interest rate to identify a loan supply shock. We show that this scheme achieves a cleaner identification of the shock when credit market imperfections prevent the equilibrating role of the interest rate.

Our identification strategy is also a departure from earlier analyses that impose a sign restriction on output to identify a credit supply shock (e.g., Busch, Scharnagl, and Scheithauer 2010; Tamási and Világi 2011; Hristov, Hülsewig, and Wollmershäuser 2012).[16]

[16]For example, Busch, Scharnagl, and Scheithauer (2010) and Tamási and Világi (2011) imposed a restriction on output for two quarters without

In practice, a contraction in bank lending does not necessarily lead firms to change their current production immediately. Instead, the lower availability of funding restricts production in later periods. Moreover, remaining agnostic about the response of output helps us distinguish a credit-specific demand shock from an aggregate demand shock.

While a decline in the volume of bank loans must follow both adverse loan supply and demand shocks by design, a negative loan supply shock should not decrease loan demand, and a negative loan demand shock should not reduce loan supply in the joint identification of both shocks. These restrictions are intuitive and similar to the assumption in the bank lending model of Hülsewig, Mayer, and Wollmershäuser (2006). Joint restrictions on lending standards and loan demand allow for a clean identification of a loan supply shock from a loan demand shock when the bank lending rate fails to respond to excess loan demand. Our identification strategy shares the same spirit as Helbling et al. (2011), who controlled for an endogenous credit response to expected fluctuations in future activity using sign-restriction VARs.[17]

We simultaneously identify multiple structural shocks.[18] Identifying each structural shock individually does not guarantee the orthogonality of the multiple shocks, thus casting doubt on whether the identified shocks are truly structural. As in Helbling et al. (2011), we limit the baseline model to the identification of two shocks (loan supply and loan demand) because the more orthogonal conditions are imposed, the harder it is to obtain impulse vectors satisfying the sign restrictions. Table 3 summarizes the sign restrictions used in the baseline VAR model. The symbol "?" indicates that the signs of the responses are indeterminate a priori.

simultaneously identifying aggregate demand or aggregate supply shocks, which may contaminate their "identified" credit supply shock. Hristov, Hülsewig, and Wollmershäuser (2012) imposed a restriction on output for a year, which prevents the author from identifying the real effect of credit supply shocks in the short run.

[17]To purge the potential demand channel, Helbling et al. (2011) required that the decline in credit not be followed by a decrease in productivity or an increase in default rates. They did not impose any restriction on the response of output.

[18]Because the number of structural shocks is still less than the number of variables, this model is partially identified.

Table 3. Sign Restrictions on a Contractionary Shock: Baseline Model

Structural Shock	d_t	s_t	l_t	r_t	y_t
Loan Supply Shock	≥ 0	≤ 0	≤ 0	?	?
Loan Demand Shock	≤ 0	≥ 0	≤ 0	?	?

Notes: Restrictions are imposed for two quarters. ? denotes indeterminate responses a priori.

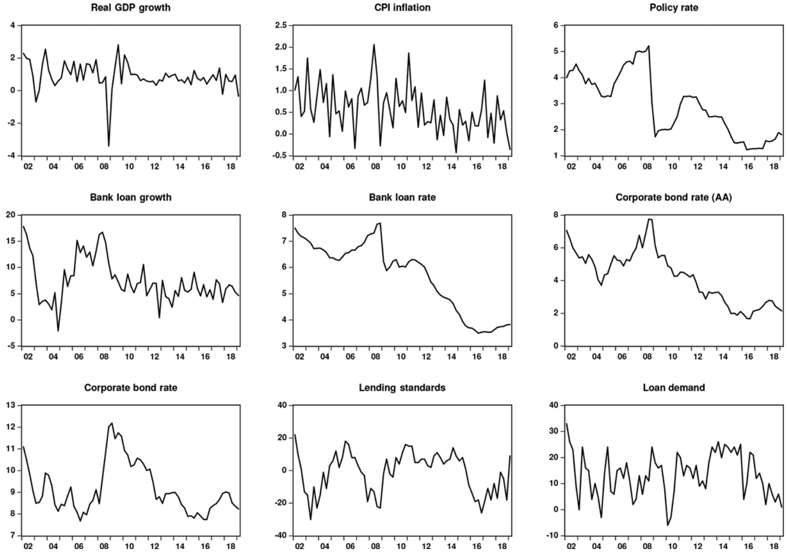
We estimate the VAR model in levels because a large body of the literature on this issue suggests that this is still desirable even if the variables have unit roots (e.g., Sims, Stock, and Watson 1990). Although the Bayesian information criterion suggests two lags, we use four lags ($p = 4$) in the baseline model, considering the quarterly frequency of the data. Following Uhlig (2005), all restrictions are imposed for two quarters ($k = 2$) following the initial shock. We evaluate the sensitivity of the results to these specifications in section 5.

3.4 Korean Macroeconomic Data

We use the Korean economy as a benchmark for the following Bayesian VAR analysis to illustrate the failure to identify a loan supply shock when relying on the interest rate. We then demonstrate how the alternative identification scheme resolves this issue. We choose Korea because it has one of the most extended bank loan officer surveys available and ample data availability compared with EMEs, especially detailed data on bank loans to the nonfinancial business sector and corporate bond markets.[19] These data are

[19]We consulted with the Banking System Analysis team at the Bank of Korea and learned about the high quality of the Korean bank loan officer survey. After the Asian financial crisis in 1998, the Bank of Korea learned the importance of the timely monitoring of the banking sector and has since invested resources in constructing and conducting the survey. For the survey of commercial banks we use in the present study, two members of the Banking System Analysis team visit the headquarters of each bank on a quarterly basis, and their counterparty from the bank in charge is typically a high-level manager with sufficient knowledge about the banking system. Given the long-term relationship between the Bank of Korea and surveyed commercial banks, these managers take the survey seriously.

Figure 5. Korean Economic Data: 2002:Q1–2019:Q1



Notes: Bank loan growth, real GDP growth, and the inflation rate are the quarter-on-quarter growth of CPI deflated total bank loans to the business sector, real GDP, and the level of CPI, respectively. The policy rate is measured by the overnight call rate. All data are taken from the Bank of Korea.

crucial for understanding the transmission mechanism of a bank loan supply shock.

Figure 5 shows the evolution of the key macrovariables as well as bank lending standards and loan demand at a quarterly frequency. The inflation rate, policy rate, and corporate bond yields are also displayed because they are used in the extended model presented in section 5.3 to investigate the comprehensive effect of loan supply and loan demand shocks as well as their transmission channel.[20] To ease

Even if measurement errors exist due to careless responses, they will go against finding any sensible results from the VAR analysis using the survey as the main input.

[20] Although we use the weighted composite indicator for bank lending standards and loan demand throughout the paper, the results are robust to the use of an indicator specific to small and medium-sized enterprises. The correlation between this indicator and the composite indicator is 0.88 for lending standards and 0.83 for loan demand.

the comparison, these variables are shown in the first (log) difference (quarter-over-quarter growth) except for the interest rate.

Although Korea is a small open economy, using a closed-economy framework hardly affects the extent to which bank lending to non-financial firms is dominated by national banks, as documented by Banker, Chang, and Lee (2010). Korea adopted a flexible exchange rate regime throughout the sample period, which mitigated the direct impact of foreign shocks on domestic bank lending. Moreover, most existing studies using a sign-restriction approach to identify credit supply shocks in the small open-economy context do not include the exchange rate in their VAR system (Busch, Scharnagl, and Scheithauer 2010; Helbling et al. 2011; Hristov, Hülsewig, and Wollmershäuser 2012; Gambetti and Musso 2017). Indeed, if some studies do, they do not impose any restrictions on the exchange rate to identify credit supply shocks (Tamási and Világi 2011; Finlay and Jääskelä 2014). Thus, for the parsimony of the model, we abstract from any foreign variables and the exchange rate.

At the beginning of the sample, business-sector bank lending plummeted with the economic downturn in 2003, driven by the bursting of the credit card lending boom. Bank lending picked up quickly and expanded rapidly until the sharp recession in 2008–09, which is consistent with the ample evidence on excessive domestic credit expansion as a robust indicator of financial crisis globally (Gourinchas and Obstfeld 2012). Then, bank lending growth has moderated over the past decade. The problem of using an identification scheme based on the bank lending rate readily stands out at first glance. For example, a sharp drop in the bank lending rate—supported by an expansionary monetary policy—in the early stage of the global financial crisis (2008:Q4–2009:Q1) masks deteriorating conditions in the bank loan market (reflected by the increase in loan demand accompanied by the tightening of lending standards and a decline in the volume of bank loans). The deterioration in credit market conditions is also reflected in the sharp increase in corporate bond yields, especially for risky borrowers.

If we conduct the standard sign-restriction approach using quantity (i.e., the volume of loans) and price (i.e., bank lending rate) information alone, the decline in the observed volume of bank loans is likely to be attributed to a decrease in loan demand, implying that this is an optimal response of firms facing a reduction in loan demand for their products. However, if the decline in bank lending is driven by a supply-side disruption despite the increase in demand, this implies a more binding borrowing constraint, and therefore the adverse effect on the macroeconomy could be more significant. Moreover, if the interest rate fails to restore the loan market equilibrium, the economic consequences and optimal policy responses might be different than the demand-driven decline in credit. We delve into a more formal analysis to demonstrate the identification problem and provide a solution.[21]

4. Baseline Results

4.1 Results from Using Conventional Sign Restrictions

Before we present the main results using our preferred identification scheme, we show how standard sign restrictions relying on the price-quantity framework fail to identify a loan supply shock. This example illustrates the importance of the nonprice information from the bank loan officer survey when identifying bank loan supply shocks, which is particularly true for bank-based economies in which the unique role of banks in alleviating information asymmetry during turbulent times results in countercyclical loan demand.[22]

Following much of the literature on identifying a credit supply shock using the sign-restriction approach, we impose restrictions on price (i.e., bank lending rate (r_t)) and quantity (i.e., the volume of

[21] A standard VAR approach using short-run restrictions (i.e., Cholesky ordering) may still achieve a clean identification of loan supply and demand shocks as long as the information from the bank loan officer survey is used. If lending standards and loan demand can capture bank loan dynamics as predicted by the supply and demand interpretation, additional identifying assumptions (i.e., sign restrictions) would be unnecessary, and inferences of the structural shocks would be straightforward. In online appendix B, we demonstrate that this is not necessarily the case and that the sign-restriction approach is more desirable.

[22] For example, the government ownership of banks is common in bank-based economies, and the lending decisions of these banks are influenced by factors other than the interest rate (Dinç 2005) in contrast to private banks (Brei and Schclarek 2013). In addition, nonprice lending terms based on the soft information produced from a long-term relationship between banks and firms can be more important than the interest rate when banks make their lending decisions (Uchida, Udell, and Yamori 2012). Thus, considering a factor other than the bank lending rate is particularly crucial in bank-based economies.

Table 4. Conventional Identifying Assumptions on a Contractionary Shock

Structural Shock	l_t	r_t	y_t
Loan Supply Shock	≤ 0	≥ 0	?
Loan Demand Shock	≤ 0	≤ 0	?

Notes: Restrictions are imposed for two quarters. ? denotes indeterminate responses a priori.

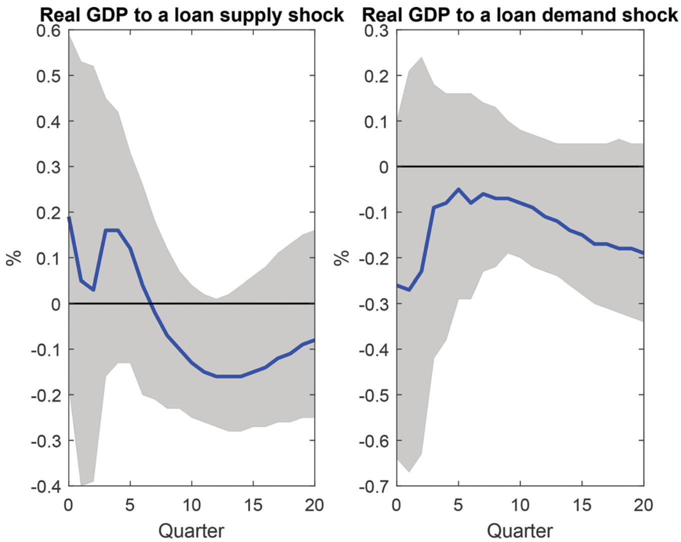
bank loans (l_t)). This identifying assumption corresponds to table 4, and the rest of the identification procedure is the same as in the baseline model discussed in sections 3.2 and 3.3. Here, we illustrate the most parsimonious model; however, the results remain similar when we include other macroeconomic variables such as prices and the policy rate and impose a set of sign restrictions on these variables following the literature (Busch, Scharnagl, and Scheithauer 2010; Helbling et al. 2011; Hristov, Hûlsewig, and Wollmershäuser 2012; Gambetti and Musso 2017).

Figure 6 shows the effects of negative loan supply and loan demand shocks on output. Following Uhlig (2005), the solid lines plot the median impulse responses, and the shaded areas note their 16th and 84th percentile bands from 200 accepted draws. Under the conventional identification scheme using the bank lending rate, a negative loan supply shock does not have any recessionary effect on output.[23] This finding is clearly at odds with the theoretical predictions and existing empirical evidence, indicating the poor identification of a loan supply shock. Using the spread between the bank lending rate and policy rate instead delivers similar results (see figure A.4 in online appendix A). These results also corroborate the suggestive evidence from the panel estimation in which the bank lending rate does not reflect credit market conditions in bank-based economies.

Against this background, we analyze the effects of bank loan supply and demand shocks on the Korean economy using our preferred

[23] Increasing the length of restriction horizons only exacerbates the failure in the identification. The results are available upon request.

Figure 6. The Response of Output: Conventional Identifying Assumptions Using the Lending Rate



Notes: A negative loan supply shock (left) and a loan demand shock (right) are identified by restrictions on the bank lending rate and the volume of bank loans. Solid lines plot the median impulse responses, and the shaded areas note their 16th and 84th percentile bands from 200 accepted draws.

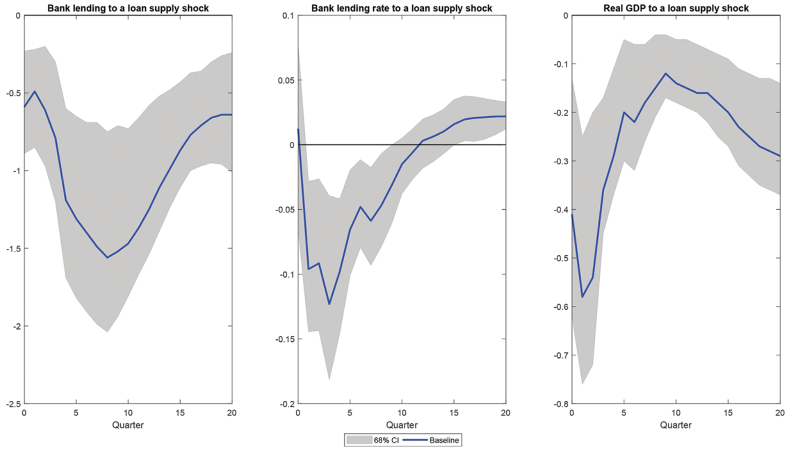
identification strategy in three steps. First, we derive the impulse responses of the variables in the VARs to the identified shocks. Second, we compute the variances of the macrovariables attributed to these shocks. Third, we decompose historical output fluctuations into the parts explained by each of the structural shocks to evaluate their role over business cycles.

4.2 Impulse Responses

Figure 7 shows the responses of the macrovariables to adverse bank loan supply shocks.[24] A decline in bank loans follows an adverse loan supply shock by design. However, the response is persistent

[24]The median and confidence intervals are computed from all the impulse responses that satisfy the sign restrictions. Using the terminology of Paustian (2007) and Fry and Pagan (2011), the confidence intervals reflect both the

Figure 7. The Responses to a Negative Loan Supply Shock



Notes: Solid lines plot the median impulse responses, and the shaded areas note their 16th and 84th percentile bands from 200 accepted draws.

despite the two-quarter restriction. We impose no restrictions on the response of the bank loan rate and output, leaving it open agnostically. The bank loan rate decreases sharply in response to a negative loan supply shock. This finding is no longer surprising because we have already demonstrated that the bank loan rate fails to capture adverse credit market conditions. In contrast to the conventional identifying assumption, we find a strong negative effect on real GDP. The quantitative effect of the identified loan supply shocks is significant (a 0.6 percent drop in real GDP after two quarters) and persistent, in line with Meeks (2012)'s findings for the United States (a 1 percent drop in industrial production) and those of Hristov, Hülsewig, and Wollmershäuser (2012) for the euro area (a 0.6 percent drop in real GDP) using a similar sign-restriction approach.

sampling uncertainty and the modeling uncertainty stemming from the non-uniqueness of the identified shocks. In section 5.2, we check the sensitivity of the results using the median target method proposed by Fry and Pagan (2011).

A vast body of the empirical literature, including Lown and Morgan (2006), Helbling et al. (2011), Hristov, Hülsewig, and Wollmershaüser (2012), Meeks (2012), and Bassett et al. (2014), has focused only on credit supply shocks rather than credit demand shocks because it is difficult to distinguish the latter from aggregate demand shocks.[25] Unlike these earlier studies, we explicitly disentangle loan demand shocks from loan supply shocks using the information from the bank loan officer survey.

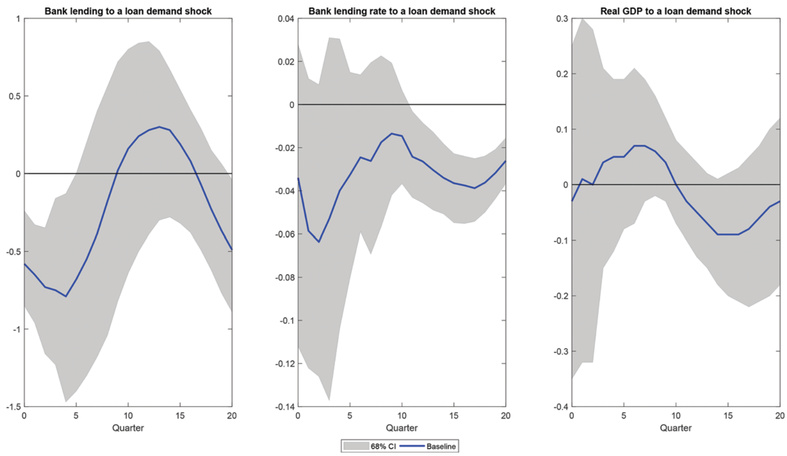
Figure 8 shows that the decline in bank loans due to the reduction in loan demand does not have any adverse effect on output. If anything, subsequent analyses point to the positive effect on output, which seems puzzling if a decrease in loan demand is an optimal response by firms facing a reduction of demand for their products.[26] However, considering the implication of credit market imperfections on a firm's choice of external debt (Diamond 1991; Chemmanur and Fulghieri 1994; Hale 2007; De Fiore and Uhlig 2011), a decline in loan demand signals easier access to public debt markets for financing.[27] In a related study using a sign-restriction VAR approach, Peersman (2011) found that loan supply and demand shocks have contrasting effects on euro-area output. He interpreted this puzzling effect by noting that exogenous loan demand shocks capture the consequences of changes in access to alternative forms of finance or shifts in borrowers' preferred volume of lending. In section 4.5, we test this mechanism using data on corporate bond spreads.

[25] Finlay and Jääskelä (2014) is an exception, as they identified both credit supply and demand shocks by imposing sign restrictions on the volume of credit and credit spreads for three small open economies (Australia, Canada, and the United Kingdom). However, using corporate bond spreads as a price indicator of bank credit is questionable, as bank financing and bond financing are not perfect substitutes. Moreover, corporate bond spreads are known to be an independent business cycle indicator via a risk channel (e.g., Gilchrist and Zakrajšek 2012 and Faust et al. 2013).

[26] Because the impact of both identified shocks on the volume of bank loans is the same, the difference in the size of the effect cannot explain the qualitative difference in the effects on output.

[27] This is also consistent with Friedman and Kuttner (1993) and Bernanke and Gertler (1995)'s arguments that after a negative shock, bank loan demand may increase to finance working capital and inventories due to limited access to market finance.

Figure 8. The Responses to a Negative Loan Demand Shock



Notes: Solid lines plot the median impulse responses, and the shaded areas note their 16th and 84th percentile bands from 200 accepted draws.

4.3 Variance Decomposition

We evaluate the quantitative importance of these two structural shocks for explaining the variation in bank loans, the bank loan rate, and real GDP. Table 5 shows that a loan supply shock explains a substantial share of the variation in bank loans (20 percent) and real GDP (28 percent) after one quarter. The significant role of the shock in the short run is by construction (i.e., the sign restrictions applied to the first two quarters). After five years, this shock explains about 10 percent of the variation in each variable, within a range of 10 percent and 20 percent for output demonstrated in earlier studies using the sign-restriction approach (Helbling et al. 2011; Hristov, Hülsewig, and Wollmershäuser 2012; Meeks 2012; Finlay and Jääskelä 2014; Halvorsen and Jacobsen 2014).

While a bank loan demand shock explains 26 percent of the variation in bank loans after one quarter, the importance of the shock quickly diminishes over the estimation horizon. After five years, a loan demand shock explains only 6 percent of the variation in real GDP, which is consistent with its insignificant effect on the output

Table 5. Forecast Error Variance Decomposition: Baseline Model

Structural Shock	Horizon (Quarters)	Bank Loans	Bank Loan Rate	Real GDP
Loan Supply Shock	1	20.32	8.07	27.91
	4	10.65	9.88	10.35
	20	10.23	10.29	10.02
Loan Demand Shock	1	26.31	10.31	6.26
	4	6.03	6.40	7.02
	20	6.43	6.60	6.64

Notes: The share of forecast error variance decomposition (percent) explained by (orthogonal) loan supply and loan demand shocks. The reported variance decomposition does not necessarily add up to 100 percent because other unidentified shocks make up the balance.

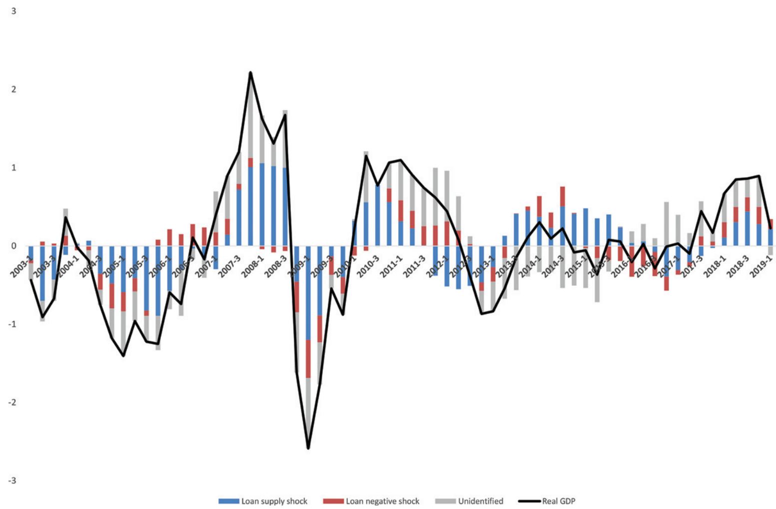
shown in the impulse response function analysis. Taken together, loan supply and demand shocks are not dominant drivers of output fluctuations in Korea on average, but rather play a non-negligible role.[28]

4.4 Historical Decomposition of Output Fluctuations

While the previous exercise illustrated the overall importance of the identified structural shocks for explaining the macrovariables, it is interesting to learn how their contribution changes over business cycles, especially during the global financial crisis period. Using a dynamic stochastic general equilibrium (DSGE) model augmented with financial frictions, Perri and Quadrini (2018) claimed that credit shocks are more relevant than productivity shocks for explaining the global financial crisis. Faust et al. (2013) found that the ability of credit market variables to forecast economic activity is more potent during recessions than expansions. Bank loan supply

[28]The variance decomposition exercise here should be taken with caution because we identified only a subset of structural shocks. The reported variance decomposition does not necessarily add up to 100 percent because other unidentified shocks make up the balance. See Fry and Pagan (2011) for further details.

Figure 9. Historical Decomposition of Output Fluctuations



Notes: The solid black line denotes the structural residuals of real GDP during the sample period. The blue and red bars denote the contribution of loan supply and loan demand shocks in the residuals, respectively (see online version at http://www.ijcb.org for figures in color). Other unidentified shocks make up the balance.

shocks may also have asymmetric importance between expansions and recessions despite their moderate importance in variance decomposition (table 5).

Figure 9 shows the historical decomposition of real GDP during the sample period.[29] Loan supply shocks accounted for 40 percent of the Korean output decline during the global financial crisis, consistent with earlier findings for other regions that demonstrate the moderate role of loan supply shocks for the full sample but a substantially more significant role during crisis periods (Meeks 2012; Gambetti and Musso 2017). Loan supply shocks also played a dominant role during the earlier expansion period before the recession, consistent with a credit-driven boom followed by a bust. The contribution of loan supply shocks has been moderated since then.

[29] Because we use four lags in the baseline model, the historical decomposition starts from 2003:Q1.

While loan demand shocks contribute a non-negligible share of the output decline, their contribution over business cycles is somewhat limited.

4.5 Discussion of the Results

Using the preferred identifying assumption based on the Korean bank loan officer survey, we find robust evidence of the recessionary effect of a negative bank loan supply shock. On the contrary, we do not see any adverse effect on the output of a negative bank loan demand shock, which seems puzzling from the prediction of a standard frictionless model in which a firm's demand for credit is determined by the expectation of demand for its products. However, our finding is consistent with the prediction of theories on the choice between bank loans and publicly traded debt (Diamond 1991; Chemmanur and Fulghieri 1994; Hale 2007; De Fiore and Uhlig 2011). According to the theoretical prediction under credit market imperfections, the preference for public debt over bank debt is more likely for high-quality projects (e.g., less uncertainty about future cash flows, higher collateralized value), and thus we would expect higher relative demand for bank debt in recessions, especially in bank-based economies.

In this case, a reduction in demand for bank loans may signal an improvement in access to other sources of financing and alleviated borrowing constraints, meaning that the non-recessionary effect we find is unsurprising. To test this hypothesis, we include the credit spread, measured by the difference between risky and safe corporate bond yields, in the baseline VAR model. The credit spread captures distress in corporate bond markets, thereby measuring whether an alternative financing condition is alleviated after a loan supply or demand shock. We use the same set of sign restrictions as in table 3 and do not impose any sign restrictions on the response of the credit spread to let the data speak for themselves.

Figures A.5 and A.6 in online appendix A compare the responses of the macrovariables to loan supply and demand shocks when the credit spread is included in the baseline VAR model. The contrasting responses of the credit spread to these shocks shed light on the mechanism through which each shock affects the real economy. Despite the decline in the bank lending rate following the negative loan supply shock, the credit spread increases sharply, suggesting that firms' access to the public debt market becomes limited. Thus, the identified negative loan supply shock corresponds to an economy-wide contraction in credit supply, which serves as a driver of output fluctuations. On the contrary, the credit spread falls significantly after the negative loan demand shock, implying that firms benefit from the alleviated financing conditions in the public debt market and, therefore, the relaxed borrowing constraints. With the inclusion of a credit spread variable, we now find an expansionary effect of the negative loan demand shock. Taken together, the extended model highlights the imperfect substitutability between bank loans and corporate bonds and its consequence on the macroeconomy.[30]

5. Robustness Checks

5.1 Alternative VAR Specification

Following Uhlig (2005), we impose sign restrictions for the two quarters after the structural shock. However, setting the length of the restrictions is still an open choice. We test the sensitivity of the baseline results by varying the restriction horizons ($k = 1$ and 3). We also check the robustness by changing the lag orders of the VAR system ($p = 2$ and 6). Figure A.7 in online appendix A shows that none of these changes affects the qualitative effects of the identified shocks on output.

5.2 Median Model

We plot the pointwise posterior medians of the impulse response functions from the 200 accepted draws to summarize the dynamic response of each variable to a loan supply/demand shock. However, Fry and Pagan (2011) and Inoue and Kilian (2013) criticized the use of the medians of different impulse response functions because the

[30] The substitutional role between bank and bond financing in driving the macroeconomy is also consistent with the finding of Choi (2020), who showed that the effect of bank lending shocks on output in the U.S. economy has substantially declined with the development of its public debt markets over time.

medians at each horizon are likely to be obtained from different models, which makes economic interpretation difficult. Following Fry and Pagan (2011), we compute the responses of the median model determined by minimizing the distance between the impulse responses of each of the accepted models and median impulse responses over a fixed horizon (20 quarters). We measure the distance by the sum of the squared difference between the impulse responses of the accepted models and median impulse responses. Consistent with findings of Busch, Scharnagl, and Scheithauer (2010), we find a negligible difference (see figure A.8 in online appendix A).

5.3 Extended Model

So far, we have imposed minimal sign restrictions to identify only two structural shocks in a small VAR system and mainly studied their effects on output, ignoring variables related to prices and monetary policy stance. Through the lens of a small-scale New Keynesian framework, we extend the baseline VAR model to include these additional variables. However, the theoretical effects of a loan supply shock on the price level and policy rate are indeterminate. For example, a negative loan supply shock may decrease prices because of the contraction in aggregate demand induced by the decrease in credit volume (Curdia and Woodford 2010; Gertler and Karadi 2011). By contrast, the same shock may increase prices by raising the cost of credit or real wages (Gerali et al. 2010). Depending on the response of prices, the optimal monetary policy response would differ as well. Thus, we do not impose any restrictions on the additional variables when identifying loan supply and loan demand shocks and let the data speak for themselves, similar to Busch, Scharnagl, and Scheithauer (2010), Hristov, Hülsewig, and Wollmershaüser (2012), and Gambetti and Musso (2017).

From an econometric point of view, such a model may require a larger number of sign restrictions to ensure the identification of the structural shocks (Faust 1998; Paustian 2007). In this case, increasing the number of identified innovations can help uncover the correct sign of the impulse response functions of interest at the expense of higher computational burden. We choose the restrictions deliberately to rule out the potentially confounding influences of other structural shocks such as monetary policy, aggregate supply, and

Table 6. Sign Restrictions on a Contractionary Shock: Extended Model

Structural Shock	d_t	s_t	l_t	r_t	y_t	p_t	i_t
Loan Supply Shock	≥ 0	≤ 0	≤ 0	?	?	?	?
Loan Demand Shock	≤ 0	≥ 0	≤ 0	?	?	?	?
Monetary Policy Shock	?	?	?	?	≤ 0	≤ 0	≥ 0
Aggregate Supply Shock	?	?	?	?	≤ 0	≥ 0	?
Aggregate Demand Shock	?	?	?	?	≤ 0	≤ 0	≤ 0

Notes: Restrictions are imposed for two quarters. ? denotes indeterminate responses a priori.

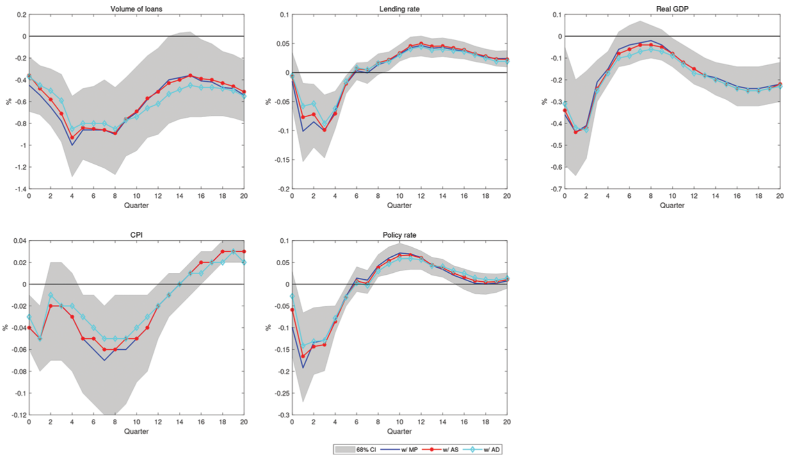
aggregate demand shocks on our results. For example, a monetary policy shock moves policy rates in the opposite direction to output and inflation. An aggregate supply shock such as technology, oil price, and labor supply shocks moves prices and output in the opposite directions, whereas an aggregate demand shock such as consumption, preference, and investment demand shock moves prices, policy rates, and output in the same direction. Hence, we do not impose any restrictions on the four variables related to bank loans to identify any of these structural shocks because of their ambiguous theoretical effects on these variables.

However, the joint identification of all the structural shocks heightens the computational burden because more matrices $Q^{(k(j))}$ need to be discarded to obtain impulse responses that satisfy the restrictions. As a compromise, instead of identifying five orthogonal structural shocks simultaneously,[31] we identify each of the three new structural shocks jointly with the existing loan supply and demand shocks in turn and then check whether the newly added structural shock influences the main findings. Table 6 summarizes the identification restrictions for all the structural shocks in the extended model (the sign of the shocks is normalized to indicate a contractionary shock).

We start by estimating the extended model by identifying contractionary monetary policy shocks jointly with negative loan supply

[31] When identifying the five structural shocks simultaneously, we did not obtain a sufficient number of correct draws of the impulse vectors from 10^7 draws.

Figure 10. The Responses to a Negative Loan Supply Shock: Extended Model

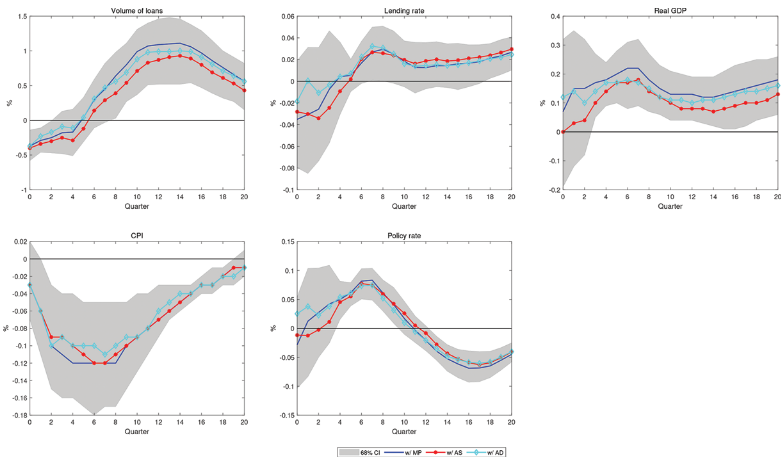


Notes: Solid blue lines plot the median impulse responses, and the shaded areas note their 16th and 84th percentile bands from 200 accepted draws of the extended model in which loan supply and loan demand shocks are identified with monetary policy shocks. The red circled and the blue diamond lines plot the median impulse responses of the extended model in which loan supply and loan demand shocks are identified with aggregate supply and aggregate demand shocks, respectively. (See online version at http://www.ijcb.org for figures in color.)

and demand shocks. The simultaneous identification of monetary policy shocks is useful, as it tests whether shifts in banks' loan supply directly influence economic activity independent of the existence of a bank lending channel of monetary policy (Kashyap, Stein, and Wilcox 1993). The key factor in identifying a negative loan supply shock from a bank lending channel of monetary policy is the sign of the policy rate response: if negative loan supply shocks induce monetary policy loosening, the negative effect on output is independent of the bank lending channel of monetary tightening. We further estimate the extended model in the presence of the identified aggregate supply shock and aggregate demand shock, in turn, to check the robustness of our findings.

Figures 10 and 11 show the responses of the five variables (bank loans, lending rate, real GDP, CPI, and the policy rate) to both loan

Figure 11. The Responses to a Negative Loan Demand Shock: Extended Model



Notes: Solid blue lines plot the median impulse responses, and the shaded areas note their 16th and 84th percentile bands from 200 accepted draws of the extended model in which loan supply and loan demand shocks are identified with monetary policy shocks. The red circled and the blue diamond lines plot the median impulse responses of the extended model in which loan supply and loan demand shocks are identified with aggregate supply and aggregate demand shocks, respectively. (See online version at http://www.ijcb.org for figures in color.)

supply and demand shocks.[32] When jointly identified with a monetary policy shock, their effects on the volume of bank loans, the lending rate, and output are similar to those in the baseline model (see figures 7 and 8). Moreover, negative loan supply shocks are now followed by a decline in prices and accommodative monetary policy, which favors the theoretical predictions presented by Curdia and Woodford (2010) and Gertler and Karadi (2011).

Importantly, a decrease in bank loans now has an expansionary effect on output if driven by a decline in loan demand. Unlike the case of a loan supply shock, the central bank responds to the expansion by tightening its monetary policy. Taken together, the sharp

[32]Figures A.9–A.11 in online appendix A summarize the responses of these variables to the monetary policy shock as well as aggregate supply and demand shocks.

difference in the response of output and the policy rate between figure 10 and figure 11 emphasizes the importance of identifying the factors behind the decrease in bank loans to obtain the optimal policy mix. When jointly identified with aggregate supply and aggregate demand shocks, the effects of loan supply and demand shocks hardly change from the case of monetary policy shocks, confirming the robustness of our findings.

5.4 Extension to the Japanese Economy

As a final robustness check, we investigate whether the identification issue we found from the Korean data exists in a country with a similar financial structure. This is an important test to provide external validity to our main findings. We choose the Japanese economy for this exercise, given its heavy reliance on bank financing discussed in the previous section. Figure A.12 in online appendix A shows the evolution of the relevant variables during the sample period (2000:Q1–2019:Q2). As the Japanese economy has been subject to the zero lower bound (ZLB) constraint, only minimal movement in interest rates is observed. After applying the same treatment of the data and identification assumption, we cannot identify a loan supply shock when using the bank lending rate. Figure A.13 in online appendix A shows that a negative loan supply shock does not have any adverse effect on output, which cannot be squared with any theoretical prediction. Perhaps this finding is not surprising given the ZLB constraint throughout the sample period.

Once we apply our preferred identifying assumptions based on the bank loan officer survey, we find results consistent with the Korean case. Figure A.14 in online appendix A shows that the response of the bank lending rate to the negative loan supply shock is minimal and not statistically different than zero, indicating the failure of the bank lending rate to reflect credit market conditions. The negative loan supply shock has a significantly negative effect on output, which is in sharp contrast to the evidence from the identification using the bank lending rate. Figure A.15 in online appendix A shows that the response of output to the negative loan demand shock is non-negative, as in the Korean case. Again, this finding demonstrates that the decline in bank lending due to a reduction in loan demand is not recessionary.

However, the estimation results of the Japanese economy should be interpreted with caution because the reason why the bank lending rate fails to capture the credit market conditions in Japan (i.e., the binding ZLB constraint) is different than in Korea. Nevertheless, the exercise using the Japanese data again illustrates how the information from the bank loan officer surveys can improve the identification of structural shocks when conventional sign restrictions using the price-quantity framework cannot be applied because of the ZLB constraint.

6. Conclusion

We establish novel stylized facts about bank lending using bank loan officer surveys. The stylized facts illustrate why conventional identifying assumptions using the bank lending rate are unsuitable when bank loans and corporate bonds are not readily substitutable from a borrower's perspective. As a result, a standard identifying assumption using the bank lending rate and volume of loans alone may result in a failed identification of loan supply and demand shocks.

Motivated by these findings, we provide a perspective on the link between credit and the macroeconomy by applying the sign-restriction VAR approach to Korean and Japanese data. We find that the decline in bank loans is associated with the different economic outcomes depending on the supply and demand factors behind the decline. The macroeconomic effects of loan supply and demand shocks in the Korean economy are consistent with the theoretical prediction under credit market imperfections in which bank loans and direct financing are not perfect substitutes, thereby highlighting the unique role of bank financing during turbulent times. As illustrated by the Japanese example, the information from bank loan officer surveys can be particularly helpful when the ZLB constraint prevents us from applying sign restrictions on the interest rate.

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Ethics, Culture, and Higher Purpose in Banking: Post-Crisis Governance Developments*

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This paper examines the roles of ethics, culture, and higher purpose in banking, defining these concepts and discussing how they are related. Developments in these areas since the financial crisis are discussed in the context of governance in banking. The theoretical and empirical research on ethics, culture, and purpose is reviewed, including a discussion of a framework for diagnosing bank culture. The paper closes with a discussion of the regulatory policy implications of the review.

JEL Codes: G20, G21, G2.

1. Introduction

Ever since the end of the 2007–09 financial crisis, regulators in the United States and Europe have shown increasing interest in examining the potential of the "softer" aspects of corporate governance in banking as a way to enhance banking stability without sacrificing economic growth. A key component of these softer aspects is corporate culture in banking (e.g., Dudley 2014, Financial Stability Board 2014, and Lo 2016). The reason is that failures of corporate culture and weaknesses in corporate governance were blamed for unethical behavior that contributed to the crisis (e.g., Dahlgren 2016;

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Kirkpatrick 2009; Thakor 2016a, 2019; and Winter 2011). There were consequently considerable efforts by bank regulators and industry groups to highlight culture as deserving of more attention to prevent a recurrence of some of the failures that preceded the 2007–09 crisis.[1] So the question is: what has to change?

In addressing this question, I comment on ethics, culture, and higher purpose.[2] These are all related ideas, of course, but they are also distinct enough to deserve being discussed separately. Each of these terms is defined, and I discuss the state of affairs in banking with respect to these issues. The view taken in this paper is that the firm's business strategy and higher purpose shape its culture, and the behavior of its employees—both ethical and unethical—is then influenced by this culture. The goals of the paper are primarily twofold. The first is to review post-crisis developments in the areas of ethics and corporate culture in banking. To this, I add higher purpose—a new topic on which research is still at a very early stage—and discuss what banks are doing on this front. The second goal is to connect these post-crisis developments to the related literature in banking to provide a regulatory perspective that is related to the research that preceded the crisis.

The key findings are as follows. First, unethical behavior in banking is a major regulatory concern, but ethics cannot be improved sufficiently by relying solely on contractual resolutions, regulatory monitoring, or explicit regulation of executive compensation in banking. This is because organizational culture exerts a powerful mediating influence, and it must be better understood.

Second, banks—many of which were fined heavily for legal ethical transgression prior to and during the 2007–09 crisis—have increasingly begun to emphasize corporate culture, and researchers have begun to develop theoretical models of bank culture. There is also empirical evidence emerging that bank culture matters for economic outcomes. However, large-scale empirical evidence on the magnitude

[1] See, for example, Dudley (2014).

[2] This focus distinguishes this paper from my earlier papers in which I focused more on regulatory and related issues and the design of a financial system that is healthy (and not crisis prone); see Thakor (2014, 2015b, 2018). Theories of financial crises include Brunnermeier and Oehmke (2013) and Thakor (2012), and empirical evidence on the role of capital and cash injections appears in Berger and Bouwman (2013) and Bergman, Iyer, and Thakor (2020).

and nature of culture change in banking and its effect on bank behavior is still lacking. This presents an opportunity for future research. This opportunity is particularly germane to post-crisis regulatory developments. For example, the Dutch Corporate Governance Code, adopted in December 2016, emphasizes culture and stipulates that banks report their values and a code of conduct.

Third, organizational higher purpose is a relatively new concept in banking, but there are signs that banks are beginning to realize its potential. I review the small body of research on organizational higher purpose and provide some anecdotal evidence on its adoption in banking. I also review some empirical evidence from outside banking. I conclude this discussion by pointing out the potential dark side of banks publicly embracing a higher purpose.

Finally, I offer some tentative thoughts on how regulators may wish to treat ethics, culture, and higher purpose in an integrated manner to engage banks in a dialogue, and how the existing tools of prudential regulation may be useful in influencing these choices by banks. I also discuss how some regulatory developments are already moving in this direction.

This paper is related to many different strands of the literature, and the relevant papers will be discussed in the sections that follow in the context of the specific topics. This paper builds on Thakor (2020) where I briefly sketched post-crisis developments in ethics, culture, and corporate governance in banking. This paper substantially expands the discussion in that predecessor, taking a deeper dive and providing a more thorough analysis that connects the issues here to a broader literature.

The rest of this paper is organized as follows. In section 2, I provide an overview of the literature on ethics, culture, and higher purpose, highlighting the relationship between these concepts. Section 3 specifically discusses ethics and culture in banking. In section 4, I discuss higher purpose. Section 5 concludes with a discussion of regulatory policy implications.

2. A Framework for Ethics, Culture, and Higher Purpose

Before examining each of these ideas, it is useful to define them and explain how they differ and how they are related.

Ethics. In economics, ethical behavior is typically viewed as behavior that is not only legal but is also not socially "censured behavior" (e.g., Shleifer 2004). Examples of unethical behavior provided by Shleifer (2004) include child labor, corruption, excessive executive compensation, corporate earnings manipulation, and involvement of universities in commercial activities. Unethical behavior is often described as "misconduct" of some sort in the firm's behavior with respect to its customers or competitors. For example, in Thanassoulis (2020), it is firms cutting corners on product quality by underinvesting in the variable cost of production. In Song and Thakor (2020), it is a bank "mis-selling" a financial product, i.e., selling a product to a customer when the bank knows that there is a high probability (less than 1) that the product is not suitable for that customer. An example they provide is an adjustable-rate mortgage given to a customer whose income makes it likely that the mortgage payments will be unaffordable when the initial teaser rate goes up in the future. While all illegal behavior is clearly unethical, there can be unethical behavior that is legal (e.g., an employee shirking in effort supply relative to what the employer expects). One can think of unethical behavior as violation of an implicit contract when formal contracting is incomplete, as in the Grossman and Hart (1986) framework.

Culture. While unethical behavior can be reduced through intrusive and direct monitoring, regulation, and penalties for detected violations of ethical norms (see Song and Thakor 2020), these mechanisms are costly and do not account for the powerful effect of organizational culture on individual behavior. An organization's culture is a set of explicit and implicit contracts and (often unwritten) rules of conduct that determine how people in the organization behave. The study of corporate culture was pioneered by Crémer (1993), Hodgson (1996), Kreps (1990), and Lazear (1995). As Hermalin (2000) points out, Kreps's (1990) theory of corporate culture depends on the following features: (i) formal contracts to cover all foreseen contingencies are too costly; (ii) firms and their employees are repeat players; (iii) inducing cooperation through repeated play is cheaper than inducing it contractually; (iv) many repeated games have multiple equilibriums; and (v) not all contingencies can be foreseen, which adds to the need for incomplete contracts. While elements (i)–(iii) play a role in culture, we need either (iv) or (v) to make culture a compelling determinant of behavior beyond explicit contracts (see Hermalin 2000). Thus, in Kreps's (1990) model, culture is what generates a "focal point" effect and guarantees a specific (desired) equilibrium when multiple equilibriums exist. Likewise, culture is what helps determine behavior in the face of unforeseen contingencies being encountered. That is, unforeseen contingencies can make it infeasible to obtain the desired unique equilibrium via explicit contracting.

The observation that changing organization culture can potentially influence more ethical behavior in a way that explicit contracting or regulation cannot is what attracts the attention of bank regulators when they ponder approaches to improving ethical behavior in financial services.

Higher Purpose. An interesting question that often arises has to do with the factors that shape organizational culture. Corporate strategy is an important factor, as emphasized by Song and Thakor (2019). Bartlett and Ghoshal (1994) view purpose as an essential precursor of effective strategic management, and many papers have provided evidence on the economic effects of higher purpose (e.g., Gartenberg and Serafeim 2019, and Grant et al. 2007). Quinn and Thakor (2018) discuss the ways in which organizational higher purpose affects culture.

What is higher purpose? There is not a consensus definition in the literature, but there are common elements in the way higher purpose is defined by various papers. Bartlett and Ghoshal (1994) define it as "the statement of a company's moral response to its broadly defined responsibilities, not an amoral plan for exploiting commercial opportunity." Quinn and Thakor (2019) define it as a prosocial contribution goal that transcends the usual business goals like profit maximization but is intrinsically a part of the business of the organization. Gartenberg, Prat, and Serafeim (2019) argue that purpose need not be explicitly prosocial but should be viewed more broadly as the company's "reason for being." Similarly, Henderson and Van den Steen (2015) define purpose as "a concrete goal or objective for the firm that reaches beyond profit maximization." These differences notwithstanding, what is common in these definitions is that higher purpose represents a contribution goal of the company that goes beyond the usual business goals like shareholder value maximization, and most of this literature emphasizes the importance of the authenticity of purpose and its consequent influence on business decisions. For example, Gartenberg, Prat, and Serafeim (2019) state that a company's primary purpose is not necessarily that which is stated in written documents or plaques on the wall. They state: "It is precisely this implicit aspect of purpose—that purpose is only effective insofar as it is actually adopted by employees within the firm—that creates the challenge for academics to study it meaningfully, across firms and over time." The idea is that employees will not "actually adopt" an organizational higher purpose in their decision-making unless they view it as authentic, rather than merely window dressing (see also Quinn and Thakor 2019).

While we would expect an organization's embrace of higher purpose—especially one that is prosocial—to shape its culture to generate more ethical behavior, this need *not* be so. This is because society's definition of ethical behavior evolves over time and not always in ways that are consistent with the way an organization might choose its purpose. Shleifer (2004) points out that "behavior that is ethical in some idealized society might make matters worse in the real world. For example, the ethical norm against debt or interest, which might have been justifiable a millennium ago, is clearly no longer efficient." This means that, in the context of banking, regulators cannot simply talk about strengthening bank culture and improving ethical behavior. Rather, they also need to engage banks in discussion of their higher-purpose statements and the influence on culture and behavior.

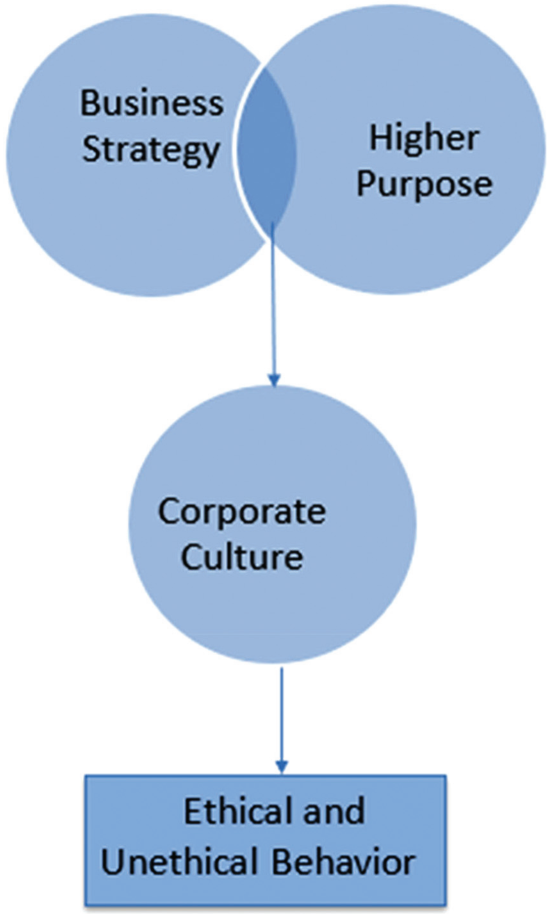
Figure 1 provides a pictorial depiction of the link between strategy, purpose, culture, and ethics. It illustrates that the firm makes decisions at the intersection of its business strategy and higher purpose (e.g., Quinn and Thakor 2019), so its culture is shaped to support these decisions and this, in turn, affects behavior, both ethical and unethical.

3. Ethics and Culture in Banking

3.1 Ethics

In this section, I begin by providing some examples of what major banks are doing on the issues of ethics and culture and link these practices to the literature. The definition of ethical behavior for

Figure 1. A Framework for Ethical Behavior, Culture, and Higher Purpose



the bank is that the bank behaves in a manner that complies not only with the law but also with the spirit of regulation. This means not selling products to customers that may be unsuitable for them, avoiding cheating customers and counterparties in other ways, and not taking actions—including excessively risky lending—that abuse the taxpayer-funded safety net that protects banks. When institutions that operate in the financial market behave ethically and

Table 1. Fines Paid Since Financial Crisis by U.S. Banks

Bank of America	$76.1 billion
JP Morgan Chase	$43.7 billion
Citigroup	$19.0 billion
Deutsche Bank	$14.0 billion
Wells Fargo	$11.8 billion
RBS	$10.0 billion
BNP Paribas	$9.3 billion
Credit Suisse	$9.1 billion
Morgan Stanley	$8.6 billion
Goldman Sachs	$7.7 billion
UBS	$6.5 billion

avoid misconduct in their dealings with customers (e.g., Thanassoulis 2020), market participants develop trust in them, as shown by Guiso, Sapienza, and Zingales (2008) and Thakor and Merton (2019).[3] Nonetheless, the substantial fines paid by banks since the financial crisis paint a somewhat troublesome picture about ethics in banking. By early 2018, U.S. banks had paid $243 billion in fines since the financial crisis,[4] and it is expected that globally, banks will pay $400 billion in fines by end-2020. Table 1 provides a list of the top banks in terms of fines paid.

One has to be careful in interpreting what these fines convey. As far as I know, none of these cases went to trial, so the fines do not necessarily reflect violations of ethics or laws in every case. But these fines damage the reputation of the industry. A few bad apples can create a negative reputational externality for the whole industry, even if most institutions are behaving ethically. There is empirical evidence of some ethical violations leading up to the 2007–09 crisis. See, for example, Piskorski, Seru, and Witkin (2015), who document information misrepresentation in sales of mortgages. This misrepresentation involved false information about the true quality of assets in contractual disclosures made by selling intermediaries in the interagency market.

[3]Sapienza and Zingales (2011) review the literature.

[4]See Goldstein (2018).

The good news, however, is that many of the big banks are now emphasizing ethical behavior and culture much more. For example, I picked the top two banks in table 1 and looked at their 2018 annual reports. Here are some excerpts:

Bank of America:

- "Our *culture* of careful expense management . . . " (emphasis mine).
- "100 Best Companies to Work for."
- "We were recognized for our employment practices and commitment to being a good place to work, our customer service . . . ".
- "Our ability to deepen customer and client relationships is driven in part by the investment we are making to provide the best client care in the industry."

JP Morgan Chase:

- "First and foremost, we look at our business from the point of view of the customer."
- "We take care of our employees."
- "We need to continue to restore trust in the strength of the U.S. banking system . . . ".

The public recognition by banks of the importance of ethics is an encouraging sign. However, there is a word of caution. The values espoused by banks on their websites and in posters on the walls inside their buildings must be *authentic*; see earlier discussion of Gartenberg, Prat, and Serafeim (2019) on this issue. Otherwise, it will breed cynicism among employees and other stakeholders. Every organization I know likes to put up posters listing the "values" of the organization that are supposedly embedded in its culture. But are the values practiced? It is often hard for an outside observer to know, but later in the paper I discuss recent research that addresses this question.

Having said this, it is important to note that ethical behavior can be influenced, but it is much more difficult to legislate it. And, even if it can be legislated, better ethics is not a free lunch. Song and Thakor (2020) develop a model which shows that when incentive contracts are designed to raise the level of ethical behavior, there is less innovation in financial products, and banks with higher ethical standards tend to attract less talented managers than those with lower ethical standards. The intuition is that incentivizing the provision of privately costly unobservable effort by the bank employee requires a bonus for selling a successful innovation, and the likelihood of a sale declines as the bank raises its ethical standard, where the ethical standard determines the "acceptable" probability of mis-selling an innovation to a customer, for example. This creates tension between the goal of promoting innovation and the desire for better ethics, thereby posing a dilemma for regulators. Song and Thakor (2020) show that higher capital requirements in *both* depository and shadow induce banks to provide a better way to raise ethical standards[5] than imposing penalties for unethical behavior or directly regulating executive compensation. The crux of their reasoning is that ethical standards are difficult to legislate, but they *can* be influenced through the traditional tools of prudential regulation.

3.2 Bank Culture

The focus of the analysis in Song and Thakor (2020) is on how compensation contracts of bank managers can be designed to elicit the desired ethical standards. In view of the limitations of optimal contracting to improve ethics that Song and Thakor (2020) have highlighted, the literature on corporate culture discussed in section 2 suggests that one possible way to improve ethics while minimizing these adverse consequences is to strengthen bank culture. The concept of culture is admittedly somewhat nebulous—as William Dudley, former president of the Federal Reserve Bank of New York, said: "Culture is like a gentle breeze. You cannot see it, but you can feel it."[6] However, there has been a surge of recent research interest in this topic. Corporate culture in a nonbanking context has been examined recently in numerous papers. See, for example, Gorton and Zentefis (2019), Guiso, Sapienza, and Zingales (2015), and Van den

[5]Higher capital can also improve ethics in banking through other channels like reputation (e.g., Boot, Greenbaum, and Thakor 1993) and enhanced pledgeability in the bank's promises to depositors (e.g., Donaldson, Piacentino, and Thakor 2018).

[6]See Dudley (2014).

Steen (2010). Morrison and Shapiro (2016) provide a review of bank culture.

Lo (2016) observes: "Culture is a potent force in shaping individual and group behavior, yet it has received scant attention in the context of financial risk management and the 2007–09 financial crisis." He presents an excellent overview of culture from multiple dimensions—psychology, sociology, and economics—and presents a framework for analyzing culture for financial institutions.

In Thakor (2016a), I discuss how one can use the Competing Values Framework (CVF) to make the seemingly nebulous concept of culture concrete and measurable. This is a framework developed in the organizational behavior literature (e.g., see Cameron and Quinn 1999). Like Lo (2016), in Thakor (2016a), I focus on what culture means, why it matters, and how it can be changed. I also discuss the lessons for regulators. The main point of that discussion is that regulators can deal with culture in a practically sensible way. Specifically, regulators do not necessarily need to tackle, head on, the thorny issue of how to measure culture and build a regulatory framework around it.[7] Rather, as Song and Thakor (2019) show, they can get banks to focus more on developing "safety-oriented" cultures by[8]

- increasing capital requirements,
- limiting interbank competition,
- reducing the probability of bailouts.

Moreover, culture choice is contagious, so if a few large banks orient their cultures in a certain way, others will follow.

In the CVF description of bank culture presented by Thakor (2016a), there are four dimensions of culture: Collaborate, Control,

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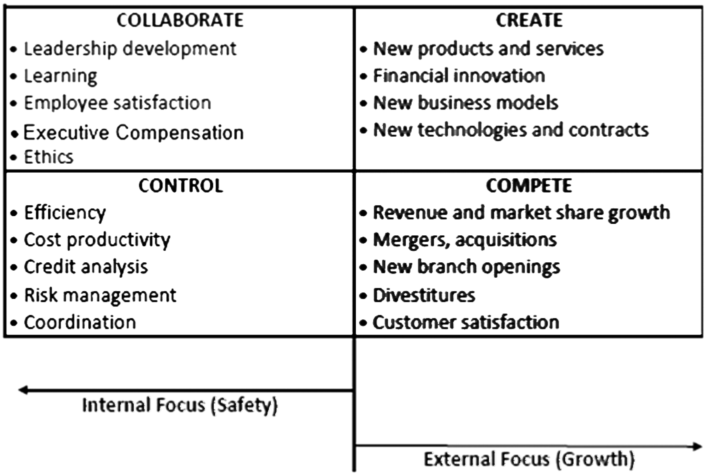
[7] "Measuring" culture for regulation will likely tempt banks to manipulate their culture measures, apart from also suffering from the Goodhart critique.

[8] See also Thakor (2018). Song and Thakor (2019) distinguish between "growth-oriented" and "safety-oriented" cultures as follows. A growth-oriented culture is one that focuses on top-line (loan) growth, whereas a safety-oriented culture focuses on minimizing loan defaults by dedicating resources to credit analysis. Because of resource constraints, a greater allocation of resources to loan origination (to facilitate loan growth) implies a smaller allocation to credit analysis, so the bank's choice of culture also determines the optimal contracts to incent a specific kind of behavior, with the noncontractual aspects of culture exerting an additional influence.

Figure 2. The Competing Values Framework for Bank Culture



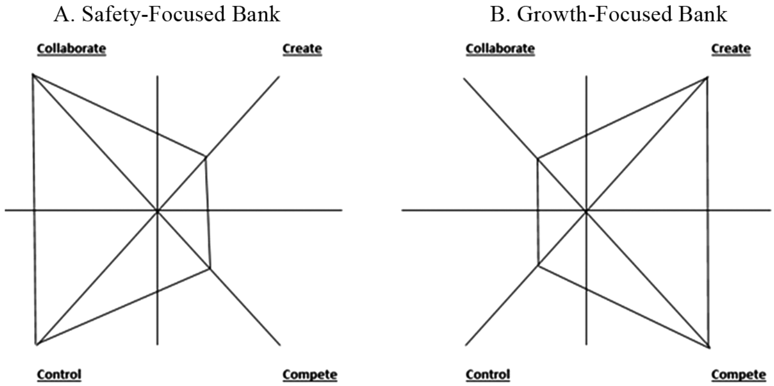
Compete, and Create. See figure 2, which provides examples of the bank's activities in the four dimensions. Each dimension represents a set of activities to which resources are allocated.

The activities in all four quadrants are intended to create value but in different ways, as described below. The emphasis the bank places on activities in any quadrant relative to the other quadrants reflects the bank's (resource allocation) strategy and its culture, because this emphasis will determine the kinds of explicit and implicit contracts the bank will use as well as noncontractual mechanisms it will deploy to produce the desired behaviors from its employees. Using the CVF culture diagnostic instrument that can be used to survey the bank's employees, one can pictorially depict any bank's culture, as shown in figure 3.

Collaborate refers to all the bank's activities directed at its own employees—their training, leadership development, learning, job satisfaction, work habits, and morale. The design of executive compensation and the development of ethical standards are also part of this quadrant.

Control refers to all of the bank's internal processes, including those designed to manage the bank's various risks, product and

Figure 3. Two Different Bank Culture Profiles



service quality, and costs. These are also activities to facilitate intra-bank coordination. The goals are efficiency and risk management.

Compete refers to all the activities the bank engages in to increase its competitiveness in the markets in which it currently operates. The goals here are an increase in market share in the loan and deposit markets, revenue growth, and shareholder value creation. The focus is on improving effectiveness in the bank's interactions with its external stakeholders.

Create refers to the bank's innovation activities, designed to enhance organic growth. New business models and innovation in financial instruments and services all fall into this quadrant. Laeven, Levine, and Michalopolous (2015) develop a model which includes both real-sector technological innovation by entrepreneurs and financial innovation by banks. The paper shows that technological innovation and economic growth ultimately stop unless financiers like banks innovate in enhancing screening of entrepreneurs. Thakor (2012) provides a theory in which financial innovation can contribute to the innovating institutions experiencing funding dry-ups that could bankrupt them, and a crisis could ensue if sufficiently many institutions are affected.

The Collaborate and Control quadrants include activities that are focused on what is internal to the organization—its own people (Collaborate) and its own processes (Control). For a bank, a safety-focused culture is one that would involve substantial resource allocation to activities in these quadrants. The Create and Complete quadrants include activities that are "external facing" and involve interactions with external stakeholders such as customers, shareholders, and competitors. A growth-oriented culture is one that would allocate substantial resources to activities in these quadrants. Thus, the culture dichotomy in Song and Thakor (2019) collapses Collaborate and Control into one choice of culture (safety oriented) and Create and Compete into another choice of culture (growth oriented).

In the CVF, the four quadrants represent four distinct approaches to value creation that have similarities and differences. Collaborate and Control are similar in their internal focus, whereas Create and Compete are similar in their external focus. Control and Compete are similar in their emphasis on tangible forms of value creation where outcomes are relatively easy to observe and base contracts on. So activities in these quadrants are more amenable to output measurement, explicit contracting, and well-specified rules of conduct. By contrast, the activities in Collaborate and Create emphasize less tangible forms of value creation over more ambiguous time horizons, and outcomes are harder to measure (at least over time horizons comparable for activities in Control and Compete). Relative to Control and Compete, there is greater reliance on implicit (and incomplete) contracting and less on explicit contracting. Consequently, "operating rules of conduct" are more flexible in order to deal with the greater likelihood of unforeseen contingencies.

As a result of these differences, any choice of culture involves tensions; e.g., at the margin, focusing more on innovation (Create) requires a greater tolerance for failure (i.e., less effective risk management in Control). Given constrained resources, focusing on activities in one quadrant comes at the expense of activities in another quadrant. The bank's choice of culture will depend both on its business strategy and its higher purpose.

Figure 3 shows two hypothetical examples of bank cultures.

The culture in 3A depicts a bank that is safety focused, whereas the culture in 3B depicts a bank that is growth focused. This is the dichotomy characterized in the theory of bank culture in Song and Thakor (2019). Which culture the bank chooses is a matter of strategy and its beliefs about the quality of the asset pool it is screening from.[9] Song and Thakor (2019) show that if the belief is that the borrower pool is of high quality—so the marginal value of screening loan applicants is low—then the bank prefers a growth-oriented culture. If the borrower pool is believed to be of low quality, the bank prefers a safety-oriented culture.

While the Song and Thakor (2019) analysis solves for optimal incentive contracts to align the bank employee's actions with the bank's strategic goals (growth versus safety), it shows that the *non-contractual* aspects of culture can improve the alignment attainable with optimal contracts. This involves use of soft information signals that are not mutually verifiable and hence cannot be used for contracting but can be used for rewards and punishments. For example, these signals can be used for promotion and span-of-control decisions. All agents understand how these decisions will be made, and they represent aspects of the bank's culture, but they are "unwritten rules" of conduct and are not included in explicit contracts. Thus, the Song and Thakor (2019) analysis provides another perspective on how culture can act as a coordinating mechanism for obtaining the desired behavior in an incomplete contracting setting that Kreps (1990) highlighted as an important ingredient in models of corporate culture.

In the context of ethics, the Kreps (1990) approach would say that it is virtually impossible (or exorbitantly costly) to write down every future contingency in which an employee could choose between an ethical decision and a multitude of possible unethical decisions involving varying degrees of transgression. Given the inefficiency of explicit contracting in such a setting, the bank's culture can be an effective mechanism for achieving the desire behavior.

Song and Thakor (2019) also show that market forces influence the bank's choice of culture. Specifically, as interbank competition increases, banks are more inclined to choose growth-oriented cultures. A decrease in competition makes a safety-oriented culture more attractive ceteris paribus.

[9]As in Laeven, Levine, and Michalopoulos (2015), the raison d'etre for the existence of the bank in Song and Thakor (2019) is that it provides screening of borrowers, as in Coval and Thakor (2005) and Ramakrishnan and Thakor (1984). Screening is meant to resolve information reliability problems. Allen (1990) provides a theory of financial intermediation in which the reliability of information being sold is a central friction.

What is the empirical evidence on how culture affects banking outcomes? There is a growing empirical literature that uses the CVF as a culture identifier and examines its relationship to various outcomes. Fiordelisi, Raponi, and Rau (2015) document that banks with low capital ratios, poor performance, and high credit risk tend to attract regulatory enforcement actions.[10] Moreover, non-sanctioned banks with a high probability of being sanctioned tend to change their cultures to be more safety focused (Culture profile 3A). Barth and Mansouri (2020) provide evidence that banks that have stronger growth-focused cultures (more emphasis on Compete and Create) have higher stock returns. Song and Thakor (2019) predict that banks with stronger growth-oriented cultures will exhibit higher revenue growth, and the theories in Thakor (2015a, 2016b) show that during good economic times, banks will lower credit standards, lend more, have higher growth, and be valued more highly by investors. Thus, the Barth and Mansouri (2020) finding is consistent with these theories. Further, Barth and Mansouri (2020) also find that banks with stronger Create cultures will experience higher revenue growth but higher bankruptcy risk. This is consistent with the theory in Thakor (2012) which predicts higher bankruptcy risk for more innovative banks.

The empirical papers that use the CVF to assess bank culture basically rely on the argument in Crémer (1993) and Hoberg and Phillips (2016)—there is a common language and vocabulary within the firm that is used in the management discussion and analysis (MD&A) section of the firm's 10-K reports and it reflects the firm's corporate culture. So these papers use the text of banks' MD&A section to extract words that correspond to the CVF quadrant descriptors and thereby infer culture.

One limitation of these studies is that one cannot assess how authentic the firm's commitment to a "stated" culture is, i.e., are the words in financial statements just part of "politically correct" communication to investors or do they represent a set of corporate values that are consistently practiced? There has not been much empirical work done on this, but recent research by Grennan (2019) is illuminating. That paper uses a simple but clever aspect of culture to

[10]This is consistent with the evidence in Berger and Bouwman (2013) that banks with higher capital have a higher probability of surviving a crisis.

examine its effect on bank performance—the consistency with which culture is communicated to different stakeholder groups. Using historical versions of websites from 2004 to 2017 for 300 U.S. banks, Grennan (2019) finds that a majority of banks communicate their values inconsistently across websites themes (i.e., tabs on websites labeled "about us," "career," "community," "culture," and "investor relations"). Her most important empirical finding is that banks that communicated their culture values consistently before the 2007–09 financial crisis experienced better operating and stock performance during the crisis.[11] Indeed, for each additional cultural value that is miscommunicated prior to the crisis, a bank lost an annualized 2.8 percent to 3.3 percent during the financial crisis from July 2007 to December 2008.

An important contribution that empirically examines the impact of bank culture using a plausible proxy for culture is Ellul and Yerramilli (2013). That paper does not rely on a direct measurement of culture, but rather constructs a "risk-management index" (RMI) to assess the strength and independence of the risk-management function at bank holding companies. One can view the RMI as proxying for the bank's risk-management culture. They show that a stronger risk-management culture leads to lower tail risk, lower nonperforming loans, and better operating and stock return performance.

Regulators have an expressed interest in promoting stronger safety-oriented cultures in banks. For example, the Dutch Corporate Governance Code of 2016 emphasizes the importance of the role of risk management and internal controls as important components of the bank's culture. The Code encourages banks to establish their risk appetite, codify it, and integrate it into the organization's work processes.[12]

There does not appear to be systemic evidence on *how* bank culture has changed since the financial crisis. Given the elevated regulatory focus on safety and soundness and the heavier reliance on stress tests and capital regulation, one suspects a shift toward more safety-oriented cultures. But this conjecture awaits empirical testing.

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[11] Grennan's (2019) hypothesis is that consistency, as measured by her, is a proxy for authenticity.

[12] See van Zijl, van der Bie, and Vorst (2017), for example.

However, the empirical evidence available to date indicates that bank culture has a potentially significant effect on bank behavior.

4. Higher Purpose

In this section, I discuss the relevance of organizational higher purpose to banking.

4.1 Organizational Higher Purpose and Banks

The notion of organizational higher purpose has gained theoretical traction in recent years. See, for example, Gartenberg, Prat, and Serafeim (2019), Hedblom, Hickman, and List (2019), and Henderson and Van den Steen (2015). Quinn and Thakor (2019) emphasize that organizational higher purpose is a contribution goal that transcends the usual business goals—profits or shareholder value—yet intersects these goals, so it is *connected* to the firm's business. It is *not* charity. These prosocial higher-purpose goals include taking a broader perspective on the stakeholders who should matter to the bank, including employees, customers, and society at large; many such examples are discussed in Quinn and Thakor (2019) and Thakor (2019).[13] In this sense, the notion of a higher purpose is consistent with the fundamental principle in the Dutch Corporate Governance Code of 2016 that banks should focus on *long-term stakeholder value creation*. While one typically thinks of a directive like that conflicting with shareholder value maximization, Thakor and Quinn (2019) provide a formal model in which an authentic higher purpose can, under some conditions, lead to higher profits and shareholder value in the long run, despite short-term profit sacrifices. This means that while long-term stakeholder value maximization may conflict with shareholder value, it need not, especially if the former is part of an authentic higher-purpose pursuit. What does this imply for banking?

As I discussed earlier, higher purpose influences the bank's culture, and this affects employee behavior, both ethical and unethical.

[13] A recent survey by Bunderson and Thakor (2020) reveals that an organizational higher purpose is actually more meaningful and impactful for employees when it is focused on stakeholders other than shareholders than when it is primarily focused on shareholders.

Thus, purpose can be a complement to the usual channels of executive compensation, capital requirements, and regulatory jawboning in changing bank behavior. We do not as yet have a formal theory of higher purpose in banking, but in Thakor (2019), I point out what higher purpose could mean in banking. Specifically, I argue that it could help to achieve the twin goals of financial stability *and* economic growth in the real sector through the actions of banks, goals that many believe conflict with each other. Moreover, visible pursuit of higher purpose will also contribute to a rebuilding of trust in banks. Shleifer (2004) argues that competition may encourage unethical behavior. However, recently Thakor and Merton (2019) provide a theory of the role of trust in bank lending in which depository institutions have an advantage over nondepositories in developing trust. Their theory highlights the role of trust in the competitive interactions between banks and nonbanks.

Banks have begun to think about higher purpose. I looked at the financial statements and websites of three of the banks in table 1 and found the following in their 2018 annual reports and/or on their websites:

Bank of America:

- “We did this by living our purpose, which is to help make our clients’ lives better through the power of every connection we can make.”

JP Morgan Chase:

- “We lift up our communities.”
- “[We started our] *Advancing Cities* initiative to support wage and job growth in communities most in need of capital.”

Morgan Stanley:

- “We believe capital can work to benefit all of society.”
- “We make this belief a reality by putting clients first, leading with exceptional ideas, doing the right thing, and giving back.”

The authenticity of these purpose statements is a matter for future research to determine, but the interesting empirical evidence provided by Gartenberg, Prat, and Serafeim (2019) is that an authentic higher purpose communicated with clarity improves operating and shareholder value performance in firms. I believe that in banking it will improve stability without sacrificing economic growth. As far as I know, regulators have not done anything explicitly on this front, although the Dutch Corporate Governance Code of 2016 has some elements of this embedded in it. To be clear, as mentioned earlier, I do *not* believe higher purpose can always be effectively legislated or regulated. Rather, I am proposing that bank regulators ought to understand its power and make it a part of their dialogue with banks, and think of regulatory directives that can encourage the adoption of authentic higher purpose in banking.

This dialogue can point to examples of how some banks are authentically pursuing higher purpose. An interesting example is the Bank of Bird-in-Hand in southern Pennsylvania. It is now a full-service bank whose purpose is to provide banking services to the underbanked Amish community. It seeks to foster local economic development and does so in part by supporting community projects like hay auctions (see Volz 2019).

4.2 Higher Purpose, Relationship Banking, and Bank Capital

Relationship banking is a key part of the business model of many depositories, and it helps to distinguish banks from shadow banks that compete aggressively in transaction lending. Rajan (1992) and Sharpe (1990) developed some of the early theories of relationship lending and focused on the economic effects of proprietary information generation during bank–borrower relationships. Boot and Thakor (2000) show that when faced with increased competition from other banks and the capital market, relationship lending optimally shrinks but banks deepen their relationship lending focus—and hence the value-added in each relationship loan—to increase their distinctiveness. Song and Thakor (2007) provide a model that links the bank's deposit funding choice (core deposits versus purchased money) to its lending choice (relationship versus transaction loans), thereby highlighting a new type of "balance sheet matching." Their main result is that relationship borrowers find bank loans more valuable when the probability of interim loan termination due to the bank's funding drying up is lower, because the longevity of the bank–borrower relationship is especially important to relationship borrowers who experience increasing benefits of relationship banking as the duration of the relationship grows. Empirical evidence on the link between relationship-lending duration and the benefits of relationship borrowing is provided by Lopez-Espinosa, Mayordomo, and Moreno (2017), who document that the benefits of relationship borrowing begin to accrue to borrowers only after two years of the relationship. This is why in the Song and Thakor (2007) model relationship lenders rely more on core deposits, which are stickier than purchased funds.

A simple extension of this logic indicates that banks with higher capital ratios—which have higher continuation probabilities—will be more attractive to borrowers who seek relationship loans, because they will perceive higher total surplus from dealing with such banks.[14] Empirical evidence in support of this implication is provided by Schwert (2018), who documents that borrowers that are more bank dependent (i.e., those who value relationship loans more) are matched in equilibrium with banks that have higher capital ratios. That is, higher bank capital contributes to an increase in the surplus created by relationship lending.[15]

Relationship lending has numerous benefits for banks and their borrowers that combine to generate relationship-related surplus. On the theoretical front, Boot and Thakor (1994) develop an infinite-horizon credit contracting model in which relationship lending helps to reduce the use of costly collateral. Ferri, Minetti, and Murro (2019) provide empirical evidence that stronger bank relationships in which banks have greater access to soft information about borrowers make these borrowers have greater export resilience in the face

[14] How this surplus will be shared will depend on the competitive structure of the credit market. But if the bank as well as the borrower share in this surplus so that each gets a portion of it, then borrowers who value relationship loans more will gravitate to banks with higher capital, and those banks will prefer these borrowers.

[15] Borrower capital ratios may also play a role in influencing economic outcomes. Donaldson, Piacentino, and Thakor (2019) develop a model in which high consumer leverage leads to high unemployment in a general equilibrium.

of trade collapse, especially when these borrowers are firms that are at an early stage of internationalization.

Organizational higher purpose can facilitate relationship banking. If the bank's higher purpose is to further the interests of the communities in which it operates, it can do so by adding more value to its relationship borrowers. The example of the Bank of Bird-in-Hand illustrates this kind of higher purpose. Higher purpose is especially relevant in the context of relationship banking because the soft information that is an integral part of relationship banking necessitates reliance on incomplete contracts. As discussed earlier, it is precisely in these kinds of settings that purpose and culture have important roles to play in affecting bank behavior through noncontractual mechanisms. To the extent that higher bank capital generates greater surplus in relationship banking, an increase in bank capital can also elevate the value of higher purpose in banking.

The notion that the adoption of an authentic higher purpose can benefit the bank's customers and thus increase consumer welfare is in the spirit of the long-term stakeholder value creation prescription in the Dutch Corporate Governance Code of 2016. Quinn and Thakor (2019) discuss that there are three kinds of higher purposes that organizations adopt: customer-centric, employee-centric, and explicitly prosocial. So while not all higher-purpose statements are explicitly prosocial, they do address a broader set of stakeholders than shareholders, and attending to customer welfare is a frequently adopted higher purpose.

4.3 How Does Higher Purpose Affect Culture?

Because a firm that makes decisions at the intersection of its higher purpose and its business strategy inevitably allocates resources in a manner that is consistent with its articulated purpose, it is easy to see how purpose shapes culture, in context of the discussion in section 2. Explicit as well as implicit contracts end up being influenced by the higher purpose, and this affects the culture of the organization.

Quinn and Thakor (2019) provide numerous examples of how organizational higher purpose influences organizational culture. I discuss one of them here as an illustration of how purpose shapes culture. Sandler, O'Neill, and Partners, a mid-sized investment bank, lost a third of its workforce during the 9/11 terrorist attacks. Jimmy Dunne, the new CEO, articulated a higher purpose that involved viewing employees as part of the "Sandler family." This led to the company paying the families of dead employees the salaries and benefits of these employees for an extended time period. The impact of this purpose on the firm's culture is described in Quinn and Thakor (2019). Specifically, employee "back-biting" was discouraged by the emergent culture, so, for example, when an executive came to Jimmy Dunne to "confidentially" complain about another employee, Dunne began dialing the other employee's phone number so he could come over and listen to what was being said about him. The person who had come to complain was shocked and stopped his complaining. Dunne stated that this kind of openness improved teamwork and collaboration. This is an example of how noncontractual mechanisms are used to reinforce certain aspects of the organization's culture, thereby influencing how the organization works and the economic outcomes it achieves.

The Song and Thakor (2019) model predicts that culture will be "contagious" in the sense that the choice of a particular culture orientation by a few banks will influence other banks to adopt the same culture. This proclivity of culture suggests that higher purpose too will propagate across banks. From a regulatory policy standpoint, this implies that the adoption of authentic prosocial purpose in banking can begin with a few (highly visible) banks, and it will subsequently spread to other banks.

4.4 Is There a Dark Side to Higher Purpose?

Organizational higher purpose could be misused in at least three ways. First, it may be inauthentic, in which case it is likely to be recognized as such by employees and be ineffective at best and breed cynicism at worst (see Quinn and Thakor 2019). Second, it could be used by the bank's leadership as an excuse for poor performance—"we are not doing well financially because we are devoting resources to higher purpose." In this case, higher purpose can be used to obstruct effective corporate governance and it will have two adverse consequences: (i) it will alienate investors, possibly leading to CEO replacement (see Oehmke and Opp 2020 for a model in which social impact requires investors to internalize social costs), and (ii) it will diminish the credibility of higher-purpose initiatives at both the bank in question and other banks, including those that may be pursuing authentic higher purpose. Third, the bank's leadership could invest in initiatives that yield them private benefits—including the pursuit of political agendas—and "package" these as higher-purpose initiatives.[16] It is precisely because of the last two possibilities that Milton Friedman proposed profit maximization as the only goal firms should have. Endorsing the pursuit of multiple objectives by the bank can be a license to have poor corporate governance and bad investments. In banking this is a particularly important problem because it can threaten the public safety net. So in that sense, paradoxically, the stated purpose of embracing a corporate higher purpose that benefits the community ends up hurting the public interest by weakening the taxpayer-funded safety net![17]

Thakor and Quinn (2019) explicitly account for these possibilities in their formal analysis. They show that these possibilities lead to reduced higher-purpose investments by firms and also possibly higher wage costs and external financing costs relative to the situation in which these incentive frictions are absent (first best). That is, the firms that misuse higher purpose create a negative externality for firms that pursue authentic higher purpose. This is why it is important for banks to have an authentic higher purpose and make decisions at the *intersection* of higher purpose and prudent business goals such as long-run shareholder value maximization. As pointed out earlier, this need not conflict with attending to the welfare of stakeholders besides shareholders, i.e., this intersection of higher purpose and shareholder value is not empty. Banks need to have long-term financial viability that does not undermine the interests of depositors and the public safety net if they are to pursue a sustainable and authentic higher purpose.

[16]It could also embolden special interest groups to put pressure on banks to make loans to their favored constituencies—loans that may be imprudent from the bank's perspective—to serve the bank's stated higher purpose. This could imperil the bank's financial health.

[17]Safety nets such as deposit insurance provide banks with a funding cost advantage over nonbanks, and this can have a potentially profound impact on how the credit market segments itself. See Donaldson, Piacentino, and Thakor (2020). Merton and Thakor (2019) show why deposit insurance can be welfare enhancing even when bank runs are not a problem.

5. Conclusion

This paper has provided an assessment of changes in ethics, corporate culture, and higher purpose in banking since the financial crisis and has highlighted organizational higher purpose as an area deserving of greater recognition and emphasis by banks. I end now with a brief discussion of the takeaways for bank regulations on these issues.[18] First, preaching the importance of ethics to banks or even imposing penalties on banks for ethical transgressions may not be as effective as higher capital requirements in generating more ethical behavior.[19] Thus, a familiar tool of prudential regulation—capital requirements—can be used to even improve ethical behavior. However, ethics is not a free good, and higher ethical standards may be associated with lower financial innovation. Second, the organizational culture in banks can exert a powerful influence on the behavior of bank employees and can determine not only how ethical banks are but also the effectiveness of the risk-management systems they develop, the default losses they experience (that is, the strength of their safety-oriented cultures), and the tail risks they take. Culture is now being explicitly addressed in regulatory directives. For example, the Dutch Corporate Governance Code of 2016 addresses culture both directly by requiring a report on the adopted code of conduct and indirectly through its emphasis on risk management and internal controls codification and integration into work processes. Third, organizational culture in banks is influenced by the higher purpose they choose to embrace and the business strategies they adopt. While purpose and culture may not always be effectively legislated via regulation, regulatory practices have already begun to integrate elements of culture and purpose into the overall framework for bank regulation, which is a good sign. Current research suggests that greater

[18]Bhattacharya, Boot, and Thakor (1998) provide a pre-crisis perspective on the economics of bank regulation and the regulatory challenges involved.

[19]The advantage of capital requirements, especially those that are enshrined in bank regulation and involve minimums that are not subject to regulatory discretion, is that they can generate the desired effects without being potentially distorted by regulatory career concerns. See Boot and Thakor (1993) for an example of how regulatory career concerns can lead to regulators delaying the closure of troubled banks, relative to the social optimum.

dialogue between banks and regulators on these issues seems worthwhile. Such a dialogue can illuminate some of the practical issues banks and regulators will need to confront in applying in a financial services context the lessons learned by nonfinancial firms in the adoption of higher purpose, as well as the lessons learned through research on this topic.

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The Power of Forward Guidance and the Fiscal Theory of the Price Level*

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Standard models predict implausible responses to forward-guidance announcements when interest rates are pegged (the "forward-guidance puzzle"). This paper develops conditions for regime-switching models to exhibit a forward-guidance puzzle, and shows when the fiscal theory of the price level does—and does not—resolve the forward-guidance puzzle. Forward guidance has reasonable effects when real fiscal revenues are very unresponsive to government debt, but in some empirically relevant cases, inflation *must* ensure debt stability and forward-guidance puzzles are still there. Cyclical variation in deficits also affects the power of forward guidance.

JEL Codes: E63, D84, E50, E52, E58, E60.

1. Introduction

In standard macroeconomic models with an interest rate peg, announcements about the path of future nominal interest rates can have unbounded effects on inflation today. Further, a promise to cut a future interest rate has *larger* effects on today's inflation than the same cut in the current rate. This counterintuitive phenomenon, which Del Negro, Giannoni, and Patterson (2015) call the "forward-guidance puzzle," implies that central bankers can strongly influence inflation simply by announcing future policy actions when interest rates are constrained by the zero lower bound (ZLB). Many papers

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offer solutions of the puzzle, i.e., models that only allow for bounded unexpected changes in inflation and therefore explain the limited effectiveness of real-life forward-guidance policies. Cochrane (2017) shows that the fiscal theory of the price level (FTPL) can rule out large unexpected jumps in inflation.[1] His logic suggests that debt-stabilizing or “Ricardian” fiscal policies provide the fiscal backing for forward guidance to have power, while non-Ricardian policies give inflation a debt-stabilizing role that may limit the magnitude of inflation responses to new information. However, Cochrane does not specify fiscal assumptions that lead to well-behaved forward-guidance announcements.

This paper shows when the FTPL does—and does not—resolve the forward-guidance puzzle in New Keynesian models. In the standard modeling environment we consider, fiscal policy is either Ricardian or non-Ricardian depending on how often and the extent to which real fiscal surpluses respond to debt in a “passive” (i.e., debt-stabilizing, à la Leeper 1991) manner versus an “active” manner. Sufficiently active policies, such as permanent active fiscal regimes, typically rule out unreasonable responses to forward-guidance announcements. Furthermore, *some* non-Ricardian fiscal policies involving recurring passive and active fiscal regimes are able to resolve forward-guidance puzzles (even when the forward-guidance announcement occurs during a passive fiscal regime). However, some non-Ricardian policies involving recurring fiscal regime changes do not resolve the puzzle. As examples, we show that some estimated non-Ricardian fiscal rules eliminate forward-guidance puzzles, while others do not.

We furthermore examine impulse responses to forward-guidance announcements in cases where the fiscal theory rules out forward-guidance puzzles. Forward-guidance announcements that lower expected nominal interest rates *eventually* lower inflation and

[1]The FTPL literature highlights the role that *both* monetary and fiscal policy play in determining the price level (e.g., see Leeper and Leith 2016 or Cochrane 2020 for a thorough review). A major strand of the literature studies how the equilibrium properties of standard macro models depend on the conventional assumption that governments conduct a Ricardian fiscal policy, i.e., a policy that generates sufficient real fiscal revenues to ensure debt stability. Therefore, for our purposes, we use “FTPL” to refer to the analysis of the interaction of *non-Ricardian* fiscal policy and monetary policy.

output. This is true even when forward guidance is conducted during a transient passive fiscal regime. Whether inflation initially rises or falls in response to this kind of announcement depends on the maturity structure of debt, and also whether surpluses are procyclical or countercyclical. Countercyclical policy can mitigate the power of forward guidance, while forward guidance has ambiguous effects under a procyclical fiscal regime. For one special calibration of procyclical surpluses in a simple model, forward-guidance solutions diverge to negative or positive infinity, which highlights one caveat to our finding that permanent active regimes rule out unreasonable forward-guidance effects, and one potential peril of pairing monetary forward guidance with austerity policy.

This paper also presents a framework for studying the effects of anticipated structural changes. Specifically, we offer a solution algorithm for anticipated structural changes in a general class of Markov-switching dynamic stochastic general equilibrium (DSGE) models, and necessary and sufficient conditions for when a given model of this form exhibits a puzzle. This contribution directly extends that of Gibbs and McClung (2020), who provide the corresponding solution algorithm and set of conditions for ruling out forward-guidance puzzles in a general class of single-regime linearized DSGE models. The algorithm and conditions presented in this paper are applied to test the FTPL, but others could apply these techniques to study the effects of forward guidance, or other anticipated structural changes, in uncertain environments.

After a brief literature review, section 2 presents key analytical results in a simple model. Section 3 develops a general framework for studying forward guidance in regime-switching models. Section 4 studies the forward-guidance puzzle in New Keynesian models, including models with estimated fiscal rules, and models with rich maturity structure and cyclical policy. Section 5 concludes.

1.1 Literature Review

We contribute to a literature examining monetary-fiscal interactions in zero lower bound environments. Cochrane (2017, 2018a, 2018b, 2020) extensively studies forward guidance and the fiscal theory, but his focus is not on the forward-guidance puzzle per se. Caramp and Silva (2018) argue that the direct response of fiscal transfers to monetary policy generates wealth effects that explain the monetary forward-guidance puzzle, but their analysis abstracts from fiscal theory considerations, including issues of fiscal solvency and fiscal regimes.[2]

Chung, Davig, and Leeper (2007), Davig and Leeper (2011), Bianchi and Ilut (2017), Bianchi and Melosi (2017), Corhay, Kung, and Morales (2017), Cho and Moreno (2019), and Ascari, Florio, and Gobbi (2020) all examine the effects of recurring fiscal policy regimes on expectations. Additionally, Sims (2013), Leeper and Leith (2016), and Corhay, Kung, and Morales (2017) all examine the interaction of unconventional monetary policy, debt maturity structure, and non-Ricardian fiscal policy. Ascari, Florio, and Gobbi (2020) discuss forward guidance on future policy *regimes* and its implications for the efficacy of monetary and fiscal policy at the zero lower bound. Unlike the above papers, we identify the fiscal assumptions that preclude a forward-guidance puzzle.

This paper also adds to a large literature addressing the forward-guidance puzzle. Early motivation for the literature comes from papers such as Drumond, Martins, and Verona (2013), Carlstrom, Fuerst, and Paustian (2015), and Del Negro, Giannoni, and Patterson (2015), in which the authors observe large, even unbounded, responses of inflation and output to forward-guidance announcements in standard DSGE models. This theoretical prediction is not easily reconciled with the data:[3] the Federal Open Market Committee's forward-guidance announcements *modestly* affected long-term yields and interest rate expectations (Gürkaynak, Sack, and Swanson 2005, Moessner 2013, and Swanson and Williams 2014), inflation expectations (Del Negro, Giannoni, and Patterson 2015), or perhaps barely impacted yields and expectations at all (Kool and Thorton 2015). Announcements may also contain forecasts of many macrovariables, which lead to qualitatively different responses to forward guidance than Del Negro, Giannoni, and Patterson (2015)

[2]We note that an exogenous fiscal transfers rule—a special case of a permanent active fiscal policy—cannot be endogenous to monetary policy. Consequently, a forward-guidance announcement in a model with exogenous surpluses does not trigger the movements in expected transfers that appear necessary to generate a forward-guidance puzzle in their framework.

[3]See Moessner, Jansen, and de Haan (2017) for a survey of the empirical literature on forward guidance.

predict (Campbell et al. 2012, Nakamura and Steinsson 2018). Some work even suggests that standard models make reasonable predictions: Bundick and Smith (2020) show that the predictions of Del Negro, Giannoni, and Patterson (2015) rely on unreasonably large forward-guidance shocks, and D'Amico and King (2015) show that empirical responses grow as the horizon of guidance is extended into the future.

Empirical findings notwithstanding, standard models predict counterintuitive effects of forward guidance. We seek a theoretical resolution to this phenomenon, and other resolutions of the puzzle include life-cycle considerations (Del Negro, Giannoni, and Patterson 2015), sticky information (Carlstrom, Fuerst, and Paustian 2015; Chung, Herbst, and Kiley 2015; Kiley 2016), borrowing constraints (McKay, Nakamura, and Steinsson 2016), bounded rationality (Cole 2020; Gabaix 2020), common knowledge considerations (Angeletos and Lian 2018), state of the economy (Keen, Richter, and Throckmorton 2017), credibility (Haberis, Harrison, and Waldron 2019), limited foresight (Garcia-Schmidt and Woodford 2019), level-k thinking (Farhi and Werning 2018), and heterogeneous beliefs (Andrade et al. 2019).

2. Basic Results in a Simple Model

We only need an endowment economy with flexible prices to illustrate the basic results of the paper:

$$i_t = E_t \pi_{t+1} \tag{1}$$

$$b_t = \beta^{-1} \left(b_{t-1} - \pi_t \right) + i_t - \tau_t \tag{2}$$

$$i_t = \phi^{s_t} \pi_t + \epsilon_t^m \tag{3}$$

$$\tau_t = \gamma^{s_t} b_{t-1} + \epsilon_t^f, \tag{4}$$

where $0 < \beta < 1$, i is the nominal interest rate, π is inflation, b is real government debt, τ is real fiscal surpluses, and ϵ^f and ϵ^m are iid shocks. All variables are expressed in terms of percentage deviations from steady state.[4] (1) and (2) are the Fisher relation and

[4] This model is a special case of the model presented in section 3 of Leeper and Leith (2016). Alternatively, we could linearize the fiscal variables, b and τ, and

intertemporal government budget constraint, respectively, while (3) and (4) are the monetary and fiscal policy rules.

The variable s_t is an exogenous two-state Markov process that changes the monetary and fiscal "regime" over time, e.g., because the behavior of governments may vary over time. The current government's response of surpluses to outstanding debt (i.e., the current fiscal "regime") can be succinctly summarized in terms of γ: a one percentage deviation of debt from steady state triggers a γ percentage deviation of surpluses from steady state. This paper, and the FTPL at large, considers two types of fiscal regimes: (i) when $s_t = M$, fiscal policy is "passive" and $|\beta^{-1} - \gamma^M| < 1$; and (ii) when $s_t = F$, fiscal policy is "active" and $|\beta^{-1} - \gamma^F| > 1$. For reasonable calibrations, this condition boils down to $\gamma^F < \beta^{-1} - 1 < \gamma^M$. The transition probabilities are $Pr(s_t = M|s_{t-1} = M) = p_M$ and $Pr(s_t = F|s_{t-1} = F) = p_F$. Throughout this paper, agents have full-information rational expectations and observe all contemporaneous endogenous and exogenous variables, including s_t, such that $E_t z_{t+1} = Pr(s_{t+1} = M|s_t)E(z_{t+1}|s_{t+1} = M, \mathcal{I}_t) + (1 - Pr(s_{t+1} = M|s_t))E(z_{t+1}|s_{t+1} = F, \mathcal{I}_t)$, where z is any model variable and $\mathcal{I}_t$ is agents' time-t information set. Substituting (4) into (2) reveals the crucial difference between the two regimes:

$$b_t = (\beta^{-1} - \gamma^{s_t})b_{t-1} + i_t - \beta^{-1}\pi_t - \epsilon_t^f. \tag{5}$$

If we set $s_t = M$ and hold it fixed over time, then the autoregressive coefficient in (5), $\beta^{-1} - \gamma^M$, is less than one.[5] Thus, a permanent passive fiscal regime guarantees the dynamic stability of debt (around its steady state) over time given *any* sequence of π_t, i_t, etc. In other words, a fixed (i.e., permanent) passive fiscal regime is a debt-stabilizing or "Ricardian" policy. Because inflation does not need to depend on debt or taxes when the government stabilizes debt using passive fiscal policy, a "Ricardian equilibrium" of the model exists in which $\{\pi_t\}$ is entirely determined by (1) and (3). When monetary policy is active ($\phi^M > 1$), the Ricardian equilibrium is the unique equilibrium. We can obtain this equilibrium solution

log-linearize remaining variables in keeping with the approach of other papers in the literature, but this would not affect the qualitative results in this paper. Also, we assume that steady-state real debt is strictly positive throughout this paper.

[5]We tacitly assume that γ^M is small enough to satisfy $|\beta^{-1} - \gamma^M| < 1$.

by substituting (3) into (1) and solving the Fisher relation forward for π_t. Then b_t passively adjusts to satisfy the government budget constraint (2), taking the solution for π as given. The Ricardian equilibrium for π_t and b_t is then given by

$$\pi_t = -(\phi^M)^{-1}\epsilon_t^m$$
$$b_t = (\beta^{-1} - \gamma^M)b_{t-1} + (\beta^{-1}/\phi^M)\epsilon_t^m - \epsilon_t^f.$$

The standard assumptions in macroeconomics, namely active monetary policy and passive fiscal policy, select the Ricardian equilibrium. The Ricardian equilibrium is therefore the "standard" equilibrium of this model. Its existence depends on the fiscal stance; if we instead choose to impose a fixed active fiscal regime, then the last equation becomes a dynamically *unstable* process for debt—active fiscal policy is non-Ricardian policy. Under non-Ricardian policy, π_t must bear the brunt of stabilizing debt around its steady state: high (low) debt calls for high (low) inflation. There is a good economic motivation for why debt-stabilizing inflation occurs under non-Ricardian policy: households view their bond holdings (government debt) as net wealth when Ricardian equivalence fails, and therefore anything that raises debt and the rate of return on debt can increase aggregate demand and inflation. This failure of Ricardian equivalence has implications for monetary policy as well: a policy that lowers interest rates for an extended period of time also lowers debt service cost (and hence debt) and interest receipts to bondholders, which reduces households' net wealth and therefore reduces demand and inflation.

Since debt-stabilizing inflation is necessary in any stationary equilibrium with non-Ricardian fiscal policy, inflation, debt, interest rates and surpluses are jointly determined by the full system of equations (1)–(4). In other words, non-Ricardian fiscal policies *only* permit non-Ricardian (stationary) equilibriums in which variation in the debt affects inflation, etc. When monetary policy is "passive" (i.e., $\phi^F < 1$),[6] a unique equilibrium exists under a fixed active fiscal regime. We can obtain this solution by substituting (4) into (2), solving (2) forward, taking expectations, and imposing the Fisher

[6] We assume ϕ^{s_t} is non-negative for all s_t.

Table 1. Determinacy Conditions with Permanent Regimes

	AM: $\phi > 1$	**PM: $\phi < 1$**
PF: $\gamma \in (\beta^{-1}-1, \beta^{-1}+1)$	Determinate	Indeterminate
AF: $\gamma \notin (\beta^{-1}-1, \beta^{-1}+1)$	No Stable Solution	Determinate

relation, the transversality condition, and interest rate rule which gives a solution for b_t. π_t passively adjusts to satisfy (2):[7]

$$b_t = \phi^F b_{t-1} + \frac{\beta^{-1}}{\beta^{-1}-\gamma^F}\epsilon_t^m - \frac{\phi^F}{\beta^{-1}-\gamma^F}\epsilon_t^f$$

$$\pi_t = \frac{(\beta^{-1}-\gamma^F-\phi^F)}{(\beta^{-1}-\phi^F)}b_{t-1} - \frac{\gamma^F}{(\beta^{-1}-\gamma^F)(\beta^{-1}-\phi^F)}\epsilon_t^m - \frac{\beta^{-1}-\gamma^F-\phi^F}{(\beta^{-1}-\gamma^F)(\beta^{-1}-\phi^F)}\epsilon_t^f.$$

Table 1 summarizes the determinacy properties of the simple model with fixed policy regimes. Consistent with the above discussion of Ricardian and non-Ricardian policy, we need to pair an active policymaker with a passive policymaker to ensure the existence of a unique equilibrium. Two passive regimes lead to indeterminacy—a familiar consequence of passive monetary policy, since standard macro analysis assumes passive fiscal policy.

Most papers assume a fixed fiscal regime, but this assumption ignores evidence of recurring fiscal regime change in the United States.[8] Recurring regime changes capture variation in the government's fiscal priorities over time, and they could reflect changes in the demand for spending (e.g., in war versus peacetime). Moreover, these recurring changes could affect households' expectations, and therefore the transmission of forward guidance.

Active and passive fiscal regimes recur provided that $p_F < 1$, $p_M < 1$. As before, the question of identifying Ricardian policies

[7] Alternatively, we could solve (2) forward, take expectations, impose the transversality condition, etc., and obtain the same solution for π_t.

[8] See Davig and Leeper (2007a, 2011), Bianchi and Ilut (2017), Bianchi and Melosi (2017), and Chen, Leeper, and Leith (2018), among others.

boils down to identifying fiscal policies, indexed by $(p_M, p_F, \gamma^M, \gamma^F)$, that ensure the asymptotic stability of the debt process (5). We choose the mean square stability concept of Costa, Fragoso, and Marques (2005) to determine when debt is stable.[9] An application of techniques from Costa, Fragoso, and Marques (2005) gives the condition under which fiscal policy ensures mean square stability of the government debt.

THEOREM 1. *Let* $h_F = \beta^{-1} - \gamma^F$ *and* $h_M = \beta^{-1} - \gamma^M$ *and assume* $p_M + p_F \geq 1$. *A fiscal policy,* $(p_M, p_F, \gamma^M, \gamma^F)$, *is Ricardian if and only if*

$$(p_M + p_F - 1)h_F^2 h_M^2 < 1$$
$$p_M h_M^2(1 - h_F^2) + p_F h_F^2(1 - h_M^2) + h_M^2 h_F^2 < 1.$$

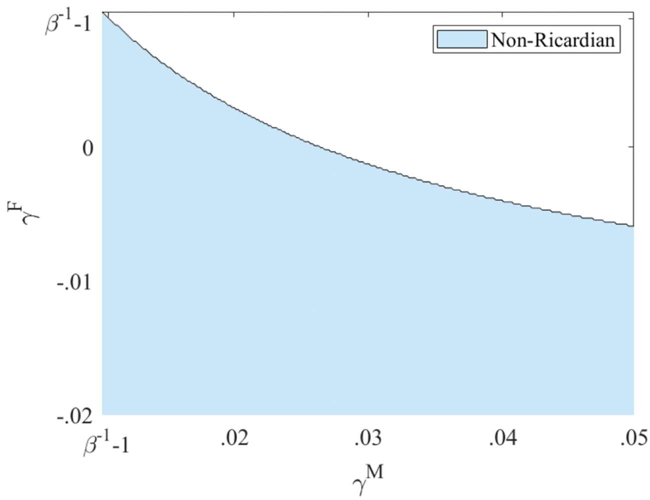
Proof. See appendix A.1. ■

Figure 1 displays combinations, (γ^M, γ^F), that satisfy theorem 1 conditions for given p_M, p_F. Ascari, Florio, and Gobbi (2020) first used these conditions to select mean square stable solutions of a similar model of the FTPL. For the conditions in theorem 1 to be satisfied, active regimes must be sufficiently short-lived and/or timid (i.e., p_F (γ^F) must be relatively low (high)), and passive regimes must be sufficiently persistent and strong (i.e., p_M and γ^M must be relatively high). If the conditions in theorem 1 are satisfied by fiscal policy, then fiscal policy is Ricardian and a mean square stable Ricardian equilibrium exists. If these conditions are violated, perhaps because passive fiscal regimes have short expected durations or because active regimes are highly persistent, then fiscal policy is non-Ricardian and *any* mean square stable equilibrium of the model must be a non-Ricardian equilibrium.

Theorem 1 implies that any fiscal policy is either Ricardian or non-Ricardian, even if said policy involves both passive and active regimes. The FTPL primarily focuses on the impact of non-Ricardian fiscal policy on equilibrium dynamics and, accordingly,

[9]Farmer, Waggoner, and Zha (2009, 2011), Cho (2016), and Foerster et al. (2016), among others, have popularized the use of the mean square stability concept in Markov-switching DSGE environments. Interested readers are referred to those papers for discussions on the mean square stability concept.

Figure 1. Ricardian vs. Non-Ricardian Policy



Note: The white region is the set of Ricardian fiscal policies.

our focus is on the interaction of non-Ricardian policy and monetary forward guidance.

2.1 Forward Guidance

Forward guidance can come in the form of an announcement about future policy actions, including future interest rate policy. To see how policy *regimes* alter the effects of announcements in our model, suppose the public becomes aware of $\epsilon^m_{t+j} \neq 0$ at time t (such that $E_t\epsilon^m_{t+j} = \epsilon^m_{t+j}$). In the Ricardian solution the magnitude of the response of inflation, $\partial\pi_t/\partial\epsilon^m_{t+j} = -(\phi^M)^{-j-1}$, is strictly increasing in j if monetary policy is passive ($\phi^M < 1$); passive monetary policy can induce responses to anticipated ϵ^m_{t+j} that resemble qualities of the forward-guidance puzzle described in the introduction. As $\phi^M \rightarrow 0$, consistent with an interest rate peg ($\phi^M = 0$), the response of inflation to any anticipated policy shock becomes unbounded. On the other hand, $\partial\pi_t/\partial\epsilon^m_{t+j} = -\beta\gamma^F(\beta - \gamma^F)^{-j-1}$ in the non-Ricardian equilibrium (with $\phi^F = 0$), which is bounded for all j and strictly decreasing (in magnitude) in j if fiscal policy is permanently active.[10] This exercise suggests that (i) models with interest rate pegs, or passive monetary policy generally, are susceptible to a forward-guidance puzzle; (ii) non-Ricardian fiscal policy gives inflation a debt-stabilizing role that may preclude the puzzle.

Here we show that non-Ricardian fiscal policy does not always eliminate the forward-guidance puzzle. We follow Del Negro, Giannoni, and Patterson (2015) and much of the literature and model monetary forward guidance as credible news about the future path of nominal interest rates, $\{i_t\}$. For example, a forward-guidance announcement at $t = 0$ could fix agents' expectations of the path of interest rates from $t = T - j$ where $T > t$ and $1 \leq j \leq T$. In this context, a forward-guidance puzzle emerges if the response of inflation explodes or otherwise fails to converge as $T \to \infty$. Given this definition, one can check if (1)–(4) is susceptible to a puzzle simply by examining what happens when the central bank announces a permanent peg: $i_t = \bar{\imath}$ where, importantly, $\bar{\imath}$ does not equal the steady-state interest rate ($\bar{\imath} \neq 0$, since i is log-linearized around steady state with zero inflation).[11] Some manipulations of (1)–(4) give us the system of equations for this exercise:

$$\bar{\imath} = E_t \pi_{t+1} \tag{6}$$

$$b_t = \left(\beta^{-1} - \gamma^{s_t}\right) b_{t-1} + \bar{\imath} - \beta^{-1}\pi_t. \tag{7}$$

The fiscal and monetary policy shocks are shut down in this exercise, because they do not matter for our assessment of the forward-guidance puzzle. Fiscal policy, $(p_M, p_F, \gamma^M, \gamma^F)$, is non-Ricardian, which means that any equilibrium of the model is non-Ricardian. As before, we attempt to find a non-Ricardian forward-guidance solution by solving (7) forward to obtain b_t (after taking expectations, imposing the Fisher relation, transversality condition) and

[10] Derivatives in this paragraph come from the Ricardian solution, $\pi_t = -\sum_{j\geq 0}(\phi^M)^{-j-1} E_t \epsilon^m_{t+j}$, and the non-Ricardian solution, $\pi_t = (1 - \beta\gamma^F) b_{t-1} - \sum_{j\geq 0}(\beta^{-1} - \gamma^F)^{-j-1} \left(\beta\gamma^F E_t \epsilon^m_{t+j} + (1 - \beta\gamma^F) E_t \epsilon^f_{t+j}\right)$.

[11] More generally, we could assume that the central bank makes an announcement at $t = 0$ about the future path of interest rates from $t = 0$ to $t = T \geq 0$: $\{i_t\}^T_{t\geq 0}$. We assume $i_t = \bar{\imath}$ and $T \to \infty$ to simplify the exposition, but this simplifying assumption does not matter for the conditions governing the emergence of a forward-guidance puzzle.

forcing π_t to passively satisfy the government budget constraint at the end of each period. Begin by forwarding (7) one period and taking expectations

$$\begin{aligned} E_t b_{t+1} &= E_t\left(\left(\beta^{-1} - \gamma^{s_{t+1}}\right) b_t + \bar{\imath} - \beta^{-1}\pi_{t+1}\right) \\ &= \delta_t b_t + \bar{\imath}(1 - \beta^{-1}), \end{aligned}$$

where $\delta_t = E_t\left(\beta^{-1} - \gamma^{s_{t+1}}\right)$. Now, expectations depend on s_t, and this fact allows us to use a regime-dependent representation of the above equation:[12]

$$\begin{aligned} b_t^M &= \delta_M^{-1}\left(p_M E_t b_{t+1}^M + (1-p_M) E_t b_{t+1}^F + (\beta^{-1} - 1)\bar{\imath}\right) \\ b_t^F &= \delta_F^{-1}\left(p_F E_t b_{t+1}^F + (1-p_F) E_t b_{t+1}^M + (\beta^{-1} - 1)\bar{\imath}\right), \end{aligned}$$

where b_t^M (b_t^F) is b_t when $s_t = M$ ($s_t = F$) and $\delta_M = p_M\left(\beta^{-1} - \gamma^M\right) + (1-p_M)\left(\beta^{-1} - \gamma^F\right)$, $\delta_F = p_F\left(\beta^{-1} - \gamma^F\right) + (1 - p_F)\left(\beta^{-1} - \gamma^M\right)$. In matrix form,

$$\begin{aligned} \begin{pmatrix} b_t^M \\ b_t^F \end{pmatrix} &= \underbrace{\begin{pmatrix} p_M\delta_M^{-1} & (1-p_M)\delta_M^{-1} \\ (1-p_F)\delta_F^{-1} & p_F\delta_F^{-1} \end{pmatrix}}_{A} \begin{pmatrix} E_t b_{t+1}^M \\ E_t b_{t+1}^F \end{pmatrix} \\ &\quad + \begin{pmatrix} \delta_M^{-1}(\beta^{-1} - 1)\bar{\imath} \\ \delta_F^{-1}(\beta^{-1} - 1)\bar{\imath} \end{pmatrix}. \end{aligned} \tag{8}$$

We solve (8) forward to obtain the forward-guidance solution, which is only possible if the eigenvalues of A are inside the unit circle.[13] If this eigenvalue condition is satisfied, then the forward-guidance responses of b_t and therefore π_t, which passively adjusts to satisfy (7) given b_t, are bounded and convergent. Otherwise, a forward-guidance puzzle emerges: news about the distant future generates unbounded, or nonconvergent, responses in b_t and therefore π_t.

[12] Davig and Leeper (2007b) cast their model in a regime-dependent or "quasi-linear" form as well. Unlike Davig and Leeper (2007b), we do not cast the model in a quasi-linear form in order to study the uniqueness of equilibrium.

[13] Alternatively, we could obtain the forward-guidance solution by first getting an expression for b_t from (7), taking expectations, and solving $b_t = E_t\{(\beta - \gamma^{t+1})^{-1}\left(b_{t+1} - \bar{\imath} + \beta^{-1}\pi_{t+1}\right)\}$ forward. Appendix A.8 shows that this approach yields the same solution for b_t as solving (8) forward.

PROPOSITION 1. *Consider (1)–(4) and suppose the fiscal policy is non-Ricardian. The model does not exhibit a forward-guidance puzzle if and only if*

$$|(p_M + p_F - 1)/(\delta_F \delta_M)| < 1$$
$$|p_F/\delta_F + p_M/\delta_M| - (p_M + p_F - 1)/(\delta_F \delta_M) < 1,$$

where $\delta_M = p_M\left(\beta^{-1} - \gamma^M\right) + (1 - p_M)\left(\beta^{-1} - \gamma^F\right)$, $\delta_F = p_F\left(\beta^{-1} - \gamma^F\right) + (1 - p_F)\left(\beta^{-1} - \gamma^M\right)$.

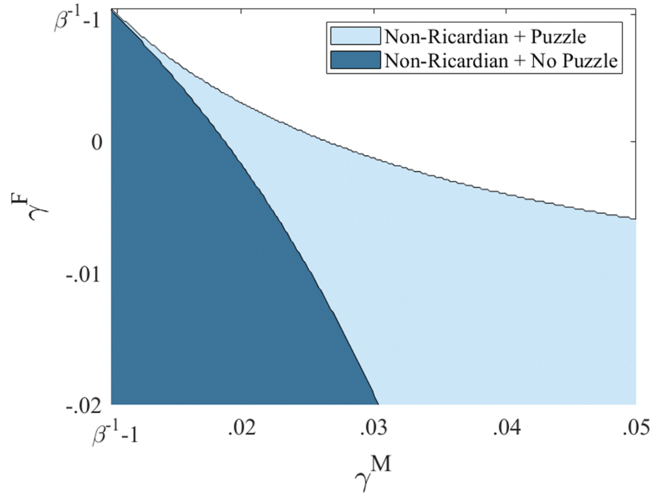
Proof. See appendix A.2. ■

Proposition 1 gives us the condition for ruling out a forward-guidance puzzle in the simple model (1)–(4). The condition leads us to several important conclusions:

- Permanent active fiscal policy precludes forward-guidance puzzles. To see this, set $p_F = 1$ and $p_M = 0$, so that the conditions in proposition 1 collapse down to $|1/\delta_F| = |1/(\beta^{-1} - \gamma^F)| < 1$.
- A permanent *absorbing* active fiscal regime is not sufficient for ruling out a forward-guidance puzzle in economies that allow for a transient passive fiscal spell. Again, set $p_F = 1$ such that the first condition becomes $|p_M/(\delta_M \delta_F)| < 1$. Sufficiently high values of p_M and γ^M will violate this condition; forward-guidance puzzles can emerge in economies with strong and/or persistent passive regimes, even if agents anticipate an absorbing active fiscal regime.
- With recurring regimes ($p_M < 1$ and $p_F < 1$) the solution typically exists in both states, if it exists at all. This is a consequence of "expectations effects" of regime switching; even if a forward-guidance announcement occurs during an active fiscal regime, agents place probability on experiencing a passive government during the forward-guidance horizon. Thus forward guidance only has reasonable, bounded effects during an active fiscal regime if it has reasonable effects during a passive regime.

Figure 2 plots the eigenvalue condition in proposition 1 in (γ^M, γ^F)-space for $p_F = p_M = .95$. Values of (γ^M, γ^F) in the

Figure 2. Forward-Guidance Puzzle in Benchmark Model



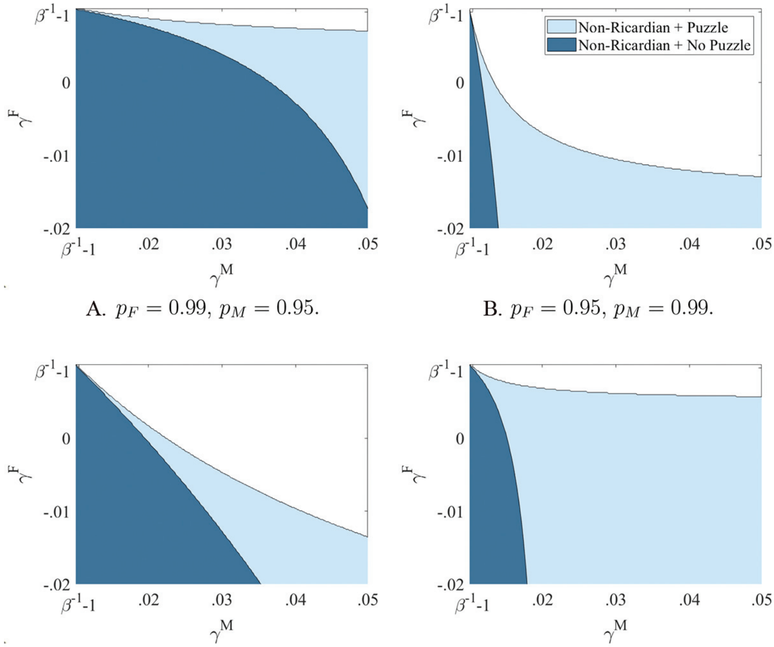
Note: The white region is the set of Ricardian fiscal policies.

northeast corner of figure 2 are the least active, most passive fiscal policies. Figure 2 shows that surpluses need to be sufficiently unresponsive to debt (i.e., γ^F or γ^M must be sufficiently small or negative) to deliver well-behaved responses to a forward-guidance announcement. Importantly, figure 2 shows that some non-Ricardian policies are susceptible to forward-guidance puzzles.

Figure 3 plots the eigenvalue condition in proposition 1 for different values of p_M, p_F. It is clear that the effects of forward guidance are sensitive to transition probabilities:

- More persistent active fiscal regimes (higher values of p_F) shrink the region of (γ^M, γ^F)-space that leads to a forward-guidance puzzle (see figure 3, panel A). The opposite is true with more persistent passive regimes (see panel B).
- Increasing *both* p_F and p_M shrinks the Ricardian region of (γ^M, γ^F)-space, since persistent active fiscal regimes strain debt stability. At the same time, persistent passive fiscal regimes enlarge the non-Ricardian region of (γ^M, γ^F)-space that leads to a forward-guidance puzzle (see figure 3 panel D).

Figure 3. Forward-Guidance Puzzle and Transition Probabilities



A. $p_F = 0.99$, $p_M = 0.95$.

B. $p_F = 0.95$, $p_M = 0.99$.

C. $p_F = 0.9$, $p_M = 0.9$.

D. $p_F = 0.99$, $p_M = 0.99$.

Note: The white region is the set of Ricardian fiscal policies.

Decreasing the persistence of both regimes has the opposite effects (panel C).

We emphasize that it is generally possible to obtain a stable minimal state variable (MSV) equilibrium of (1)–(4) that assumes the form

$$\pi_t = \Omega_\pi(s_t)b_{t-1} + \Gamma_\pi(s_t)u_t \tag{9}$$

$$b_t = \Omega_b(s_t)b_{t-1} + \Gamma_b(s_t)u_t, \tag{10}$$

where $u = (\epsilon^m, \epsilon^f)'$, even in cases where (i) fiscal policy is non-Ricardian (i.e., theorem 1 conditions are not satisfied) and (ii) a forward-guidance puzzle emerges (i.e., proposition 1 conditions are not satisfied). As such, the forward-guidance puzzle can emerge even when other stable equilibriums exist. Importantly, however, these MSV solutions are not forward-guidance solutions; (9)–(10) only relate equilibrium b and π to contemporaneous fundamental variables, and this may prevent agents who inhabit the MSV equilibrium from fully incorporating forward-guidance information in their decisionmaking. Because we seek to determine when forward-guidance puzzles emerge, section 2.1 and proposition 1 focus on rational expectations solutions in which agents fully utilize information about anticipated structural changes. Section 3 offers a general approach for obtaining these solutions in more sophisticated models.

3. A General Approach to Forward Guidance

Unlike the simple model of section 2, more advanced regime-switching models cannot be solved analytically. This section presents tractable numerical techniques for approaching forward guidance in a general class of regime-switching DSGE models.

Specifically, this section presents a solution technique for the responses of endogenous variables to a wide variety of policy announcements and anticipated structural changes, including monetary forward-guidance announcements. Our innovation generalizes techniques from Kulish and Pagan (2017) and Gibbs and McClung (2020) to Markov-switching DSGE models of the form

$$x_t = A^{(s_t)} E_t x_{t+1} + B^{(s_t)} x_{t-1} + C^{(s_t)} u_t + D^{(s_t)}, \qquad (11)$$

where x_t is an $n \times 1$ vector of endogenous variables, u_t is an $m \times 1$ vector of iid mean-zero exogenous shocks, and s_t is an exogenous S-state Markov process with transition matrix, P, where $p_{ij} = Pr(s_{t+1} = j | s_t = i)$ is the (i, j)-th element of P.[14] Notice that equations (1)–(4) jointly share the functional form (11). Moreover, (11) nests the class of linear DSGE models studied by Kulish and Pagan (2017) (i.e., when $S = 1$).

We model any policy announcement or anticipated structural change as follows. Suppose at time 0 agents become aware of N

[14]We assume that shocks are iid for exposition's sake. We could straightforwardly generalize our results in this section to a model class with serially correlated shocks.

structural changes that occur at horizons $0 \leq T_1 < T_2 < \ldots < T_N$. These anticipated structural changes could, for example, arise from monetary forward guidance as in Del Negro, Giannoni, and Patterson (2015), or from forward fiscal guidance as in Canzoneri et al. (2018).[15] The anticipated changes imply the following time-varying structural model:

$$x_t = A_i^{(s_t)} E_t x_{t+1} + B_i^{(s_t)} x_{t-1} + C_i^{(s_t)} u_t + D_i^{(s_t)} \quad \text{for } T_i \leq t < T_{i+1} \tag{12}$$

for $i = 1, \ldots N$, where $T_0 = 0$ and $T_{N+1} \to \infty$. We assume that agents do not know the future path of s_t (i.e., $E_t x_{t+1} = E(x_{t+1}|x_t, u_t, s_t) = \sum_{j=1}^{S} p_{s_t j} E(x_{t+1}|x_t, u_t, s_{t+1} = j)$). This assumption is not restrictive: if policymakers control s_t, they can simply announce a path for s_t in the form of N structural changes at horizons $0 \leq T_1 < T_2 < \ldots < T_N$. Our use of the exogenous Markov process s_t therefore allows us to model any uncertainty about the economy's structure that remains after a sequence of future changes becomes anticipated. For example, section 2 studies the effects of an announcement about the path for future interest rates when agents are uncertain about the future fiscal regime.

Appendix A.3 presents a recursive solution technique that returns a solution of the system (12) (i.e., a forward-guidance solution). To use the solution method, follow these steps:

(i) Select an MSV solution for $t \geq T_N$:[16]

$$x_t = \Omega^{(s_t)} x_{t-1} + \Gamma^{(s_t)} u_t + \xi^{(s_t)}. \tag{13}$$

The MSV solution (13) provides an "asymptotic" model of the economy after the anticipated changes end. Determinacy

[15] Canzoneri et al. (2018) study announcements about changes in future government spending in a prototypical New Keynesian model with an interest rate peg. The anticipated structural changes they study assume the form of the anticipated changes we study here.

[16] See Farmer, Waggoner, and Zha (2009, 2011), Maih (2015), Cho (2016), Foerster et al. (2016), and Barthelemy and Marx (2017) for alternative solution techniques. Notice also that (12) assumes the form (11) for $t \geq T_N$. Finally, the models we study in section 4 satisfy $D_N^{s_t} = \xi^{(s_t)} = 0^n$ for all s_t.

is *not* a requirement for our method to work (if multiple solutions (13) exist, choose one).

(ii) Compute the matrix sequence, $\{\Omega_t^{(s_t)}, \Gamma_t^{(s_t)}, \xi_t^{(s_t)}\}_{t=0}^{T_N-1}$:

$$\Omega_t^{(s_t)} = \left(I - A_i^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} B_i^{(s_t)} \tag{14}$$

$$\Gamma_t^{(s_t)} = \left(I - A_i^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} C_i^{(s_t)} \tag{15}$$

$$\xi_t^{(s_t)} = \left(I - A_i^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} \left(D_i^{(s_t)} + A_i^{(s_t)} E_t\left(\xi_{t+1}^{(s_{t+1})}\right)\right), \tag{16}$$

where $(\Omega_{T_N}^{(s_t)}, \Gamma_{T_N}^{(s_t)}, \xi_{T_N}^{(s_t)}) = (\Omega^{(s_t)}, \Gamma^{(s_t)}, \xi^{(s_t)})$ is given by (13) in the first step and $i \in \{0, 1, 2, \ldots, N-1\}$ depending on t. Note that the sequence is obtained by iterating on (14)–(16) backward in time from $t = T_N - 1$ to $t = 0$. The derivation of this sequence (appendix A.3) is related to the method of undetermined coefficients.[17]

(iii) Using $\{\Omega_t^{(s_t)}, \Gamma_t^{(s_t)}, \xi_t^{(s_t)}\}_{t=0}^{T_N}$, form the forward-guidance solution:

$$x_t = \Omega_t^{(s_t)} x_{t-1} + \Gamma_t^{(s_t)} u_t + \xi_t^{(s_t)}. \tag{17}$$

Our method recovers the solution for all conceivable realizations of the Markov chain, s_t, from time 0 to time T_N. Moreover, (17) is uniquely determined by (13).

Definition 1 (forward-guidance puzzle). *Suppose at time 0 agents become aware of structural changes that will occur at $T_1, T_2, \ldots, T_N$. Then the model does not exhibit a forward-guidance puzzle if and only if $\lim_{T_1 \to \infty} x_0$ exists for all $s_0 \in \{1, \ldots, S\}$, for any given $x_{-1} \in R^n$ and for any given $u_0 \in R^m$.*

[17] Cho (2016) employs the same recursion to solve the model (11) forward to obtain solutions of the form (13). This paper contributes a backward application of that recursion to solve for rational expectations responses of x to forward-guidance announcements.

Intuitively, $\lim_{T_1\to\infty} x_0$ does not exist in two economically unreasonable cases. In the first case, $||\lim_{T_1\to\infty} x_0|| \to \infty$, which means that initial equilibrium responses are unboundedly responsive to policy changes that are scheduled to occur infinitely far in the future. The forward-guidance puzzle explored by Del Negro, Giannoni, and Patterson (2015) is a classic example of this case. In the second case, x_0 oscillates as T_1 increase, as in the models of Carlstrom, Fuerst, and Paustian (2015) that generate "reversals" in the sign of π_0 as T_1 increases. The two cases are not mutually exclusive, and we require the limit of x_0 to exist for all x_{-1}, u_0, and s_0 to help us rule out solutions to the forward-guidance puzzle that could rely on restrictive assumptions such as $x_{-1} = 0^n$ or $u_0 = 0^m$. We also note that if the $\lim_{T_1\to\infty} x_0$ does not exist for some s_0, then it will generally not exist for all s_0. Some intuition for this last claim follows from (14), which reveals that the coefficients in one regime depend on the equilibrium coefficients in all other regimes. See also section 2.1, where the solution in one policy regime depends on the other regime and vice versa.

PROPOSITION 2. *A model of the form (11) does not exhibit a forward-guidance puzzle if and only if*

- $\bar{\Omega}(s_0) = lim_{T_1\to\infty}\Omega_0(s_0)$ *exists for all* s_0.
- $r(\Psi_{\bar{F}}) < 1$,

where $r(A)$ *denotes the spectral radius of matrix* A *and*

$$\Psi_{\bar{F}} = \left(\oplus_{s_0=1}^{S}\left(I_n - A_0^{(s_0)}E_0(\bar{\Omega}^{(s_1)})\right)^{-1} A_0^{(s_0)}\right)(P \otimes I_n).$$

Proof. See appendix A.4. ■

Intuitively, the matrix conditions introduced in proposition 2 tell us when the limit of (14)–(16) exists. If this limit exists, then x_0 converges for any x_{-1}, u_0 as $T_1 \to \infty$. To check these conditions, we only need to iterate on (14) and compute $r(\Psi_{\bar{F}})$ when (14) converges.[18] These matrix operations are easier than computing the full

[18]If the model under study is a purely forward-looking model, then $\bar{\Omega}(s_0) = 0_n$ for all s_0, and one only needs to compute $r(\Psi_{\bar{F}})$ to determine when the model exhibits the forward-guidance puzzle.

forward-guidance solution and they obviate the need for extensive robustness testing involving many different forward-guidance experiments before one can claim that a model is not susceptible to a forward-guidance puzzle.[19]

3.1 Monetary Forward Guidance

Section 2.1 studies a special case of the section 3 method in which the central bank announces an interest rate peg at $t = 0$ that is in effect from $t = 0$ to $T_1 \to \infty$.[20] Many papers study the effects of a time-$t = 0$ forward-guidance announcement that pegs interest rates at the ZLB from $t = 0$ to $T_1 = T$, after which a new monetary policy regime begins for $t > T$.[21] Other studies consider the effects of a time $t = 0$ announcement that i will be pegged at steady state until $T_1 = T$, when interest rates are dropped to the ZLB for one period, after which a new monetary policy regime begins for $t > T$. Section 4 considers both experiments and applies proposition 2 to determine when a model subject to those experiments has a forward-guidance puzzle.

4. New Keynesian Model

Section 2 presents the paper's basic findings using a flexible-price model. While this model can be analytically solved, we turn to models with sticky prices to generate more interesting impulse responses to forward-guidance announcements, and to compare the effects of forward-guidance announcements in models with estimated fiscal rules. Moreover, we can compare the impact of other fiscal theory

[19] Proposition 2 generalizes the main result of Gibbs and McClung (2020) to the class of regime-switching models (11). Gibbs and McClung (2020) show that the conditions stated in proposition 2 are a special case of the E-stability conditions that govern when adaptive learning agents can learn a solution of the form (13). Further, Gibbs and McClung (2020) apply this paper's section 3 methodology to a New Keynesian model with recurring active and passive fiscal regimes in order to better illustrate the idea that E-instability, and not indeterminacy, predicts whether a model and model solution is susceptible to a forward-guidance puzzle.

[20] Appendix A.8 shows how to recover proposition 1 using the general methodology of section 3 and proposition 2. For larger models that do not admit analytical solutions, we rely on the section 3 method for numerical solutions.

[21] In the models we study, i is defined in percent deviations from steady state. Therefore, throughout this paper, we peg i at the ZLB by setting $i = -\bar{\imath}$ where $\bar{\imath}$ is the steady-state nominal interest rate.

features, such as debt maturity structure, and procyclical and countercyclical fiscal policy, on the transmission of forward guidance in a sticky-price framework.[22]

The following comprises a simple New Keynesian model, augmented to include long-term debt and recurring policy regimes:

$$y_t = E_t y_{t+1} - \sigma^{-1}(i_t - E_t \pi_{t+1}) \tag{18}$$
$$\pi_t = \beta E_t \pi_{t+1} + \kappa y_t \tag{19}$$
$$i_t = \phi_y^{s_t} y_t + \phi_\pi^{s_t} \pi_t \tag{20}$$
$$\tau_t = \gamma^{s_t} b_{t-1} + \gamma_y^{s_t} y_t \tag{21}$$
$$b_t = \beta^{-1} b_{t-1} - (1-\rho) P_t^m - \tau_t - \beta^{-1} \pi_t \tag{22}$$
$$P_t^m = -i_t + \beta \rho E_t P_{t+1}^m, \tag{23}$$

where y is the output gap. (18) and (19) are the New Keynesian IS and Phillips equations, (20) and (21) are the policy rules, and (22) is the government's budget constraint.[23] If $\kappa \to \infty$ (i.e., if prices become flexible) and if $\rho = \phi_y^{s_t} = \gamma_y^{s_t} = 0$, (18)–(23) collapses to a model of the form (1)–(4). We abstract from exogenous shocks in (18)–(23) because they do not matter for our results.[24]

Equation (23) gives the price of a "bond portfolio" that the government uses to finance deficits. The portfolio has a geometrically decaying maturity structure, as in Cochrane (2001) and Eusepi and Preston (2018), among others. In the true nonlinear model

[22]Sticky prices are not necessary to study how some of these features affect inflation responses to forward guidance, but we need sticky prices to study output responses.

[23]The fiscal variables in (21) and (22) are again log-linearized around their respective steady states, and we further let b equal real government debt. Alternatively, we could define b as debt to GDP, which would alter the derivation of (22), but it would not alter the main qualitative results in figures 4–5 and 7–9. Similarly as in section 2, we could linearize the fiscal variables, b and τ, and log-linearize remaining variables in keeping with the approach of other papers in the literature, but this would not affect the qualitative results in this paper.

[24]To see this, consider section 3.1; we may model any forward-guidance announcement that changes $\{E_0 i_t\}_{t=0}^T$ by selecting the right sequence of coefficients $\{A_i^{(s_t)}, B_i^{(s_t)}, D_i^{(s_t)}\}_{i=0}^N$, which agents are assumed to observe and incorporate in their expectations formation at time $t = 0$. If one wants to include demand, supply, policy shocks, etc., they may—and these shocks may matter for the empirical fit of the model—but these shocks do not determine whether a model exhibits a forward-guidance puzzle. As such, we abstract from them.

underlying (18)–(23), one unit of the portfolio purchased today pays one unit of nominal income tomorrow, $\rho \in [0, 1]$ the period after, ρ^2 the period after that, and so on. When $\rho = 0$, all debt is short term, and all debt is in consols when $\rho = 1$. The log-linearized conditions for the government budget constraint, and the bond price, which relates short-term interest rates to bond prices via a no-arbitrage condition, are, respectively, (22) and (23).

We include a richer maturity structure of debt because of its importance for monetary transmission in a non-Ricardian policy framework. In a model with all short-term debt ($\rho = 0$), a policy that lowers the path of interest rates also lowers the debt level and interest receipts, which lowers demand since households view their bond holdings (i.e., government debt) as net wealth. When $\rho > 0$, however, the same policy also raises the bond price, P_t^m, which raises the market value of *outstanding* debt and induces a surprise increase in the ex post real rate of return on bonds and interest receipts at every level of inflation at the time of announcement.[25] This suggests that a forward-guidance announcement may either increase or decrease aggregate demand at the time of announcement, depending on the short or long maturity structure. Importantly, it is the *change* in bond prices that raises aggregate demand when the debt maturity is long; a policy that raises the bond price for extended periods eventually lowers interest receipts and aggregate demand, regardless of the maturity structure.

4.1 Calibration and Determinacy

Table 1 describes the determinacy properties of (18)–(23) when regimes are permanent, with a slight modification: monetary policy is active if $\phi_\pi > 1 - \frac{1-\beta}{\kappa}\phi_y$ and passive otherwise. To our knowledge, no general analytical determinacy conditions exist for

[25]When $\rho > 0$, the ex post rate of return on debt, b_{t-1}, depends on both the policy rate, i_{t-1}, and on the price of bondholders' claims to the portfolio in time t, P_t^m. One can show that the log-linearized expression for ex post real interest rate, r, is $r_t = \beta\rho P_t^m - \pi_t - P_{t-1}^m$. For given π_t and P_{t-1}^m, a rise in P_t^m increases r. However, a sustained rise in $\{P_t^m\}$ (e.g., the rise implied by a forward-guidance policy that lowers i for extended periods of time) does not induce a sustained increase in r. To see this, suppose $P_t^m = P_{t-1}^m = P^m$, then $r = (\beta\rho - 1)P^m - \pi_t$ which is decreasing in P^m.

Table 2. Calibration

	Benchmark 1	Benchmark 2	Davig and Leeper (2007a)	Davig and Leeper (2011)
p_M	.95	.95	.9372	.94
p_F	.95	.95	.948	.95
γ^M	.0175	.0175	.0136	.071
γ^F	0	0	$-.0094$	$-.025$
γ_y^M	0	0	.4596	.498
γ_y^M	0	0	.2754	.324
ρ	.1	.9	0	0
$\o_\pi^M$	1.1	1.1	1.1	1.1
$\o_\pi^F$	.5	.5	.5	.5
$\o_y^M$	.1	.1	.1	.1
$\o_y^F$	.1	.1	.1	.1

Notes: We also assume $\beta = .99$, $\sigma = 1$, $\kappa = .05$, and $\bar{b}/\bar{Y} = 1$ where $\bar{b}(\bar{Y})$ is steady-state real debt (output). The Davig and Leeper (2007a) calibration is reported in tables 4.2 and 4.3 of Davig and Leeper (2007a), and the Davig and Leeper (2011) calibration is reported in table 2 of Davig and Leeper (2011).

(18)–(23) when $p_M < 1$ and $p_F < 1$, but Cho and Moreno (2019), McClung (2019), and Ascari, Florio, and Gobbi (2020) study equilibrium multiplicity issues in models of the FTPL with recurring fiscal and monetary regimes.

Table 2 presents calibration details. We consider three different fiscal policy rule calibrations for the model (18)–(23). The "benchmark" calibration imposes $\gamma^F = 0$, such that fiscal surpluses evolve exogenously in the active regime, and a value of γ^M that is low enough to rule out a forward-guidance puzzle in the recurring-regimes model. To compare the effects of forward guidance across different debt maturity structures, we pair the benchmark rule with short maturity structure ($\rho = .1$) and then separately with long maturity structure ($\rho = .9$). We also consider calibrations of (21) that are motivated by the estimated fiscal rules in Davig and Leeper (2007a, 2011). Those papers estimate a two-state univariate model of fiscal surpluses that resembles (21) using U.S. data.[26] In table 2, we

[26] Davig and Leeper (2007a, 2011) specify fiscal surpluses rules of the form $\tau = \gamma_0(s_t) + \gamma(s_t)b_{t-1} + \gamma_y(s_t)y_t + \gamma_g(s_t)g_t + \sigma(s_t)\epsilon_t^f$, where g is government

choose monetary policy parameters that ensure determinacy after forward guidance, based on the determinacy criteria in Cho (2016, 2020).

4.2 The New Keynesian Forward-Guidance Puzzle

4.2.1 Benchmark Calibration

Here we apply proposition 2 to (18)–(23) to determine when fiscal policy selects puzzle-free equilibriums in the model with sticky prices. Extensive numerical analysis confirms that the qualitative results in section 2 carry over to the model with sticky prices: some non-Ricardian fiscal policies rule out forward guidance, while others entail too much passive policy.[27] Also as before, a permanent active fiscal regime is sufficient to rule out a forward-guidance puzzle.

PROPOSITION 3. *Consider (18)–(23) and assume (i) a temporary interest rate peg (such that $\phi_\pi = \phi_y = 0$ for $0 \leq t < T_1$); (ii) long-run passive monetary policy ($\phi_\pi^{s_t} = \phi_\pi$, $\phi_y^{s_t} = \phi_y$, for all $t \geq T_N$, where $0 \leq \phi_\pi < 1 - \frac{1-\beta}{\kappa}\phi_y$); and (iii) permanent active fiscal policy ($\gamma^{s_t} = \gamma$ for all t where $\gamma \notin (\beta^{-1} - 1, \beta^{-1} + 1)$). Then the model does not exhibit a forward-guidance puzzle.*

Proof. See appendix A.5. ■

Proposition 3 shows that permanent active fiscal policy solves the forward-guidance puzzle in the sticky-price model. To our knowledge, no work has shown this formally. In some models with a permanent active fiscal regime, it is also possible to derive an analytical solution to a forward-guidance announcement (e.g., see appendix A.6). We note that the section 3 approach requires (13) to exist. Hence, proposition 2 (and proposition 3) only applies to calibrations that permit well-defined post-forward-guidance solutions.

spending to output. We suppress $\gamma_0(s_t)$, g_t, and ϵ_t^f here, but extensive numerical analysis suggests that our results are unaffected by $\gamma_0(s_t)$, g_t, and ϵ_t^f.

[27]We find the sticky-price version of figure 2 closely resembles figure 2 for all values of ρ we consider. For example, see figure A.2 in the appendix.

4.2.2 Estimated Models

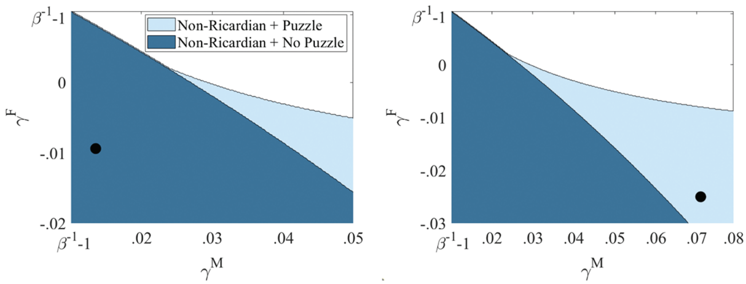
Figures 2–3 and propositions 1 and 3 inform us about the effects of forward guidance for many different calibrations of the fiscal policy rule. However, the data may only prefer some calibrations, and here we pay special attention to the effects of forward guidance in models with empirically relevant descriptions of the fiscal policy stance. First, we embed the estimated fiscal surplus rules from Davig and Leeper (2007a) and Davig and Leeper (2011), who estimate two univariate models of the form (21), into the model (18)–(23). The second exercise in this section applies the section 3 methodology to the full DSGE model of Bianchi and Ilut (2017) to determine whether they find evidence of sufficiently strong active fiscal policy to rule out a forward-guidance puzzle.[28]

Figure 4 plots (γ^M, γ^F)-space for the Davig and Leeper (2007a) and Davig and Leeper (2011) calibrations. The contrast between the two rules is stark: the Davig and Leeper (2007a) passive regime is relatively weak (i.e., γ^M is relatively low) and, consequently, the estimated fiscal rule from that paper does not induce a forward-guidance puzzle. On the other hand, the estimated rule in Davig and Leeper (2011) does provide the fiscal backing necessary for a forward-guidance puzzle to emerge. This is due to the fact that the estimated passive regime in Davig and Leeper (2011) is strongly passive (i.e., $\gamma^M = .072$). Both fiscal rules are non-Ricardian policies.

Figure 5 plots impulse responses of time $t = 0$ inflation to a one-time anticipated monetary policy shock at different horizons, T. Loosely keeping with the notation of section 3, these experiments involve an announcement at $t = 0$ that the nominal interest rate will fall to the ZLB between periods $T - 1$ and T. The interest rate is fixed at steady state between $t = 0$ and $T - 1$, and agents become

[28]See appendix A.7 for the system of equations comprising the Bianchi and Ilut (2017) model. We calibrate their model using the posterior mode estimates reported in table 1 of Bianchi and Ilut (2017). The model is a New Keynesian model with recurring active and passive fiscal and monetary regimes. We find that their estimated fiscal policy rule is non-Ricardian in the sense that it does not ensure mean square stable debt given any sequence of variables impacting the evolution of debt via the government's budget constraint. See Bianchi and Melosi (2017) and Chen, Leeper, and Leith (2018) for other papers that find evidence of recurring regime change in the U.S. monetary-fiscal stance by estimating DSGE models.

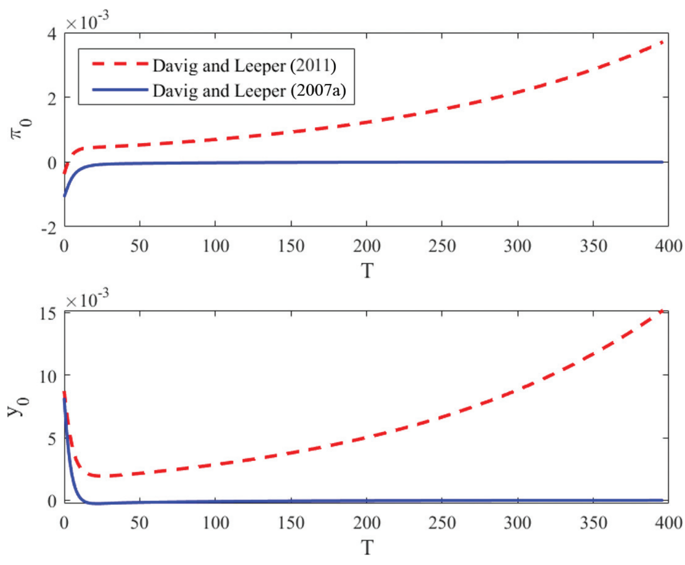
Figure 4. Forward-Guidance Puzzle and Estimated Fiscal Rules



A. Davig and Leeper (2007a) B. Davig and Leeper (2011)

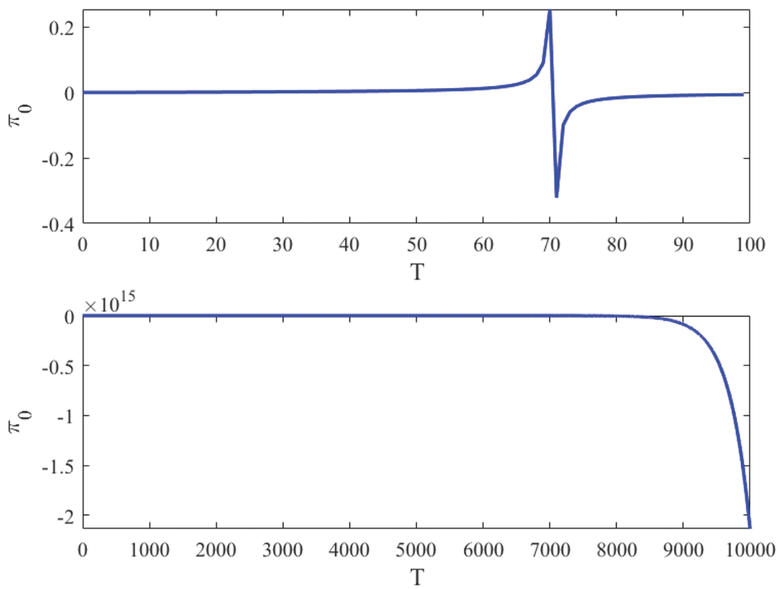
Notes: The black dot in panel A is the estimated value of (γ^M, γ^F) in Davig and Leeper (2007a). The black dot in panel B is the estimated value of (γ^M, γ^F) in Davig and Leeper (2011). The white region is the set of Ricardian fiscal policies.

Figure 5. Davig and Leeper (2007a) vs. Davig and Leeper (2011)



Notes: The dashed (solid) line shows the time-$t = 0$ responses of inflation and output to a time-$t = 0$ announcement of a one-time shock to i_T for different values of T in the model with the Davig and Leeper (2011) (Davig and Leeper 2007a) calibration. We assume i_t is in steady state (i.e., $i_t = 0$) for $t = 0, \ldots, T-1$. The vertical axes units are percent deviations from steady state (e.g., .01 is 1 percent).

Figure 6. Forward Guidance in an Estimated DSGE Model: Bianchi and Ilut (2017)



Notes: Each panel shows the time-$t = 0$ responses of inflation (π_0) to a time-$t = 0$ announcement of a one-time shock to i_T in the model of Bianchi and Ilut (2017) (see appendix A.7). We assume i_t is in steady state (i.e., $i_t = 0$) for $t = 0, \ldots, T-1$. The vertical axes units are percent deviations from steady state (e.g., .01 is 1 percent). The top panel shows π_0 for $T = 0, \ldots, 100$; the bottom panel shows π_0 for $T = 0, \ldots, 10000$.

fully aware of the time-T shock at $t = 0$. The solid line shows the responses in the model with the Davig and Leeper (2007a) calibration; the dashed line shows the responses in the model with the Davig and Leeper (2011) calibration. The figure shows that the magnitude of π_0 *grows* in T for the Davig and Leeper (2011) calibration, which is a sign of the forward-guidance puzzle in action. The opposite is true for the Davig and Leeper (2007a) calibration.

Figure 6 shows the time-$t = 0$ response of inflation to a one-time anticipated shock to nominal interest rates at horizons T in the model of Bianchi and Ilut (2017), calibrated at the posterior mode estimates reported in table 1 of their paper. As in the last exercise, the central bank announces a policy at $t = 0$ that fixes interest rates at steady state for $t = 0, \ldots, T-1$ and sets i at the ZLB between $T-1$ and T, after which normal monetary policy is conducted according to the estimated policy rules.[29] Their estimates deliver a non-Ricardian fiscal policy, which suggests that there could be no forward-guidance puzzle in their model. However, the conditions in proposition 2 are not satisfied for the Bianchi and Ilut (2017) model, calibrated at the posterior mode estimates they report. As a result, a forward-guidance puzzle emerges in simulations: the top panel of figure 6 shows that π_0 is subject to the above-mentioned "reversals" of Carlstrom, Fuerst, and Paustian (2015); the bottom panel shows that inflation is excessively responsive to news about far-away events (e.g., an announcement at $t = 0$ about a one-time shock to i_{10000} causes π_0 to drop to somewhere near $-2 \times 10^{15} \times 100\%$). Though Bianchi and Ilut (2017) find evidence of fiscal theory features in the U.S. data, they do not find evidence that U.S. fiscal policy was sufficiently active to rule out forward-guidance puzzles. In particular, their estimate of the transition probability associated with their model's passive fiscal regime is larger than 0.99—which implies that the average duration of passive fiscal regimes exceeds 100 quarters in their model—and this is one reason their model suggests a forward-guidance puzzle.

By comparing the estimated rules of Davig and Leeper (2007a, 2011), and the estimated model of Bianchi and Ilut (2017), we see that both puzzle-prone non-Ricardian fiscal policies and puzzle-free non-Ricardian policies are empirically plausible. One cannot simply disregard one non-Ricardian case in favor of the other on empirical grounds.

We emphasize one caveat to our treatment of Davig and Leeper (2007a, 2011) and Bianchi and Ilut (2017): these papers largely focus on pre-2008 U.S. data and, as such, their estimates of the persistence and strength of active and passive fiscal regimes depend on the behavior of governments during the latter half of the 20th century. It's entirely possible that the policy response to the financial crisis (e.g., the American Recovery and Reinvestment Act (ARRA) and the Troubled Asset Relief Program (TARP)) "reset" expectations,

[29] Additional details about the experiment are discussed in appendix A.7 as well.

thereby allowing for expectations of strongly active fiscal policy during the horizon over which the Federal Reserve conducted forward guidance. It's also possible that gridlock in U.S. Congress, debt ceiling debacles, and the "fiscal cliff" of 2013 encouraged expectations of strongly passive policy. Therefore, while these papers provide interesting evidence of fiscal theory effects in the U.S. data, future work could shed more light on fiscal expectations during the U.S. ZLB episode of 2008–15.

4.3 Impulse Responses

While we should expect models to generate reasonable responses to news about very distant structural changes, policymakers might also be interested in knowing the model-implied responses of inflation and output to some reasonable forward-guidance horizon, e.g., 12 quarters. This section displays impulse responses to forward-guidance announcements at $t = 0$ that fix nominal interest rates at the ZLB from $t = 0$ to $t = T = 12$.[30]

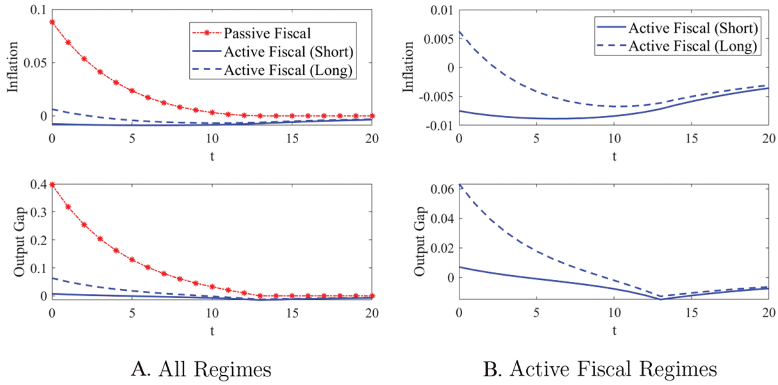
4.3.1 Permanent Regimes

Figure 7 shows the responses to 12 quarters of forward guidance when fiscal regimes are assumed permanent.[31] From panel A of figure 7, a fixed passive regime paired with a rule that implements active monetary policy after forward guidance generates large inflation and output responses that reflect the intertemporal substitution effects of lower expected real interest rates. This is a prime example of the forward-guidance puzzle. In contrast, the fixed active fiscal regimes paired with passive monetary policy post–forward guidance generate much milder responses, in line with proposition 3. Moreover,

[30] Throughout this section, we assume the economy is in steady state at $t = -1$.

[31] In the section 4.3 exercises, we calibrate the permanent regime models according to the benchmark parameter values in table 2 (e.g., for a permanent active fiscal regime model with short maturity, we calibrate the model according to the $s_t = F$ parameter values and solve the resulting linearized DSGE model with fixed coefficients using standard techniques). We choose the calibration with short-term maturity for simulations with permanent passive fiscal regimes. Under a permanent passive fiscal regime, Ricardian equivalence holds and therefore debt maturity details are irrelevant.

Figure 7. Permanent Regimes



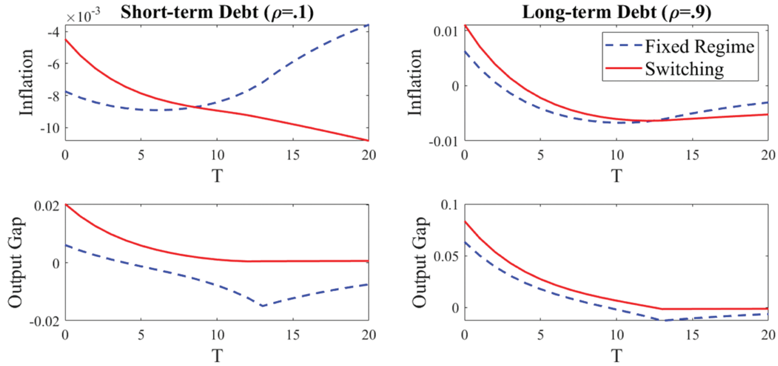
Note: The vertical axes units are percent deviations from steady state (e.g., .01 is 1 percent).

the *eventual* deflation and negative output gap reflect the above-mentioned wealth effects of lower interest rates in economies with non-Ricardian fiscal policy; a prolonged period of low interest rates eventually lowers interest receipts and the level of bonds—which households view as net wealth when fiscal policy is non-Ricardian—and therefore demand and inflation fall over the forward-guidance horizon. These wealth effects do not arise in models with Ricardian policy, such as models with a permanent passive fiscal regime. However, whether inflation *initially* rises or falls depends on the debt maturity structure: when maturity is long, news about lower interest rates initially raises the market value of *outstanding* debt and the ex post real rate of return on bonds, which raises demand and inflation at the time of announcement. Panel B of figure 7 focuses on the two active fiscal regime impulse responses in panel A, and illustrates the last point.

4.3.2 Recurring Regimes

When fiscal regime changes recur, and agents are consequently uncertain about the path of future fiscal regimes, the effects of forward guidance are similar to those displayed in figure 7—provided the fiscal policy at hand solves the forward-guidance

Figure 8. Recurring Regimes



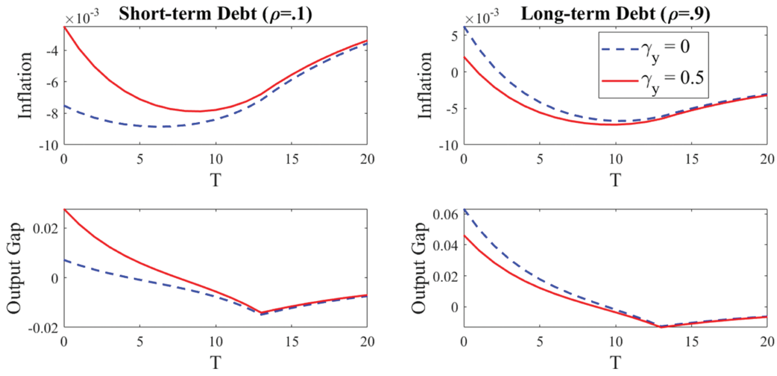
Note: The vertical axes units are percent deviations from steady state (e.g., .01 is 1 percent).

puzzle according to the proposition 2 criteria. This is true even if the forward-guidance policy is carried out during a passive fiscal regime. Figure 8 displays the responses of forward guidance using the benchmark regime-switching parameterizations. As in the experiment of figure 7, we assume that the economy is in steady state when the central bank announces that it will drop i to the ZLB for the next 12 quarters. Unlike the experiments of figure 7, which assume permanent fiscal regimes, we must specify a path for the fiscal regime, s_t. We show impulse responses when $s_t = M$ for $t = 0, \ldots, 20$ (i.e., we assume fiscal policy is passive during the forward-guidance horizon). Crucially, we also assume that agents do not know this path ex ante.[32]

Figure 8 also reproduces the impulse responses for the permanent active regime economies studied in figure 7. The impulse responses in the puzzle-free recurring-regimes models largely resemble the impulse responses in economies with permanent active fiscal

[32]That is to say, we assume that agents form rational expectations using the true transition probabilities (e.g., if $s_t = M$ then $E_t(s_{t+1} = M|s_t = M) = p_M$ where p_M is the probability of remaining in regime M). We choose this path for the fiscal regime because it attenuates the central fiscal theory mechanism in the model, which helps to prevent us from overstating the ability of the fiscal theory to rule out forward-guidance puzzles.

Figure 9. Countercyclical Fiscal Policy



Note: The vertical axes units are percent deviations from steady state (e.g., .01 is 1 percent).

policy, particularly in economies with longer maturity structures. For a model with shorter maturity, the initial responses across the two parameterizations are similar, but forward guidance has more persistent effects in the switching model due to a smaller initial fall in inflation (and hence, a larger fall in the real rate of return on bonds) in the economy with recurring regimes relative to the economy with permanent regimes (e.g., see upper left panel of figure 8). One can show that these persistent declines in inflation are quickly undone by a switch to active fiscal policy.

4.3.3 Cyclical Fiscal Surpluses

The Federal Reserve and other central banks practiced forward guidance in the aftermath of the Great Recession, at a time when some national governments had recently conducted countercyclical policies (e.g., ARRA in the United States), and other governments implemented austerity measures. In the simple model (18)–(23), we can study the interaction of monetary forward-guidance policy and cyclical fiscal policy by setting $\gamma_y \neq 0$. When $\gamma_y > 0$, surpluses are "countercyclical" in the sense that deficits rise as output falls. Otherwise, fiscal policy is procyclical. Automatic stabilizers are examples of countercyclical policy; austerity regimes are procyclical policies.

Figure 9 plots responses to the 12-quarter experiment described above when a permanent countercyclical active fiscal regime is in place.[33] We set $\gamma_y = 0.5$ such that a 1 percent increase in the output gap corresponds to a 0.5 percent increase in fiscal surpluses. This particular value of γ_y is similar to estimated values from Davig and Leeper (2007a, 2011) and Bianchi and Ilut (2017).

With short maturity structure, countercylical policy raises the responses of inflation relative to the case with $\gamma_y = 0$. We interpret this finding as follows: forward guidance causes $\pi_0 = \kappa \sum_{t\geq 0} \beta^t E_0 y_t$ to fall, and this triggers a countercyclical tax cut that counteracts the deflationary effects of forward guidance. Thus, for positive γ_y and shorter debt maturity, forward guidance has *less* deflationary effects than when $\gamma_y = 0$. With long maturity structure, the opposite result is true: forward guidance causes $\pi_0 = \sum_{t\geq 0} E_0 \beta^t y_t$ to rise, and this triggers a countercyclical tax hike that counteracts the inflationary effects of forward guidance. Appendix A.9 contains a more detailed description of these results.

Procyclical policies have the opposite effects of countercyclical policies, with a caveat: if γ_y becomes too negative, then the sign of π_0 "flips." To be concrete, we derive an analytical forward-guidance solution of (18)–(23) (see appendix A.6) and show that the sign of π_0 flips at some critical value, $\bar{\gamma}_y < 0$.[34] For the benchmark calibration, $\bar{\gamma}_y = -.247$, which is a policy that calls for a .247 percent reduction in deficits in response to a 1 percent fall in output. For γ_y near $\bar{\gamma}_y$, forward-guidance solutions diverge to negative or positive infinity.[35]

What should we value from this detour into the interaction of forward guidance and cyclical fiscal policy? For one, we learn that countercyclical policies can reduce the magnitude of inflation responses

[33] As before, we use the benchmark calibration in table 2, except as otherwise noted in the main text.

[34] The derivation assumes $\phi_\pi = \phi_y = \gamma = 0$ for all t, which simplifies the derivation without sacrificing basic fiscal theory mechanisms. The expression for the critical value is $\bar{\gamma}_y = \beta^{-1}\kappa\left(\sigma\beta\kappa^{-1}(\lambda_1 - 1) - 1\right)$ and $\gamma_0 = 1/\beta$, $\gamma_1^* = \gamma_1 = (1+\beta+\sigma^{-1}\kappa)/\beta$, $\lambda_1 = .5(\gamma_1 - \sqrt{(\gamma_1^2 - 4\gamma_0)})$, and where $|\lambda_1| < 1$ and $\gamma_0 = 1/\beta$, $\gamma_1^* = \gamma_1 = (1+\beta+\sigma^{-1}\kappa)/\beta$, $\lambda_1 = .5(\gamma_1 - \sqrt{(\gamma_1^2 - 4\gamma_0)})$, and where $|\lambda_1| < 1$.

[35] Importantly, a well-defined post-forward-guidance solution (13) does not exist at $\gamma_y = \bar{\gamma}_y$, and this prevents us from invoking proposition 3 findings when $\gamma_y = \bar{\gamma}_y$. However, by studying γ_y near $\bar{\gamma}_y$ we see that procyclical regimes interact with forward guidance in volatile ways, even if there is no forward-guidance puzzle in the definition 1 sense.

to monetary forward guidance. Thus, countercyclical responses to the Great Recession may have mitigated the power of monetary forward guidance. The model also suggests that austerity regimes can interact with monetary policy in volatile ways, sometimes leading to explosive inflation or explosive deflation.

4.4 Discussion: Limitations

Sections 2 and 4 show that the fiscal theory *can* resolve the forward-guidance puzzle, but some limitations of our approach are worth mentioning here. Our framework assumes perfect credibility and full-information rational expectations. These strong assumptions, which are standard in the fiscal theory literature and benchmark analyses of the puzzle, allow us to cleanly characterize the interaction of fiscal policy and forward guidance. However, many of the papers cited in the literature review show that deviations from the above assumptions resolve the forward-guidance puzzle, thus highlighting central roles for rationality and credibility in generating counterintuitive model predictions of the effects of forward guidance. Future work could examine interactions of deviations from rationality, non-Ricardian policy, and forward guidance.

Our calendar-based approach to modeling forward guidance, which is similar to the approach of Del Negro, Giannoni, and Patterson (2015), among others, also has limitations. This model strains credibility by assuming that central banks commit to pegging interest rates *regardless* of the magnitude of inflation and output over the forward-guidance horizon, and it fails to capture the many ways central banks give forward guidance in real life (e.g., see Moessner, Jansen, and de Haan 2017). Further, our model does not account for the fact that simultaneous announcements (e.g., quantitative easing, news about other macrovariables, etc.) could affect agents' information sets, thereby affecting the transmission of forward guidance. Reasonable alternatives to the standard model we consider include state-contingent or threshold-based promises, or communication of macroeconomic forecasts and the policy actions consistent with those forecasts ("Delphic" guidance). It is reasonable to conjecture that some of these alternatives, namely state-contingent or imperfectly credible announcements, are less susceptible to the problems we consider in a fiscal theory framework.

Finally, with the exception of the richer model of Bianchi and Ilut (2017), we study simple New Keynesian models. Appendix A.10 shows that our results in the simple New Keynesian models are robust to distortionary labor taxes, but there is room for more analysis in larger models. In sum, this paper shows that the fiscal theory *can* resolve the forward-guidance puzzle, but our results do not imply that the fiscal theory is the most reasonable solution of the forward-guidance puzzle.

5. Conclusion

We develop conditions for a regime-switching model to exhibit a forward-guidance puzzle, and show when the fiscal theory of the price level does—and does not—resolve the forward-guidance puzzle. Importantly, we find that the fiscal theory rules out puzzles, provided fiscal policy is, or is expected to be, sufficiently active. Equally important, we illustrate some empirically relevant cases for which fiscal policy is non-Ricardian, the fiscal theory determines inflation, and forward-guidance puzzles are still there. Thus, one cannot simply ignore the forward-guidance puzzle when inflation serves a necessary debt-stabilizing purpose. We also simulate the effects of announcements that lower the path of interest rates in non-Ricardian economies. Inflation and output gaps *eventually* become negative over the forward-guidance horizon, regardless of the current fiscal regime, but the initial effects of the announcement depend on debt maturity structure and whether policy is countercyclical or procyclical. Countercyclical surpluses attenuate the effects of forward guidance across different maturity structures, whereas forward guidance has ambiguous (and potentially wildly volatile) effects when surpluses are procyclical.

We leave room for future work, particularly work that addresses the important limitations of our approach discussed in section 4.4. In addition, future work could address more complicated monetary-fiscal interactions, including the interaction of cyclical fiscal policy and forward guidance, in a larger estimated model.

Appendix

A.1 Proof of Theorem 1

Define h_F and h_M as in the main text. Using Costa, Fragoso, and Marques (2005), we can show that (5) is a mean square stable process for debt if

$$r(B) = r\begin{pmatrix} p_M h_M^2 & (1-p_F)h_M^2 \\ (1-p_M)h_F^2 & p_F h_F^2 \end{pmatrix} < 1,$$

where $r(B)$ denotes the spectral radius of B. The eigenvalues of B solve the following characteristic polynomial:

$$\lambda^2 - \lambda(p_M h_M^2 + p_F h_F^2) + (p_M + p_F - 1)h_M^2 h_F^2 = 0.$$

Applying techniques from LaSalle (1986, p. 28), we conclude that both eigenvalues of B are inside the unit circle if and only if

$$|(p_M + p_F - 1)h_M^2 h_F^2| < 1 \tag{A.1}$$

$$|p_M h_M^2 + p_F h_F^2| < 1 + (p_M + p_F - 1)h_M^2 h_F^2. \tag{A.2}$$

If we further assume $p_M + p_F \geq 1$, then $|(p_M + p_F - 1)h_M^2 h_F^2| = (p_M + p_F - 1)h_M^2 h_F^2$ and $|p_M h_M^2 + p_F h_F^2| = p_M h_M^2 + p_F h_F^2$, these two conditions can be rearranged into the conditions theorem 1 presents. ■

A.2. Proof of Proposition 1

As argued in the main text, the forward-guidance puzzle does not emerge if the eigenvalues of the following matrix are inside in the unit circle:

$$A = \begin{pmatrix} p_M \delta_M^{-1} & (1-p_M)\delta_M^{-1} \\ (1-p_F)\delta_F^{-1} & p_F \delta_F^{-1} \end{pmatrix} < 1.$$

The eigenvalues of A solve the following characteristic polynomial:

$$\lambda^2 - \lambda(p_M \delta_M^{-1} + p_F \delta_F^{-1}) + (p_M + p_F - 1)\delta_M^{-1}\delta_F^{-1} = 0.$$

Applying techniques from LaSalle (1986, p. 28), we conclude that both eigenvalues of A are inside the unit circle if and only if

$$|(p_M + p_F - 1)\delta_M^{-1}\delta_F^{-1}| < 1 \tag{A.3}$$

$$|p_M\delta_M^{-1} + p_F\delta_F^{-1}| < 1 + (p_M + p_F - 1)\delta_M^{-1}\delta_F^{-1}, \tag{A.4}$$

which is the condition proposition 1 presents. ■

A.3 Forward-Guidance Solution Technique and Proof

The solution technique applies to Markov-switching DSGE models that, in the absence of an announcement about future structural changes, assume the form

$$x_t = A^{(s_t)}E_t x_{t+1} + B^{(s_t)}x_{t-1} + C^{(s_t)}u_t + D^{(s_t)}, \tag{A.5}$$

where x_t is an $n \times 1$ vector of endogenous variables, u_t is an $m \times 1$ vector of iid mean-zero exogenous shocks, and s_t is an exogenous S-state Markov process with transition matrix, P, where $p_{ij} = Pr(s_{t+1} = j|s_t = i)$ is the (i,j)-th element of P.[36]

Suppose at time 0 agents become aware of N structural changes that occur at horizons $0 \leq T_1 < T_2 < \ldots < T_N$. The announcement implies the following model structure:

$$x_t = A_N^{(s_t)}E_t x_{t+1} + B_N^{(s_t)}x_{t-1} + C_N^{(s_t)}u_t + D_N^{(s_t)} \qquad \text{for } t \geq T_N \tag{A.6}$$

$$\vdots \tag{A.7}$$

$$x_t = A_1^{(s_t)}E_t x_{t+1} + B_1^{(s_t)}x_{t-1} + C_1^{(s_t)}u_t + D_1^{(s_t)} \qquad \text{for } T_1 \leq t < T_2 \tag{A.8}$$

$$x_t = A_0^{(s_t)}E_t x_{t+1} + B_0^{(s_t)}x_{t-1} + C_0^{(s_t)}u_t + D_0^{(s_t)} \qquad \text{for } 0 \leq t < T_1. \tag{A.9}$$

We assume that agents do not know the future path of s_t (i.e., $E_t x_{t+1} = E(x_{t+1}|x_t, u_t, s_t) = \sum_{j=1}^{S} p_{s_t j}E(x_{t+1}|x_t, u_t, s_{t+1} = j)$).

[36]We assume that shocks are iid for exposition's sake. We could straightforwardly generalize our results in this section to a model class with serially correlated shocks.

The following procedure gives solutions of (A.6)–(A.9), i.e., “forward guidance solutions”:

(i) Select an MSV solution, which describes the equilibrium law of motion for $t \geq T_N$:[37]

$$x_t = \Omega^{(s_t)} x_{t-1} + \Gamma^{(s_t)} u_t + \xi^{(s_t)}. \tag{A.10}$$

The solution (A.10) provides an “asymptotic” model of the economy for $t \geq T_N$. Determinacy is *not* a requirement for our method to work (if multiple solutions (A.10) exist, choose one).

(ii) Initiate the backward recursion by forming expectations of x_{T_N} at time $T_N - 1$. To simplify the notation, let $T = T_N$. Then, $E_{T-1} x_T = E_{T-1}(\Omega^{(s_T)} x_{T-1} + \Gamma^{(s_T)} u_T + \xi^{(s_T)})$, where E_{T-1} conditions on all time $T-1$ variables including $x_{T-1}, u_{T-1}, s_{T-1}$. Substitute $E_{T-1} x_T$ into (A.5), where $(A^{(s_t)}, B^{(s_t)}, C^{(s_t)}, D^{(s_T)}) = (A_{N-1}^{(s_t)}, B_{N-1}^{(s_t)}, C_{N-1}^{(s_t)}, D_{N-1}^{(s_T)})$, and solve for x_{T-1} to recover the following rational expectations equilibrium (REE) matrices:

$$\begin{aligned}
\Omega_{T-1}^{(s_{T-1})} &= \left(I - A_{N-1}^{(s_{T-1})} E_{T-1}(\Omega^{(s_T)})\right)^{-1} B_{N-1}^{(s_{T-1})} \\
\Gamma_{T-1}^{(s_{T-1})} &= \left(I - A_{N-1}^{(s_{T-1})} E_{T-1}(\Omega^{(s_T)})\right)^{-1} C_{N-1}^{(s_{T-1})} \\
\xi_{T-1}^{(s_{T-1})} &= \left(I - A_{N-1}^{(s_{T-1})} E_{T-1}(\Omega^{(s_T)})\right)^{-1} \\
&\quad \left(D_{N-1}^{(s_{T-1})} + A_{N-1}^{(s_{T-1})} E_{T-1}\left(\xi^{(s_T)}\right)\right).
\end{aligned}$$

Hence, $x_{T-1} = \Omega_{T-1}^{(s_{T-1})} x_{T-2} + \Gamma_{T-1}^{(s_{T-1})} u_{T-1} + \xi_{T-1}^{(s_{T-1})}$, where the REE matrices $\Omega_{T-1}^{(s_{T-1})}$, $\Gamma_{T-1}^{(s_{T-1})}$, and $\xi_{T-1}^{(s_{T-1})}$ are uniquely determined for all s_{T-1}.

[37] See Farmer, Waggoner, and Zha (2009, 2011), Maih (2015), Cho (2016), Foerster et al. (2016), and Barthelemy and Marx (2017) for alternative solution techniques. The models we study satisfy $D_N^{s_t} = \xi^{(s_t)} = 0^n$ for all s_t.

(iii) Repeat this undetermined coefficients logic to obtain the solution matrices $\{\Omega_t^{(s_t)}, \Gamma_t^{(s_t)}, \xi_t^{(s_t)}\}_{t=0}^{T-1}$:

$$\Omega_t^{(s_t)} = \left(I - A_i^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} B_i^{(s_t)} \tag{A.11}$$

$$\Gamma_t^{(s_t)} = \left(I - A_i^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} C_i^{(s_t)} \tag{A.12}$$

$$\xi_t^{(s_t)} = \left(I - A_i^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} \left(D_i^{(s_t)} + A_i^{(s_t)} E_t\left(\xi_{t+1}^{(s_{t+1})}\right)\right) \tag{A.13}$$

given $(\Omega_T^{(s_t)}, \Gamma_T^{(s_t)}, \xi_T^{(s_t)}) = (\Omega^{(s_t)}, \Gamma^{(s_t)}, \xi^{(s_t)})$, where $i \in \{0, 1, 2, \ldots, N-1\}$ depending on t. Note that the sequence of matrices, $\{\Omega_t^{(s_t)}, \Gamma_t^{(s_t)}, \xi_t^{(s_t)}\}_{t=0}^{T}$, is uniquely determined by $(\Omega_T^{(s_t)}, \Gamma_T^{(s_t)}, \xi_T^{(s_t)}) = (\Omega^{(s_t)}, \Gamma^{(s_t)}, \xi^{(s_t)})$.

(iv) The forward-guidance solution is

$$x_t = \Omega_t^{(s_t)} x_{t-1} + \Gamma_t^{(s_t)} u_t + \xi_t^{(s_t)}. \tag{A.14}$$

Given $\{\Omega^{(s_t)}, \Gamma^{(s_t)}, \xi^{(s_t)}\}$, (A.14) is unique. We did not impose any restrictions on the state history, $\mathcal{S}^{T+1} = \{s_0, \ldots, s_{T+1}\}$, which means that our method provides the solution, x_t, for all conceivable realizations of the Markov chain, s_t, from time 0 to time $T+1$.

A.4 Proof of Proposition 2

First, we show that $\lim_{T_1 \to \infty} x_0$ exists for all $s_0 \in \{1, \ldots, S\}$, given any $x_{-1} \in \mathbb{R}^n$, $u_0 \in \mathbb{R}^m$ if and only if $\lim_{T_1 \to \infty} \xi_0^{(s_0)} = \bar{\xi}^{(s_0)}$, $\lim_{T_1 \to \infty} \Gamma_0^{(s_0)} = \bar{\Gamma}^{(s_0)}$, and $\lim_{T_1 \to \infty} \Omega_0^{(s_0)} = \bar{\Omega}^{(s_0)}$ exist for all s_0.

$$\begin{aligned}
\lim_{T_1 \to \infty} x_0 &= \lim_{T_1 \to \infty} \left(\xi_0^{(s_0)} + \Omega_0^{(s_0)} x_{-1} + \Gamma_0^{(s_0)} u_0\right) \\
&= \left(\lim_{T_1 \to \infty} \xi_0^{(s_0)}\right) + \left(\lim_{T_1 \to \infty} \Omega_0^{(s_0)}\right) x_{-1} + \left(\lim_{T_1 \to \infty} \Gamma_0^{(s_0)}\right) u_0,
\end{aligned}$$

which clearly exists for any given x_{-1}, u_0, s_0 if and only if $\lim_{T_1 \to \infty} \xi_0^{(s_0)} = \bar{\xi}^{(s_0)}$, $\lim_{T_1 \to \infty} \Gamma_0^{(s_0)} = \bar{\Gamma}^{(s_0)}$, and $\lim_{T_1 \to \infty} \Omega_0^{(s_0)} =$

$\bar{\Omega}^{(s_0)}$ exist for all s_0. Second, we prove the following: $\lim_{T_1\to\infty}\xi_0^{(s_0)} = \bar{\xi}^{(s_0)}$, $\lim_{T_1\to\infty}\Gamma_0^{(s_0)} = \bar{\Gamma}^{(s_0)}$, and $\lim_{T_1\to\infty}\Omega_0^{(s_0)} = \bar{\Omega}^{(s_0)}$ exist for all s_0 if and only if $\lim_{T_1\to\infty}\Omega_0^{(s_0)} = \bar{\Omega}^{(s_0)}$ exists for all s_0 and $r(\Psi_{\bar{F}}) < 1$, where

$$\Psi_{\bar{F}} = \left(\oplus_{s_0=1}^{S}\left(I_n - A_0^{(s_0)}E_0(\bar{\Omega}^{(s_1)})\right)^{-1}A_0^{(s_0)}\right)(P\otimes I_n),$$

where $\oplus_{s_0=1}^{S}\left(I_n - A_0^{(s_0)}E_0(\bar{\Omega}^{(s_1)})\right)^{-1}A_0^{(s_0)} = diag(\left(I_n - A_0^{(1)}E_0(\bar{\Omega}^{(s_1)})\right)^{-1}A_0^{(1)},\ldots,\quad \ldots,\left(I_n - A_0^{(S)}E_0(\bar{\Omega}^{(s_1)})\right)^{-1}A_0^{(S)})$. Since (14) decouples from (15)–(16), $\lim_{T_1\to\infty}\Omega_0^{(s_0)} = \bar{\Omega}^{(s_0)}$ exists independently of (15)–(16), and (15) reveals that $\bar{\Gamma}^{(s_0)}$ exists for all s_0 if $\bar{\Omega}^{(s_0)}$ exists for all s_0. Finally, define $\Psi_{\bar{A}} = \left(\oplus_{s_0=1}^{S}\left(I_n - A_0^{(s_0)}E_0(\bar{\Omega}^{(s_1)})\right)^{-1}\right)$, $\xi_t = (\xi_t^{(1)'},\ldots,\xi_t^{(S)'})'$, and $D_0 = (D_0^{(1)'},\ldots,D_0^{(S)'})'$. When $\lim_{T_1\to\infty}\Omega_0^{(s_0)} = \bar{\Omega}^{(s_0)}$ exists, ξ_t evolves backwards in time (i.e., as $t\to-\infty$ and $T_1\to\infty$) according to[38]

$$\xi_t = \Psi_{\bar{F}}\xi_{t+1} + \Psi_{\bar{A}}D_0. \tag{A.15}$$

(A.15) is a system of linear difference equations that is globally stable around the unique steady state, $\lim_{t\to-\infty}\xi_t = \lim_{T_1\to\infty}(\xi_0^{(1)'},\ldots,\xi_0^{(S)'})' = (\bar{\xi}^{(1)'},\ldots,\bar{\xi}^{(S)'})'$, if and only if $r(\Psi_{\bar{F}}) < 1$. This completes the second part of the proof. ■

A.5. Proof of Proposition 3

Let $\mathcal{U}$ denote the set of equilibriums of (14) when $i = 0$: $\mathcal{U} = \{\Omega^*|\Omega^* = (I - A_0\Omega^*)^{-1}B_0\}$, where s_t is dropped to reflect the permanence of policy regimes. For any $\Omega^*\in\mathcal{U}$ and corresponding $F^* = (I - A_0\Omega^*)^{-1}A_0$, Ω^* is a locally stable equilibrium in $\mathcal{U}$ if and only if $r((\Omega^*)'\otimes F^*) = r(\Omega^*)r(F^*) < 1$. Hence, if $r(\Omega^*)r(F^*) > 1$,

[38] Technically, our notation in the main text assumes $t \geq 0$, but we can redefine t to claim that (A.15) governs the evolution of ξ_0 as $T_1\to\infty$.

then $\lim_{T_1\to\infty}\Omega_0 \neq \Omega^*$. Given that $\gamma \notin (\beta^{-1}-1, \beta^{-1}+1)$ and an interest rate peg ($\phi_\pi = \phi_y = 0$) is in place at $t=0$, we know from the determinacy conditions reported in table 1 that there exists a unique equilibrium of (14), $\bar{\Omega}$, such that $r(\bar{\Omega}) < 1$ (i.e., $r(\Omega^*) > 1$ for all $\Omega^* \in \mathcal{U}\backslash\{\bar{\Omega}\}$). Furthermore, McCallum (2007) shows that $r(\bar{F}) < 1$, such that $r(\bar{\Omega})r(\bar{F}) < 1$, which implies that $\bar{\Omega}$ is a locally stable equilibrium of (14). We show that it is the unique locally stable equilibrium using analysis from Cho (2020). Define $D = \bar{\Omega} - \Omega^*$. Since $\Omega^*, \bar{\Omega} \in \mathcal{U}$ we can write the following:[39]

$$\begin{aligned} x_t &= \bar{\Omega}x_{t-1} \\ &= A_0\bar{\Omega}x_t + B_0x_{t-1} \\ &= A_0\Omega^*x_t + A_0Dx_t + B_0x_{t-1} \\ &= F^*Dx_t + \Omega^*x_{t-1} = F^*D\bar{\Omega}x_{t-1} + \Omega^*x_{t-1}. \end{aligned}$$

Therefore, $D = F^*D\bar{\Omega}$, which implies $vec(D) = \left((\bar{\Omega}') \otimes F^*\right) vec(D)$, such that $r(\bar{\Omega})r(F^*) \geq 1$. It immediately follows that $r(F^*) > 1$ and $r(\Omega^*)r(F^*) > 1$ since $r(\bar{\Omega}) < 1$ and $r(\Omega^*) > 1$. Hence, $\lim_{T_1\to\infty}\Omega_0$ can only be $\bar{\Omega}$, and $r(\bar{F}) = r(\Psi_{\bar{F}}) < 1$, which means that there is no forward-guidance puzzle. We also note that we rely on local stability conditions, but the assumption of passive monetary policy and active fiscal policy for $t \geq T_N$ gives us small ϕ_y, ϕ_π that are local to $\phi_y = \phi_\pi = 0$ (i.e., Ω is in a reasonably small neighborhood of $\bar{\Omega}$). ■

A.6 Analytical Solution

Suppose $i_t = 0$ for $t \geq T$ and let i_t be exogenous for $0 \leq t \leq T-1$. Further suppose that at time $t=0$, the central bank announces $\{i_t\}_{t=0}^{T-1}$. We solve for the response of inflation, π_0, to this forward-guidance announcement as follows.

First, using techniques demonstrated in Tan and Walker (2015), Leeper and Leith (2016), and Tan (2017), substitute (19) and the

[39]For simplicity, we suppress exogenous shocks and intercept terms in the model so that we can write the model in the form $x_t = A_0E_tx_{t+1} + B_0x_{t-1}$. We can obtain the same results if we include shocks and intercept terms.

equations for i_t into (18) to obtain a second-order difference equations for expected inflation:

$$E_t\pi_{t+2} - \gamma_1 E_t\pi_{t+1} + \gamma_0\pi_t = -\kappa i_t/\sigma\beta = x_t, \tag{A.16}$$

where $\gamma_0 = 1/\beta$, $\gamma_1 = (1 + \beta + \sigma^{-1}\kappa)/\beta$, and $x_t = -\kappa i_t/\sigma\beta$. We factor (39):

$$(E_t\pi_{t+2} - \lambda_1 E_t\pi_{t+1}) - \lambda_2(E_t\pi_{t+1} - \lambda_1\pi_t) = x_t,$$

where $\lambda_1 = .5(\gamma_1 - \sqrt{(\gamma_1^2 - 4\gamma_0)})$, and $\lambda_2 = .5(\gamma_1 + \sqrt{(\gamma_1^2 - 4\gamma_0)})$. Some algebra shows that $|\lambda_1| < 1$ and $|\lambda_2| > 1$. Following the literature, we solve the unstable root forward, which gives us

$$E_0\pi_{t+1} = \lambda_1^{t+1}\pi_0 - \sum_{k=0}^{t}\lambda_1^k \sum_{j=t-k}^{T-1}\lambda_2^{t-k-j-1}x_j \qquad \text{for } 0 < t < T. \tag{A.17}$$

Now, set $\gamma^{s_t} = 0$ and $\gamma_y^{s_t} = \gamma_y$, substitute (21) into (22), solve (22) forward, and impose the transversality condition to obtain an expression for b_{-1},

$$b_{-1} = E_0\sum_{t\geq 0}\beta^{t+1}\left(\gamma_y y_t + \beta^{-1}\pi_t + (1-\rho)P_t^m\right). \tag{A.18}$$

We have

$$E_0\sum_{t\geq 0}\beta^{t+1}(1-\rho)P_t^m = -\beta\rho P_t^m - E_0\sum_{t\geq 0}\beta^{t+1}i_t$$

$$E_0\sum_{t\geq 0}\beta^{t+1}\gamma_y y_t = \beta\gamma_y\pi_0/\kappa$$

$$-\beta\rho P_t^m = E_0\sum_{t\geq 0}(\beta\rho)^{t+1}i_t.$$

Substituting the above expressions into (A.18) gives

$$b_{-1} = (1 + \beta\gamma_y/\kappa)\pi_0 + E_0\sum_{t\geq 0}\left(\beta^{t+1}(\pi_{t+1} - i_t) + (\beta\rho)^{t+1}i_t\right). \tag{A.19}$$

We have $E_0 \sum_{t \geq 0} \beta^{t+1}(\pi_{t+1} - i_t) = \sigma E_0 \sum_{t \geq 0} \beta^{t+1}(y_t - y_{t+1}) = \sigma\beta/\kappa\,(\pi_0 - E_0\pi_1)$, where the first equality holds by substituting (18) into the first sum, and the second equality follows from (19). We also have $E_0 \sum_{t \geq 0}(\beta\rho)^{t+1} i_t = E_0 \sum_{t=0}^{T-1}(\beta\rho)^{t+1} i_t$,. Substituting these last expressions and $E_0\pi_1$ from (A.17) into (A.19) gives

$$\pi_0 = \Omega_\pi(T) b_{-1} + \xi(T) \tag{A.20}$$

$$\Omega_\pi(T) = \left(1 + \sigma\beta\kappa^{-1}(1-\lambda_1) + \gamma_y\beta\kappa^{-1}\right)^{-1} \tag{A.21}$$

$$\xi(T) = -\Omega_\pi(T)\left(\sum_{t=0}^{T-1}(\beta\rho)^{t+1} i_t + \beta\sigma\kappa^{-1}\sum_{j=0}^{T-1}\lambda_2^{t-j-1} x_j\right). \tag{A.22}$$

The solution for π_0 exists for any T given that $|\lambda_2| > 1$, $|\lambda_1| < 1$.

Finally, to solve for $\bar{\gamma}_y$ from section 4, set $\Omega_\pi(T)^{-1} = 0$ and solve for γ_y. Define the solution $\bar{\gamma}_y$. Intuitively, $\bar{\gamma}_y$ is the value that causes π_0 to change signs. Since $\xi(T)/\Omega_\pi(T)$ does not depend on γ_y, the solution π_0 can only change when γ_y changes via the effects of γ_y and $\Omega_\pi(T)$.

A.7 Bianchi and Ilut (2017) Model

Bianchi and Ilut (2017) estimate the following log-linearized system of equations (reported in their online appendix; details about the posterior mode estimates, including estimated steady states, are reported in table 1 of Bianchi and Ilut 2017):

$$\begin{aligned}\hat{y}_t = \tilde{g}_t &- \frac{1}{1+\Phi\gamma^{-1}} E_t(\tilde{g}_{t+1}) + \frac{\Phi\gamma^{-1}}{1+\Phi\gamma^{-1}}(\hat{y}_{t-1} - \tilde{g}_{t-1} - a_t) \\ &- \frac{1-\Phi\gamma^{-1}}{1+\Phi\gamma^{-1}}\left[\tilde{R}_t - E_t[\tilde{\pi}_{t+1}] - (1-\rho_d)d_t\right] \\ &+ \frac{1}{1+\Phi\gamma^{-1}}\left[E_t[\hat{y}_{t+1}] + \rho_a a_t\right]\end{aligned} \tag{A.23}$$

$$\tilde{\pi}_t = \frac{\kappa(1-\Phi\gamma^{-1})^{-1}}{1+\varsigma\beta}\bigg(\left[1+\frac{\alpha}{1-\alpha}\left(1-\Phi\gamma^{-1}\right)\right]\hat{y}_t - \tilde{g}_t$$
$$- \Phi\gamma^{-1}(\hat{y}_{t-1} - \tilde{g}_{t-1} - a_t)\bigg)$$
$$+ \frac{\varsigma}{1+\varsigma\beta}\tilde{\pi}_{t-1} + \frac{\beta}{1+\varsigma\beta}E_t[\tilde{\pi}_{t+1}] + \tilde{\mu}_t \quad \text{(A.24)}$$

$$\tilde{R}_t = \rho_{R,\xi_t^{SP}}\tilde{R}_{t-1} + \left(1-\rho_{R,\xi_t^{SP}}\right)\left[\gamma_{\pi,\xi_t^{SP}}\tilde{\pi}_t + \gamma_{y,\xi_t^{SP}}\left(\hat{y}_t - \hat{y}_t^*\right)\right]$$
$$+ \sigma_{R,\xi_t^{vo}}\epsilon_{R,t} \quad \text{(A.25)}$$

$$\tilde{\chi}_t = \rho_\chi\tilde{\chi}_{t-1} + (1-\rho_\chi)\iota_y(\hat{y}_t - \hat{y}_t^*) + \sigma_{\chi,\xi_t^{vo}}\epsilon_{\chi,t} \quad \text{(A.26)}$$

$$\tilde{\tau}_t = \rho_{\tau,\xi_t^{SP}}\tilde{\tau}_{t-1} + (1-\rho_{\tau,\xi_t^{SP}})\Big[\delta_{b,\xi_t^{SP}}\tilde{b}_{t-1}^m + \delta_e\left(\tilde{\epsilon}_t^S + \tilde{\epsilon}_t^L\right)$$
$$+ \delta_y\left(\hat{y}_t - \hat{y}_t^*\right)\Big] + \sigma_{\tau,\xi_t^{vo}}\epsilon_{\tau,t} \quad \text{(A.27)}$$

$$\tilde{b}_t^m = \beta^{-1}\tilde{b}_{t-1}^m + b^m\beta^{-1}\left(\hat{R}_{t-1,t}^m - \hat{y}_t + \hat{y}_{t-1} - a_t - \tilde{\pi}_t\right)$$
$$- \tilde{\tau}_t + \tilde{\epsilon}_t^S + \tilde{\epsilon}_t^L + \tilde{tp}_t \quad \text{(A.28)}$$

$$\hat{R}_{t,t+1}^m = R^{-1}\rho\hat{P}_{t+1}^m - \hat{P}_t^m \quad \text{(A.29)}$$

$$\tilde{R}_t = E_t\left[R_{t,t+1}^m\right] \quad \text{(A.30)}$$

$$\tilde{\epsilon}_t^S = \rho_{e^S}\tilde{\epsilon}_{t-1}^S + (1-\rho_{e^S})\phi_y(\hat{y}_t - \hat{y}_t^*) + \sigma_{e^S,\xi_t^{vo}}\epsilon_{e^S,t} \quad \text{(A.31)}$$

$$\tilde{\epsilon}_t^L = \rho_{e^L}\tilde{\epsilon}_{t-1}^L + \sigma_{\epsilon^L,\xi_t^{vo}}\epsilon_{e^L,t} \quad \text{(A.32)}$$

$$\tilde{tp}_t = \rho_{tp}\tilde{tp}_{t-1} + \sigma_{tp,\xi_t^{vo}}\epsilon_{tp,t} \quad \text{(A.33)}$$

$$a_t = \rho_a a_{t-1} + \sigma_{a,\xi_t^{vo}}\epsilon_{a,t} \quad \text{(A.34)}$$

$$d_t = \rho_d d_{t-1} + \sigma_{d,\xi_t^{vo}}\epsilon_{d,t} \quad \text{(A.35)}$$

$$\hat{y}_t^* = \left[\frac{1}{1-\Phi\gamma^{-1}} + \frac{\alpha}{1-\alpha}\right]^{-1}$$
$$\left(\frac{1}{1-\Phi\gamma^{-1}}\tilde{g}_t + \frac{\Phi\gamma^{-1}}{1-\Phi\gamma^{-1}}\left(\hat{y}_{t-1}^* - \tilde{g}_{t-1} - a_t\right)\right) \quad \text{(A.36)}$$

$$\tilde{\chi}_t = \frac{1}{g-1}\tilde{g}_t - e^{-1}\tilde{e}_t \quad \text{(A.37)}$$

$$\tilde{\mu}_t = \rho_{\tilde{\mu}}\tilde{\mu}_{t-1} + \sigma_{\tilde{\mu},\xi_t^{vo}}\epsilon_{\tilde{\mu},t}, \quad \text{(A.38)}$$

where $\kappa = (1-\upsilon)/(\upsilon\gamma\Pi^2)$, $g_t = 1/(1-\zeta_t)$, $\tilde{g}_t = ln(g_t/g)$, $\tilde{\mu}_t = \frac{\kappa}{1+\varsigma\beta} log(\aleph_t/\aleph)$, and $\aleph_t = \frac{1/v_t}{1/v_t - 1}$, where v_t is described in Bianchi and Ilut (2017). (A.23) describes the evolution of output, $\hat{y}$; (A.24) is the Phillips curve describing inflation, $\tilde{\pi}$; (A.25) is the monetary policy rule for nominal interest rate, $\tilde{R}$; (A.26) gives the ratio of government purchases to total government expenditure, $\tilde{\chi}$; (A.27) is the fiscal rule for real fiscal surpluses, $\tilde{\tau}$; (A.28) is the government budget constraint for the debt portfolio, $\tilde{b}^m$, with geometrically decaying maturity structure; (A.29) gives the rate of return on long-term bonds, $\hat{R}^m_{t,t+1}$; (A.30) is a no-arbitrage condition linking the nominal short-term interest rate, $\tilde{R}$, to the return on long-term debt, $\hat{R}^m_{t,t+1}$; and (A.31)–(A.38) give us short-term federal expenditures, $\tilde{e}^s$, long-term federal expenditures, $\tilde{e}^L$, term premium shock, $\tilde{tp}$, technology shock, a, demand shock, d, potential output, $\hat{y}*$, government purchases to expenditures ratio, χ, and markup shock, $\tilde{\mu}$, respectively. The market clearing condition, relating output to consumption and government purchases, is substituted into the above equations. Finally, ξ^{SP} is a three-state exogenous Markov process describing the fiscal-monetary regime, and ξ^{vo} is a two-state exogenous Markov process that captures time variation in the volatility of exogenous shocks in the model. Interested readers are referred to Bianchi and Ilut (2017) for more detail.

To compute the impulse responses in figure 6, follow these steps:

(i) Solve the model at the posterior mode reported in table 1 of Bianchi and Ilut (2017) using, e.g., techniques from Farmer, Waggoner, and Zha (2011) as in Bianchi and Ilut (2017).[40] The solution can be cast in the form (13), and it describes the evolution of the economy's variables for $t > T$, where T is the last period of the forward-guidance policy.

(ii) Shut down exogenous processes in (A.32)–(A.35) and (A.38), since they do not determine whether the model is subject to a forward-guidance puzzle.

[40] We set $\alpha = .33$ and $e = 1$, since these parameters are not reported in table 1, but we find that our qualitative results are robust to changes in these parameter values.

(iii) Apply techniques from section 3 to the system (A.23)–(A.38) to simulate the effects of a forward-guidance announcement that sets $\tilde{R}_t = 0$ from the time of announcement $t = 0$ until $T - 1$; sets $\tilde{R}_t = -\bar{\imath}$ at $t = T$, where $\bar{\imath}$ is the steady-state *net* nominal interest rate; and sets $\tilde{R}_t$ according to (A.25), where (A.25) is calibrated at the posterior mode for $t > T$.

(iv) Vary T and compute the inflation response at the time of announcement, π_0, for each T.

We also confirm that the fiscal rule calibrated at the posterior mode estimate is non-Ricardian, which means that any stable solution of the model is non-Ricardian.

A.8 Alternative Approaches to Proposition 1

This section details alternative ways of obtaining the forward-guidance solution in the simple model (1)–(4) of section 2. We explore two alternative approaches here, and show that both recover the conditions in proposition 1 that determine when the simple model is subject to a forward-guidance puzzle.

A.8.1 Alternative Approach 1: Section 3 Methodology

As in section 2, assume at $t = 0$ the central bank announces that $i_t = \bar{\imath} \neq 0$ for $t = 0, \ldots, T_1 - 1$. For $t \geq T_1$:

$$i_t = E_t \pi_{t+1} \tag{A.39}$$

$$b_t = \beta^{-1} (b_{t-1} - \pi_t) + i_t - \tau_t \tag{A.40}$$

$$i_t = \phi^{s_t} \pi_t + \epsilon_t^m \tag{A.41}$$

$$\tau_t = \gamma^{s_t} b_{t-1} + \epsilon_t^f. \tag{A.42}$$

Let $x_t = (\pi_t, b_t)'$ and $u_t = (\epsilon_t^m, \epsilon_t^f)'$. An MSV solution of (A.39)–(A.42) for $t \geq T_1$ assumes the form

$$x_t = \Omega^{(s_t)} x_{t-1} + \Gamma^{(s_t)} u_t, \tag{A.43}$$

where

$$\Omega^{(s_t)} = \begin{pmatrix} 0 & \Omega_\pi(s_t) \\ 0 & \Omega_b(s_t) \end{pmatrix}.$$

Here we treat (A.43) as (13) from section 3 in this application. For $t = 0, \ldots, T_1 - 1$:

$$x_t = A_0^{(s_t)} E_t x_{t+1} + B_0^{(s_t)} x_{t-1} + D_0^{(s_t)},$$

where

$$A_0^{(s_t)} = \begin{pmatrix} 0 & -\beta\delta_{s_t}^{-1} \\ 0 & \delta_{s_t}^{-1} \end{pmatrix} \qquad B_0^{(s_t)} = \begin{pmatrix} 0 & 1-\beta\gamma^{s_t} \\ 0 & 0 \end{pmatrix},$$

where $\delta_{s_t} = E_t(\beta^{-1} - \gamma^{s_{t-1}})$ (as in the main text of section 2). We set $u_t = 0$ for all t because these shocks are not anticipated at the time of announcement $t = 0$. Finally, $D_0^{(s_t)}$ is an exogenous vector whose terms are functions of the exogenous path for i_t, $t = 0, \ldots, T_1 - 1$.

To determine whether the model described above has a forward-guidance puzzle, we first iterate on

$$\Omega_t^{(s_t)} = \left(I - A_0^{(s_t)} E_t(\Omega_{t+1}^{(s_{t+1})})\right)^{-1} B_0^{(s_t)}. \tag{A.44}$$

If $\lim_{T_1\to\infty} \Omega_0^{(s_0)} = \lim_{t\to-\infty} \Omega_t^{(s_t)} = \bar{\Omega}^{(s_0)}$ exists for all s_0, then we need to check the condition

$$r(\Psi_{\bar{F}}) = r\left(\left(\oplus_{s_0=M}^{F}\left(I_n - A_0^{(s_0)} E_0(\bar{\Omega}^{(s_1)})\right)^{-1} A_0^{(s_0)}\right)(P \otimes I_n)\right) < 1.$$

Initiate (A.44) by computing $\Omega_{T-1}^{(s_{T-1})}$:

$$\begin{aligned}
\Omega_{T-1}^{(s_{T-1})} &= \left(I - A_0^{(s_{T-1})} E_{T-1}(\Omega_T^{(s_T)})\right)^{-1} B_0^{(s_{T-1})} \\
&= \begin{pmatrix} 1 & -\frac{\beta\delta_{T-1}^{-1} E_{T-1}\Omega_b^{(s_T)}}{1-\delta_{T-1}^{-1} E_{T-1}\Omega_b^{(s_T)}} \\ 0 & \frac{1}{1-\delta_{T-1}^{-1} E_{T-1}\Omega_b^{(s_T)}} \end{pmatrix} \begin{pmatrix} 0 & 1-\beta\gamma^{(s_{T-1})} \\ 0 & 0 \end{pmatrix} \\
&= \begin{pmatrix} 0 & 1-\beta\gamma^{(s_{T-1})} \\ 0 & 0 \end{pmatrix}.
\end{aligned}$$

Iterating further gives us the following solution for $t = 0, \ldots, T-2$:

$$\Omega_t^{(s_t)} = \begin{pmatrix} 0 & 1-\beta\gamma^{(s_t)} \\ 0 & 0 \end{pmatrix} = \bar{\Omega}^{(s_t)}.$$

Since $\bar{\Omega}^{(s_t)}$ exists, we compute $r(\Psi_{\bar{F}})$ to check whether a forward-guidance puzzle emerges. Since our previous work in this appendix implies $A_0^{(s_0)} E_0(\bar{\Omega}^{(s_1)}) = 0_n$, $\left(I_n - A_0^{(s_0)} E_0(\bar{\Omega}^{(s_1)})\right)^{-1} A_0^{(s_0)} = A_0^{(s_0)}$. Therefore,

$$\begin{aligned} r(\Psi_{\bar{F}}) &= \begin{pmatrix} p_M A_0^M & (1-p_M)A_0^M \\ (1-p_F)A_0^F & p_F A_0^F \end{pmatrix} \\ &= \begin{pmatrix} 0 & -p_M\beta\delta_M^{-1} & 0 & -(1-p_M)\beta\delta_M^{-1} \\ 0 & p_M\delta_M^{-1} & 0 & (1-p_M)\delta_M^{-1} \\ 0 & -(1-p_F)\beta\delta_F^{-1} & 0 & -p_F\beta\delta_F^{-1} \\ 0 & (1-p_F)\delta_F^{-1} & 0 & p_F\delta_F^{-1} \end{pmatrix}. \end{aligned} \tag{A.45}$$

We have that the eigenvalues of (A.45), λ, solve

$$\lambda^2\left(\lambda^2 - \lambda(p_M\delta_M^{-1} + p_F\delta_F^{-1}) + (p_M + p_F - 1)\delta_M^{-1}\delta_F^{-1}\right) = 0. \tag{A.46}$$

Since two of the four eigenvalues equal zero, we only need the roots of $\lambda^2 - \lambda(p_M\delta_M^{-1} + p_F\delta_F^{-1}) + (p_M + p_F - 1)\delta_M^{-1}\delta_F^{-1} = 0$ to be in the unit circle in order for $r(\Psi_{\bar{F}}) < 1$ to hold. The condition determining whether these roots are inside the unit circle is derived in appendix A.2. and presented in proposition 1. Therefore, $r(\Psi_{\bar{F}}) < 1$ if and only if proposition 1 is satisfied.

A.8.2 Alternative Approach 2

Section 2.1 obtains a forward-guidance solution of (1)–(4) by solving the following equation forward:

$$b_t = \delta_t^{-1}\left(E_t b_{t+1} - \bar{\imath} + \beta^{-1}E_t\pi_{t+1}\right), \tag{A.47}$$

where $\delta_t = E_t(\beta^{-1} - \gamma^{s_{t+1}})$. The last equation can be recast as (8). Alternatively, we could obtain a forward-guidance solution by solving the following equation forward:

$$b_t = E_t\{\hat{\delta}_{t+1}^{-1}\left(b_{t+1} - \bar{\imath} + \beta^{-1}\pi_{t+1}\right)\}, \tag{A.48}$$

where $\hat{\delta}_{t+1} = \beta^{-1} - \gamma^{s_{t+1}}$. We recast (A.48) as

$$\begin{aligned} b_t^M &= p_M \hat{\delta}_M^{-1} \left(E_t b_{t+1}^M - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^M | s_t = M) \right) + \dots \\ &\quad (1-p_M)\hat{\delta}_F^{-1} \left(E_t b_{t+1}^F - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^F | s_t = M) \right) \\ b_t^F &= (1-p_F) \hat{\delta}_M^{-1} \left(E_t b_{t+1}^M - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^M | s_t = F) \right) + \dots \\ &\quad p_F \hat{\delta}_F^{-1} \left(E_t b_{t+1}^F - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^F | s_t = F) \right), \end{aligned}$$

where $E_t(\pi_{t+1}^i | s_t = M) \neq E_t(\pi_{t+1}^i | s_t = F)$ for $i = M, F$, since π adjusts passively to satisfy the intertemporal government budget constraint (5) (however, $E_t(b_{t+1}^i | s_t = M) = E_t(b_{t+1}^i | s_t = F)$ for $i = M, F$ because b_t is solved forward and only depends on current and future variables). Now consider the following:

$$\begin{aligned} b_t^M &= p_M \hat{\delta}_M^{-1} \left(E_t b_{t+1}^M - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^M | s_t = M) \right) + \dots \\ &\quad (1-p_M)\hat{\delta}_F^{-1} \left(E_t b_{t+1}^F - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^F | s_t = M) \right) \\ &= p_M \hat{\delta}_M^{-1} \left(E_t b_{t+1}^M - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^M | s_t = M) \right) + (1-p_M) b_t^M \\ b_t^M &= \hat{\delta}_M^{-1} \left(E_t b_{t+1}^M - \bar{\imath} + \beta^{-1} E_t(\pi_{t+1}^M | s_t = M) \right). \end{aligned} \tag{A.49}$$

Also, from the Fisher relation,

$$\begin{aligned} \bar{\imath} &= p_M E_t(\pi_{t+1}^M | s_t = M) + (1-p_M) E_t(\pi_{t+1}^F | s_t = M) \\ &= p_M E_t(\pi_{t+1}^M | s_t = M) + (1-p_M)\beta \left(-E_t b_{t+1}^F + \bar{\imath} + \hat{\delta}^F b_t^M) \right) \\ \Longrightarrow & E_t(\pi_{t+1}^M | s_t = M) \\ &= (p_M)^{-1} \left(\bar{\imath} - (1-p_M)\beta \left(-E_t b_{t+1}^F + \bar{\imath} + \hat{\delta}^F b_t^M \right) \right). \end{aligned} \tag{A.50}$$

Substituting (A.50) into (A.49) gives

$$\begin{aligned} b_t^M &= \hat{\delta}_M^{-1} \left(E_t b_{t+1}^M - \bar{\imath} - \frac{1-p_M}{p_M} \left(\hat{\delta}_F b_t^M - E_t b_{t+1}^F + \bar{\imath} \right) + (\beta p_M)^{-1} \bar{\imath} \right) \\ b_t^M &= p_M \delta_M^{-1} E_t b_{t+1}^M + (1-p_M) \delta_M^{-1} E_t b_{t+1}^F + \delta_M^{-1} (\beta^{-1} - 1)\bar{\imath}, \end{aligned} \tag{A.51}$$

where the last equality follows from $\delta_M = p_M \hat{\delta}_M + (1-p_M)\hat{\delta}_F$ and $\delta_F = p_F \hat{\delta}_F + (1-p_F)\hat{\delta}_M$. Notice that (A.51) is the first equation of (8). Hence, the alternative solution approach presented here gives the same equation for b_t^M as (8). An analogous argument gives us b_t^F.

A.9 Cyclical Fiscal Surpluses: Supplement

In section 4.3.3, we argue that countercylical policy raises the responses of inflation relative to the case with $\gamma_y = 0$ when the maturity structure is short. With longer maturity, the opposite effects obtain: countercyclical policy actually lowers inflation relative to the benchmark case. To make sense of these results, it's helpful to solve (22) forward (and impose the transversality condition, take expectations):

$$b_{-1} - \pi_0 + \beta\rho P_0^m = E_0 \sum_{t\geq 0} \beta^{t+1}\left(\tau_t - i_t + \pi_{t+1}\right). \tag{A.52}$$

Equation (A.52) is an equilibrium condition that is satisfied at the time of announcement, $t = 0$.[41] The forward-guidance announcement we consider lowers time-0 expectations of interest rates, which raises the right-hand side of (A.52). Since b_{-1} is predetermined and P_0^m is partially determined by the forward-guidance announcement via (23), π_0 adjusts to ensure (A.52) holds. In the benchmark active fiscal regime calibration, $\gamma = 0$, such that $E_0 \sum_{t\geq 0} \beta^{t+1}\tau_t = \gamma_y E_0 \sum_{t\geq 0} \beta^{t+1} y_t = \beta\gamma_y\kappa^{-1}\pi_0$, where the last equality is obtained by solving (19) forward and making suitable substitutions. Hence, when $\gamma_y \neq 0$, the right-hand side of (A.52) also depends directly on the initial jump in inflation.

To make things more precise, assume $\rho = 0$, such that the fall in expected nominal interest rates, which raises the right-hand side of (A.52), requires π_0 to jump down in order to stabilize real debt around its steady-state value. If $\gamma_y = 0$, this fall may be relatively large. If $\gamma_y > 0$, however, a given fall in inflation *also* reduces the right-hand side of (A.52). In other words, the fall in inflation triggers a countercyclical tax cut, which helps reduce the amount of debt-stabilizing deflation needed in equilibrium. Thus, for positive γ_y and shorter debt maturity, forward guidance has less deflationary effects than when $\gamma_y = 0$.

[41] Of course, (A.52) does not describe an equilibrium *solution*.

Now assume $\rho > 0$ (e.g., $\rho = .9$ in the benchmark calibration). Again, the fall in expected inflation raises the right-hand side of (A.52), but it also raises $\beta\rho P_t^m$ by an amount that is increasing in ρ. In the benchmark calibration with $\gamma_y = 0$, the left-hand side rises by more than the right-hand side, such that π_0 has to rise to offset this increase in bond prices. When $\gamma_y > 0$, however, this rise in π_0 also increases the right-hand side of (A.52), which reduces the magnitude of the jump in equilibrium inflation. In other words, the rise in inflation triggers a countercyclical tax hike, which helps reduce the amount of debt-stabilizing inflation needed in equilibrium.

Procyclical policies have the opposite effects, but only until a certain point: if γ_y becomes too negative, then the sign of π_0 "flips." To be specific, consider the analytical forward-guidance solution of (18)–(23) that appendix A.6 derives.[42] The closed-form solution shows that the sign of π_0 flips when γ crosses $\bar{\gamma}_y < 0$, where

$$\bar{\gamma}_y = \beta^{-1}\kappa\left(\sigma\beta\kappa^{-1}(\lambda_1 - 1) - 1\right)$$

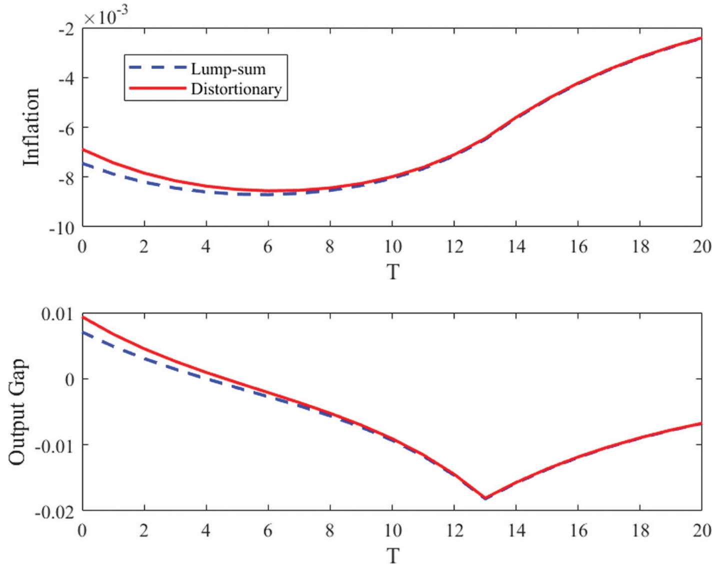
and $\gamma_0 = 1/\beta$, $\gamma_1^* = \gamma_1 = (1 + \beta + \sigma^{-1}\kappa)/\beta$, $\lambda_1 = .5(\gamma_1 - \sqrt{(\gamma_1^2 - 4\gamma_0)})$, and where $|\lambda_1| < 1$. For the benchmark calibration, $\bar{\gamma}_y = -.247$, which is a policy that calls for a .247 percent reduction in deficits in response to a 1 percent fall in output. For γ_y near $\bar{\gamma}_y$, economic responses to forward guidance diverge to positive or negative infinity. We have these extreme results near $\bar{\gamma}_y$ because the solution has a discontinuity at $\bar{\gamma}_y$, and this discontinuity is a bifurcation. Importantly, a well-defined post-forward-guidance solution (13) does not exist at $\gamma_y = \bar{\gamma}_y$, and this prevents us from invoking proposition 3 findings when $\gamma_y = \bar{\gamma}_y$. However, by studying γ_y near $\bar{\gamma}_y$ we see that procyclical regimes interact with forward guidance in volatile ways, even if there is no forward-guidance puzzle in the definition 1 sense.

A.10 Distortionary Taxation

Figure A.1 illustrates the impact of the 12-quarter forward-guidance announcement studied throughout this section in a model with distortionary labor income taxes. As in the model with lump-sum taxes,

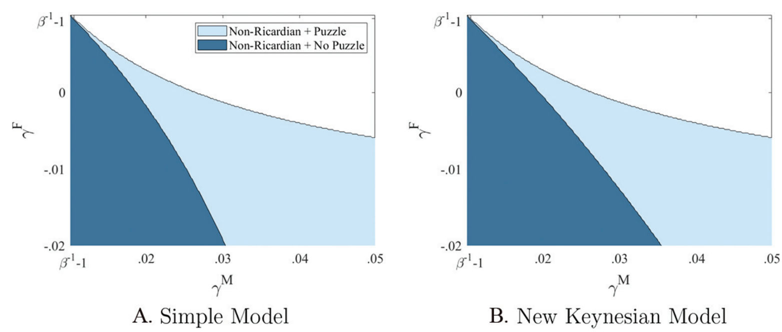
[42] The derivation assumes $\phi_\pi = \phi_y = \gamma = 0$ for all t, which simplifies the derivation without sacrificing basic fiscal theory mechanisms.

Figure A.1. Distortionary Tax



Note: The vertical axes units are percent deviations from steady state (e.g., .01 is 1 percent).

Figure A.2. Forward-Guidance Puzzle: Flexible vs. Sticky Prices



Notes: The white region is the set of Ricardian fiscal policies. $\beta = .99$, $p_M = p_F = .95$ in panels A and B.

the system of equations for the log-linearized model includes (18), (20), and (23). However some modifications are made: first, (21) determines the marginal tax rate on labor income, and since the labor income tax affects marginal costs, (19) is modified to depend linearly on the marginal tax rate, (21). Finally, (22) is modified to reflect the dependence of current fiscal surpluses on both the tax rate and labor income.[43] Figure A.1 shows that the qualitative effects of forward guidance do not vary significantly between the model with lump-sum taxes only and the model with distortionary taxes.

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Systemic Bank Risk and Monetary Policy*

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The risk-taking channel of monetary policy acquires relevance for macro policymakers only if it affects systemic risk. We find robust evidence that a monetary tightening lowers systemic risk using cross-country and time-series data in a VAR framework for 29 G-SIBs from seven countries, different risk metrics (ΔCoVaR, LRMES), as well as econometric specifications and identification schemes (panel VAR with recursive identification; proxy VARs using external instruments). We then assess implications for policy. First, we find that both U.S. and euro-area monetary policy shocks spill into other countries' systemic risk. Second, we document that macroprudential policy plays a significant role in taming the unintended consequences of monetary policy on systemic risk, particularly so for U.S. policy spillovers.

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1. Introduction

Extensive and robust micro evidence exists for the risk-taking channel of monetary policy, namely the notion that the stance of

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monetary policy affects risk-taking behavior of banks.[1] Based on that, monetary policy faces a tradeoff between the beneficial effects of expansionary policies and the unintended increase in bank risk. So far, micro evidence employed individual bank risk or balance sheet measures (for instance, Altunbas, Gambacorta, and Marques-Ibanez 2014; Jiménez et al. 2014; Ioannidou, Ongena, and Peydró 2015; Dell'Ariccia, Laeven, and Suarez 2017). The effects found therein are robust and significant, but quantitatively too small to be relevant from the perspective of macro policymakers. Furthermore, no evidence exists on systemic effects and on aggregate spillovers.[2] If effects are limited to individual bank risk, though important, they can be mitigated through microprudential regulation. In this paper we examine the impact of monetary policy on systemic risk. Given the existence of such an effect, we then analyze how this can be mitigated through a policy mix. Specifically, we assess monetary policy spillovers across different countries and study complementarities between macroprudential and monetary tools.

We assess the dynamic effects of structural monetary policy shocks on systemic bank risk measures with various VAR specifications. Our data set comprises monthly observations for 29 global systemically important banks (G-SIBs) headquartered in seven economies. The effect of monetary policy on bank risk can extend to systemwide risk through two channels, namely network connections and pecuniary externalities. In the first case, an increase in leverage brings about an increase in banks' interconnectedness in wholesale repo or CDS markets. Cascading failures then emerge in response to idiosyncratic shocks.[3] In the second case, banks, in search for yield collectively, invest in the same set of risky assets, implicitly raising the probability of a systemic crisis if shocks hit those assets.[4] In order to capture those various dimensions, and also to make sure that our results are not driven by specific measures, we employ two systemic risk metrics. ΔCoVaR measures the codependency of the financial

[1] See Borio and Zhu (2008) for the first explicit discussion of the channel. We survey the literature in section 2.

[2] See Bernanke (2009).

[3] See Caballero and Simsek (2013) or Greenwood, Landier, and Thesmar (2015) for models of financial networks.

[4] See Allen and Gale (2000) for an early formalization of this channel.

system on a particular bank's value at risk.[5] Intuitively it measures *contagion* through network connections, as it captures each institution's capacity to spread unfavorable outcomes to the rest of the system. We compute this metric using equity prices as well as CDS spreads. The latter have become known for their higher forecasting power. Our second metric, long-run marginal expected shortfall (LRMES), instead measures how much bank equity would be lost in the event of a systemic downturn, i.e., it measures an institution's systemic *exposure*.[6] It therefore captures best the consequences of fire-sale externalities in an environment with widespread risky asset commonality.

We exploit both the time-series and the cross-country dimension of our data to ensure that our results are not driven by a particular subsample or country. We estimate an international panel VAR and two proxy VARs for the United States and the euro area. The panel model allows us to study the effect of monetary policy on systemic risk in a multicountry framework which also embeds banks' cross-sectional heterogeneity. The proxy VAR allows us to verify our results under alternative and recently developed instrumental-variable techniques for shock identification. In there we use high-frequency market surprises around monetary policy announcements to isolate exogenous movements in policy.[7] In order to ensure the most accurate identification of monetary shocks, we purge these market responses from potential confounding factors, such as information effects.[8]

Our analysis is structured in three parts, in each of which we employ both our empirical frameworks. In the first part we establish that across all our specifications an exogenous tightening of monetary policy lowers all three metrics of systemic risk. The effects are robust and sizable also compared with those found in the microeconometric literature. We also make sure that our results are not solely predicated on the occurrence of the financial crisis.

[5]See Adrian and Brunnermeier (2016).
[6]See Brownlees and Engle (2017).
[7]See Gertler and Karadi (2015).
[8]See Nakamura and Steinsson (2018) and Jarocinski and Karadi (2020).

Given these findings, we embark into checking which policy mix would dampen the systemic risk response. We explore monetary policy spillovers across countries and study complementarities between prudential and monetary tools. First, we quantify how much of the effect of monetary policy on systemic risk is driven by national as opposed to U.S. monetary policy. This is against the background that Federal Reserve policy, partly due to the U.S. dollar's dominant international role, is frequently implicated with affecting global monetary and financial conditions (Rey 2015). To answer these questions, we again employ both our empirical models. First, we extract the country-specific structural monetary shocks from our panel VAR. In order to then compare effects of domestic with U.S. shocks, we derive impulse responses in a local projections framework. Second, we add risk measures of a variety of countries to both our U.S. and euro-area proxy VARs and again compare impulse responses. Our findings indicate that it is not only U.S. but also euro-area, next to domestic, monetary shocks that influence systemic bank risk in various countries. Hence spillovers exist, but they are not clearly asymmetric, nor are they predicated on the dominant international role of a currency. This seems reasonable given that the U.S. dollar has a dominant role, particularly for banks' liquidity and international deposits, mainly in countries with unstable inflation rates and weak currencies.[9] Our sample instead comprises industrialized countries whose banking systems to a larger extent rely on local currency.

At last, we examine whether the unintended consequences of monetary policy on risk can be mitigated through macroprudential policy. To this purpose we use time-series data on macroprudential regulation provided in Alam et al. (2019). First, we compute impulse responses in an interacted panel VAR in "easy" and "tight" macroprudential regimes. We find that the spillovers of monetary shocks to our marginal shortfall measure are significantly dampened, while responses of our ΔCoVaR metrics are not altered much. In a second step, we investigate the marginal effects of macroprudential actions on the monetary transmission in a panel local projections framework. To that end, we extract structural shocks from our panel as well as

[9] See European Central Bank (2019).

the proxy VAR models and compute impulse responses of macroprudential interaction terms. For U.S. shocks we find that all three risk measures are significantly less affected following a tightening of macroprudential regulation. For the euro area and the other countries we find that the dampening effect of macroprudential policy holds mainly for the LRMES measure. Overall, our findings confirm the dampening role of prudential policies in the transmission of monetary shocks.

The policy implications of our analysis can be far reaching. Among other things, they imply that monitoring systemic risk metrics can be part of the policy toolkit alongside with other economic variables. Our findings suggest that this might be particularly valuable for macroprudential policymakers. Further, our results show that global banks contribute to systemic risk in other countries following monetary shocks, which provides evidence of financial spillovers. Through this channel, monetary policy actions in one country, by affecting risk, also spill over to other countries, calling for policy coordination.

The paper is structured as follows. Section 2 reviews the literature. Section 3 presents the main results. Section 4 extends the benchmark specifications to examine the role of cross-country policy spillovers. Section 5 analyzes the policy complementarities of monetary and macroprudential tools. Section 6 concludes.

2. Literature Review

The risk-taking channel of monetary policy was discussed in early contributions by Rajan (2005) and in Borio and Zhu (2008). The theoretical literature examined the risk-taking channel on the liability side and on the asset side of banks' balance sheets. Angeloni and Faia (2013), using a dynamic general equilibrium model with fundamental bank runs, show that banks increase their leverage when policy rates are lowered, as they do not internalize the effect of their decisions on the aggregate run probability. Dell'Ariccia, Laeven, and Marquez (2014), using a static bank model with oligopolistic competition, show that lower real interest rates increase banks' incentives to choose asset profiles with higher risk-return profiles. Finally, Martinez-Miera and Repullo (2017) show in a model with a systemic risk metric that an increase of saving induces banks to economize on monitoring costs, thereby increasing banks' asset risk.

On the empirical side, numerous contributions assess the risk-taking channel using individual bank risk metrics, of either assets or liabilities, or banks' balance sheet variables. Some papers use information on changes in lending standards, for instance from rating agency estimates (Altunbas, Gambacorta, and Marques-Ibanez 2014). Others use credit registries information on default histories (Jiménez et al. 2014; Ioannidou, Ongena, and Peydró 2015; Altavilla, Boucinha et al. 2019) or banks' internal ratings on loans (Dell'Ariccia, Laeven, and Suarez 2017). Finally, some papers examine risk information from syndicated loans (Aramonte, Lee, and Stebunovs 2015). In contrast to these, we examine the impact on so-far neglected systemic risk metrics.

All of the above papers employ microeconometric panel data analysis but neglect the time-series dimension. Accounting for the endogenous response of monetary policy is important, however. Some papers do so using VAR methodologies. These include Buch et al. (2014a, 2014b), who focus on asset risk, and Angeloni, Faia, and Lo Duca (2015), who focus on liability risk. None of those papers examines the impact on systemic risk. And none takes up both a multicountry and a time-series perspective. Moreover, our work is, to the best of our knowledge, the first in this line of research to employ recently developed VAR techniques that make use of external information from market responses around monetary policy announcements.[10] Moreover, we also employ this information in local projection methods,[11] adding to the robustness of our results.

Finally, our paper is related to the growing literature on empirically measuring the effects of macroprudential policy. Most papers study the effects of changes in macroprudential measures on financial or economic conditions directly, usually employing macro data for a panel of countries (Kim and Mehrotra 2018, 2019; Alam et al. 2019; Richter, Schularick, and Shim 2019; Schryder and Opitz 2019).

[10] See Gürkaynak, Sack, and Swanson (2005) for early work, Gertler and Karadi (2015) for the first proxy VAR approach to monetary shock identification, and more recently Miranda-Agrippino and Ricco (2021), Anderson and Cesa-Bianchi (2020), and Jarocinski and Karadi (2020). For a euro-area context, see Altavilla, Brugnolini et al. (2019) and Corsetti, Duarte, and Mann (2018).

[11] See Jordà (2005).

However, there is some evidence of effects on the firm level as well (Ayyagari, Beck, and Peria 2018). Fewer papers study the interaction of macroprudential measures with monetary policy. For instance, Everett et al. (2019) do so in a euro-area context, while Coman and Lloyd (2019) do so for U.S. shocks. Our methodology builds on theirs, but—differently from them—we control for non-monetary shocks contained in market responses to policy announcements. More fundamentally, however, we are again concerned with the interaction of monetary and macroprudential policies on systemic risk measures rather than on lending volumes, as they are.

A number of policy implications emerge from our analysis. Measures of systemic risk can, for instance, be employed as variables actively monitored by policymakers. Also, since systemic risk is affected by global banks in several countries, those types of financial spillovers call for more analysis on policy coordination. Further, there are implications for policy communication and announcements. Schularick, Ter Steege, and Ward (2020) find that discretionary and unanticipated monetary policy interest rate hikes trigger crises when enacted in a boom period with easy credit conditions and in small open economies with fixed exchange rate regimes. This is not inconsistent with the finding that prolonged periods of low interest rate favor risk-taking, especially in large economies like the United States. The latter can then materialize in a crisis whenever unexpected shocks (be it an interest rate hike or the sudden emergence of foreclosures that dries out the market for asset-backed securities) make excessive leverage unsustainable. Nor is it incompatible with the notion that announced and well-calibrated increases in interest rates do not necessarily trigger financial crises, if banks and markets are given time to adjust.

3. Monetary Policy and Systemic Risk

We start by establishing our main results, namely that contractionary monetary policy shocks reduce measures of systemic risk in a sample of global systemically important banks. In terms of methodologies, we use both a panel VAR and proxy VARs. In section 3.1 we employ the panel model that allows us to test the cross-country and cross-bank validity of the effect of monetary policy on systemic risk. Hence, we can ascertain that the effects are not an artifact of certain institutions or particularities of certain countries' monetary policy. For the panel VAR we rely on traditional recursive identification schemes. Ideally, we would like to identify monetary policy shocks using high-frequency market responses around monetary policy announcements,[12] which are, however, not available for the full set of countries. Therefore, as an alternative and for robustness purposes, we estimate proxy VARs for the United States and the euro area. In these models, high-frequency market responses are used as external instruments to identify monetary shocks.[13] We additionally take care to "cleanse" these responses from nonmonetary factors. Throughout, we test robustness of our results under various model assumptions, reported in online appendix A.2 (see online appendix at http://www.ijcb.org).

3.1 Panel VAR

3.1.1 Model Description

We denote as $\mathbf{Y}_t$ the stacked version of the vector of G endogenous variables $\mathbf{y}_{i,t}$ so that $\mathbf{Y}_t = (\mathbf{y}'_{1,t}, \mathbf{y}'_{2,t}, \ldots, \mathbf{y}'_{N,t})$, where $i = 1, \ldots, N$ is the cross-sectional index and $t = 1, \ldots, T$ is the time index. The structural panel VAR can then be written as

$$\mathbf{A}_0 \mathbf{y}_{i,t} = \mathbf{k} + \mathbf{A}(L)\mathbf{y}_{i,t-1} + \boldsymbol{\epsilon}_{i,t},$$

where $\mathbf{A}(L) = \mathbf{A}_1 + \mathbf{A}_2 L + \ldots + \mathbf{A}_p L^{p-1}$ is a polynomial in the lag operator L for each cross-sectional unit i and k includes all deterministic components. The corresponding reduced-form VAR then is

$$\mathbf{y}_{i,t} = \mathbf{c} + \mathbf{B}(L)\mathbf{y}_{i,t-1} + \mathbf{u}_{i,t},$$

where $\mathbf{c} = \mathbf{A}_0^{-1}\mathbf{k}$, $\mathbf{B}(L) = \mathbf{A}_0^{-1}\mathbf{A}(L)$, and $\mathbf{u}_{i,t} = \mathbf{A}_0^{-1}\boldsymbol{\epsilon}_{i,t}$ such that $\mathbf{A}_0^{-1}$ is the contemporaneous impact matrix of the mutually uncorrelated $G \times 1$ random disturbances $\boldsymbol{\epsilon}_{i,t}$.

We estimate the model via fixed effects by demeaning. In the panel VAR, we identify structural shocks by specifying the

[12]See Gürkaynak, Sack, and Swanson (2005), Altavilla, Brugnolini et al. (2019), or Jarocinski and Karadi (2020), among others.

[13]See Gertler and Karadi (2015).

impact matrix $\mathbf{A}_0^{-1}$ as lower-triangular such that the ordering of the variables in the VAR implicitly identifies the shocks. As mentioned above, alternative high-frequency identification methods are employed further below. As is common in the literature, we order the variables as follows: macroeconomic controls, monetary policy rates, and risk metrics. This ordering implies that macroeconomic variables do not respond contemporaneously to structural monetary innovations, but that the largely market-based risk measures potentially do.

3.1.2 Data and Variables in the Panel VAR

We employ a monthly panel data set over the sample period 1992–2016 for 29 global systemically important banks (G-SIBs), as defined by the Bank for International Settlements,[14] from 11 countries which we aggregate to seven cross-sectional units, namely the United States, United Kingdom, Japan, the euro area,[15] China, Sweden, and Switzerland. All variables used in the analysis and their data sources are described in online appendix A.1.

The benchmark panel VAR specification is a model in log-levels, which includes logged CPI and GDP. The latter is interpolated using the Chow and Lin (1971) method with industrial production and retail sales as reference series. In addition to a monetary policy indicator, we add to our VAR two types of systemic risk metrics. The first metric, ΔCoVaR, quantifies the codependency of financial institutions on each other's health. Technically, ΔCoVaR measures the contribution of each institution to systemic risk as the difference between the value-at-risk of the system when the bank in question is in distress relative its median state. Intuitively, it measures the extent to which each bank contributes to systemic risk through its connection to the rest of the system. We estimate this metric using equity returns as well as CDS spreads. The second metric we consider is the long-run marginal expected shortfall (LRMES), which measures how much equity would be needed to cover losses in the event of a systemic crisis. Hence, this measure is more apt

[14] See table A.1 in online appendix A.1.

[15] Spain, Germany, France, Italy, and the Netherlands share the same monetary policy and are hence subsumed under the euro area.

to capture exposure of a particular institution to ensuing fire sales or other pecuniary externalities stemming from asset commonality. More details on both types of risk metrics are available in online appendix A.1.3. Due to the extended ubiquity of the zero lower bound, we use shadow rates as policy instruments whenever available.[16] More concretely, we use the shadow rates from Krippner (2013), which have been computed for the United States, United Kingdom, Japan, and the euro area.[17]

3.1.3 Results for the Panel VAR

Figure 1 shows estimated impulse responses to an exogenous increase in the interest rate for all seven countries in a model with 12 lags.[18] The sequence of panels in each row of the figure represents the impulse responses of the four-variable VAR with different risk metrics, namely ΔCoVaR based on equity returns, ΔCoVaR based on CDS spreads, and LRMES. The time sample is 1992:06–2016:12 for the two ΔCoVaR measures and 2000:06–2016:12 for the LRMES metric. The latter is not available earlier.[19]

In each model, GDP and the price level fall persistently after a few months, with prices featuring only a small and short-lived initial increase.[20] More central to the question at hand, all risk metrics fall significantly in all three models, albeit with somewhat different patterns. As mentioned earlier, the two measures capture different aspects of the transmission of individual bank risk to the

[16]Shadow rates can track monetary policy rates in normal times but also when the main policy rate remains near zero.

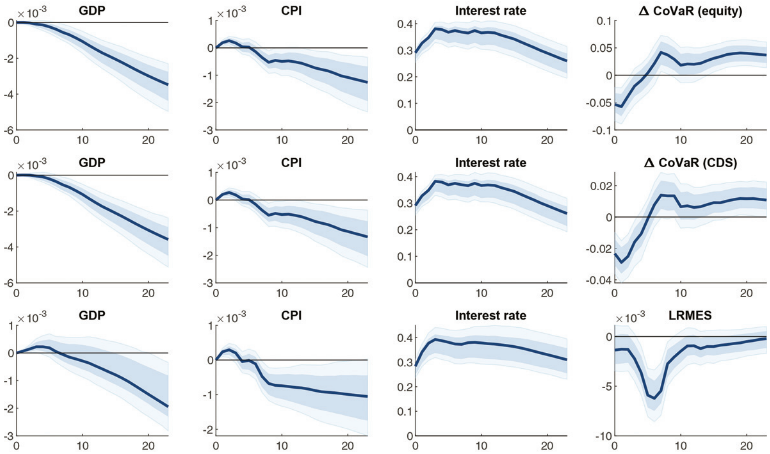
[17]For the remaining countries, we use the actual policy rates. During our sample period, these either never hit the zero lower bound (China), did so only briefly (Sweden), or adopted negative interest rates (Switzerland). Our results remain robust when using the shadow rate estimates by Wu and Xia (2016) and also when simply using policy rates.

[18]Lag length selection is guided by information criteria. The Akaike information criterion prefers 12 lags with a modest gain of going beyond 3 lags, as preferred by the Schwarz Bayesian criterion. We use 12 lags to account for the rich dynamics in our time series, but we check robustness with fewer lags.

[19]We verify that our results remain robust when we harmonize the estimations to start in mid-2000.

[20]This "price puzzle" is commonly observed using recursive identification schemes (see, for instance, Ramey 2016) and, inter alia, motivates our use of a proxy VAR setting below.

Figure 1. Panel VAR



Notes: Impulse responses in the panel VAR(12) to a monetary policy shock. Each row represents a VAR with a different risk metric (ΔCoVaR based on equity returns in the first row, ΔCoVaR based on CDS in the second, and LRMES in the third). Countries included: United States, Japan, United Kingdom, China, euro area (Germany, France, Spain, Netherlands, Italy), Sweden, and Switzerland. Time sample: 1992:06–2016:12 for ΔCoVaR measures and 2000:06–2016:12 for LRMES. Shaded areas indicate 68 percent (dark) and 90 percent (light) confidence bands using bootstrapped cross-sectional system robust standard errors.

system. ΔCoVaR captures particularly a transmission that takes place through network connections, while movements in LRMES are more closely associated with pecuniary externalities. Beyond that, the two measures also potentially capture the dynamics of systemic risk at different horizons. Both ΔCoVaR measures show most of their decline on impact, while the LRMES response is more hump-shaped, reaching its peak after about six months.

These results indicate that changes in the stance of monetary policy are not innocuous for the level of systemic risk of globally important financial institutions. In order to appreciate the relevance of our estimates, we compare their magnitude with previous studies in the microeconometric literature (reviewed in section 2) and find substantially stronger effects. In Altunbas, Gambacorta, and Marques-Ibanez (2014), Jiménez et al. (2014), and Dell'Ariccia, Laeven, and Suarez (2017), the marginal effect of a one-standard-deviation increase in the interest rate measure lies roughly at 0.1 to

0.13 standard deviations of their respective bank risk variable. Performing similar computations based on the maximum response of the three systemic risk variables considered, our results suggest that a one-standard-deviation shock to the interest rate decreases systemic risk by roughly 0.66 (ΔCoVaR) to more than one (LRMES) standard deviations. Differences in methodologies notwithstanding, we interpret these much larger effects as pointing to important macroeconomic externalities and contagion channels in the transmission of monetary shocks.

3.1.4 Robustness and Extensions

We verify robustness of our main results along several dimensions. In figure A.3 in online appendix A.2, all three risk measures continue to decline significantly when the lag length is reduced to 3, as preferred by the Schwarz Bayesian criterion, or indeed to any other number between 4 and 12. Figure A.2 shows that systemic risk responses to a monetary tightening are similar when we use actual policy rates instead of shadow rates. The same is true when using shadow rate estimates by Wu and Xia (2016). Figure A.4 confirms our results for the pre-crisis period. Finally, in earlier versions of the paper we verified our findings for panel VAR specifications in growth rates, with linear time trends and crisis dummies, and when using a mean-group estimator,[21] as well as under a FAVAR model for the U.S. economy.

3.2 Proxy VAR Using External Instruments

Identification is of critical importance in the estimation of any structural VAR model. For this reason we also test our results under recently developed and more rigorous methodologies for monetary policy shock identification. These generally consist of feeding external information into the VAR. Most often, building on early works of Kuttner (2001) and Gürkaynak, Sack, and Swanson (2005), monetary policy shocks are identified based on high-frequency movements in futures or swap prices around monetary policy meetings or press

[21] See Pesaran and Smith (1995). This specification alleviates concerns of parameter biases stemming from heterogeneity in the coefficient matrices across countries.

conferences. These surprises indicate new information to market participants that was not priced into futures contracts before the monetary policy announcements. Since they are therefore orthogonal to consensus market expectations of future macroeconomic developments, endogeneity concerns are argued to be significantly alleviated.

We follow the approach in Gertler and Karadi (2015) and include market surprise series as an instrument in a proxy VAR for the United States and the euro area. This framework is useful not only in addressing endogeneity concerns in general, but is especially suitable for our analysis based on financial market variables. Since in the benchmark panel VAR our risk measures are ordered after interest rates, they are allowed to contemporaneously respond to policy innovations. In turn, however, this recursive ordering precludes a response of policymakers to financial market stress. Such a restriction could potentially undermine the correct identification of structural monetary shocks. Using the proxy VAR approach allows us to overcome such a restriction and additionally use external information contained in the market surprise series.

3.2.1 Proxy VAR Model Description

Consider again the relation between the reduced-form and structural shocks,

$$\mathbf{u}_t = \mathbf{A}_0^{-1}\boldsymbol{\epsilon}_t,$$

now in a single-country VAR. We partition the shock vectors into those to monetary policy, indicated with a superscript p, and others, labeled with a superscript q. The corresponding vectors then read as follows: $\mathbf{u}_t = [\ u_t^p, \mathbf{u}_t^{q\prime}]', \boldsymbol{\epsilon}_t = [\ \epsilon_t^p, \boldsymbol{\epsilon}_t^{q\prime}]'$. Upon denoting the impact matrix $\mathbf{A}_0^{-1}$ as $\mathbf{S}$, our interest lies in the set of coefficients, namely column $\mathbf{s}$, that measures the initial impact to a structural monetary policy shock ϵ_t^p.[22] In what follows, we denote as $\mathbf{s}^q$ the initial impact of ϵ_t^p on $\mathbf{u}_t^q$, while s^p is the corresponding impact on the reduced-form monetary policy residual u_t^p.

[22]We may therefore leave the remaining columns of $\mathbf{S}$ undetermined.

Building on Mertens and Ravn (2013) and Stock and Watson (2018) and following Gertler and Karadi (2015), we use high-frequency market responses as an external instrument in the proxy VAR to identify the structural innovations ϵ_t^p. For these instruments to be valid, the surprise series $\mathbf{Z}_t$ needs to be *relevant* and *exogenous* as follows:

$$\mathbb{E}[\mathbf{Z}_t \ \epsilon_t^{p\prime}] = \phi \neq 0, \tag{1}$$

$$\mathbb{E}[\mathbf{Z}_t \boldsymbol{\epsilon}_t^{q\prime}] = 0. \tag{2}$$

To estimate impulse responses from the model

$$\mathbf{Y}_t = \mathbf{B}(L)\mathbf{Y}_{t-1} + \mathbf{s} \ \epsilon_t^p,$$

we obtain estimates of $\mathbf{s}$. We do so as follows. We first extract the residuals, $\mathbf{u}_t$, from the reduced-form VAR. These are then used in a two-stage least-squares regression which include $\mathbf{Z}_t$ as instruments. In the first stage, u_t^p is linearly projected on $\mathbf{Z}_t$. This delivers the fitted values $\hat{u}_t^p$. The latter, which is orthogonal to the remaining shocks $\boldsymbol{\epsilon}_t^q$, can be used in the second-stage regression:

$$\mathbf{u}_t^q = \frac{\mathbf{s}^q}{s^p} \ \hat{u}_t^p + \boldsymbol{\xi}_t.$$

The above procedure ensures that $\frac{\mathbf{s}^q}{s^p}$ is consistently estimated and can be used to obtain $\mathbf{s}$. As is common, we normalize s^p so that the initial interest rate response is equal to 1 percentage point. We estimate the proxy VAR via Bayesian methods, as now the number of observations is considerably smaller than in the panel VAR. Details are given in online appendix A.1.4.

3.2.2 Isolating Policy Shocks from Confounding Factors

A recent literature noted that, in the presence of information asymmetries between the central bank and market participants, market responses during the narrow window around monetary policy announcements could be contaminated by "information shocks" (Melosi 2017; Jarocinski and Karadi 2020; Miranda-Agrippino and Ricco 2021; and Nakamura and Steinsson 2018). This would, for instance, happen if the central bank has an informational advantage concerning the macroeconomy or the fundamental shocks hitting it. This additional information would be revealed, alongside any exogenous monetary shock alone, during the policy announcements.

For instance, an increase in expected future short-term interest rates during the central bank's press conference might in numerous instances reflect the market's assessment that the central bank considers the economy to likely perform more favorably than anticipated. One sign of such an effect would be a contemporaneous increase in the price of risky assets such as stocks. If the researcher then simply used the changes in expected interest rates as an instrument in a proxy VAR, the exogeneity assumption (1) is likely to be violated. The researcher would then measure not the impulse response to an actual exogenous monetary policy shock but instead that to some combination of fundamental shocks the central bank responds to. Based on this reasoning, we purge our shocks as follows.[23]

For the United States, we follow Miranda-Agrippino and Ricco (2021), who regress the commonly used changes in expected federal funds rates, based on futures contracts with an average maturity of about three months (FF4), on the Federal Reserve's Greenbook forecasts and their revisions. These forecasts reflect the Fed's assessment of the current and future state of the macroeconomy. However, since they are released with a lag of five years, the residuals from the regression are argued to contain those changes in expected interest rates that are primarily due to exogenous innovations in the stance of policy.

Ideally, we would like to use the same approach for the euro area. However, in this case an equivalent to Greenbook forecasts is not available. Therefore, for the euro area we adapt the procedure in Jarocinski and Karadi (2020). More precisely, we take the time series of interest rate *and* stock market index responses around monetary policy announcements and feed them into a sign-restriction

[23]Some authors have recently argued against the prevalence of central bank informational advantages; see, for instance, Bauer and Swanson (2020) and Hoesch, Rossi, and Sekhposyan (2020). However, for our purpose all that is needed is to isolate pure monetary shocks from any other confounding factors revealed during the announcement. Moreover, we verify our results when using the noncleansed interest rate series.

procedure. We then select the median-target series of those shocks as exogenous monetary innovations that lead to changes in interest rates and stock prices in opposite directions, in line with standard theory.[24]

3.2.3 Data and Variables in the Proxy VAR

The proxy VAR includes the same set of variables as the panel VAR. Instead of the shadow rates, we use interest rates with three months to two years maturity. This allows us to take into account the increased importance of communication policy adopted more aggressively by U.S. and euro-area monetary authorities and their commitment to maintain short-term rates at the zero lower bound.[25] As external instruments we use the shock series by Miranda-Agrippino and Ricco (2021) for the baseline U.S. model. For the euro area, we rely on our instrument series computed from data of changes in one-year OIS (or German government bond) yields and the Euro Stoxx 50 index around ECB announcements taken from the monetary shock database of Altavilla, Brugnolini et al. (2019).[26]

3.2.4 Results for the Proxy VARs

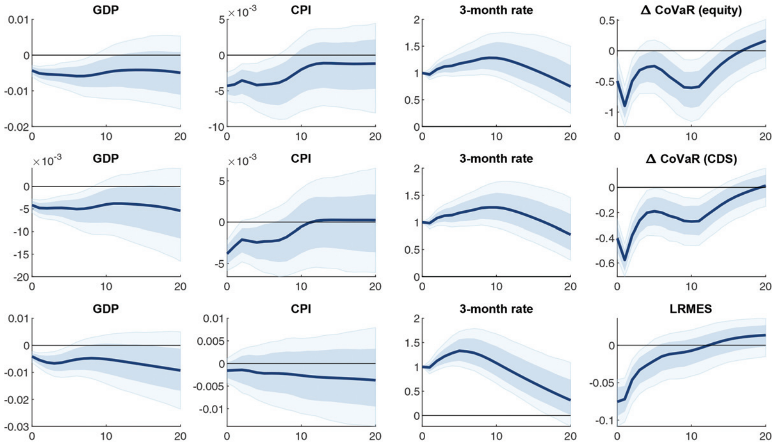
Figure 2 shows impulse responses for the U.S. economy to a contractionary monetary policy shock. In line with the panel VAR, output and prices decline. However, here they do so significantly on impact; price and output puzzles are absent. More importantly, all three risk measures significantly decline, confirming our results so far. The proxy VAR also features somewhat richer dynamics of the risk variables. LRMES declines now on impact, while both ΔCoVaR metrics exhibit a second decline after around six months. Notably,

[24]We make sure that our results are not driven by differences in these two approaches, as we verify them in a robustness exercise when cleansing via stock market responses for the U.S. model as well.

[25]The exact choice of interest rate maturity is adjusted based on the country and time period.

[26]In robustness exercises, we use the surprise data provided in Cieslak and Schrimpf (2019). We employ the one in Altavilla, Brugnolini et al. (2019) as a benchmark, as their window includes press statements and conferences in a single *monetary event window*. Details on shock aggregation are given in online appendix A.1.4.

Figure 2. U.S. Proxy VAR



Notes: Impulse responses in monthly U.S. VAR(12) to a monetary policy shock identified using high-frequency market responses of three-month federal funds futures rate (adjusted for information dissemination effects as in Miranda-Agrippino and Ricco 2021) around monetary policy announcements as external instruments. Time sample: 1992:06–2016:12 for ΔCoVaR measures and 2000:06–2016:12 for LRMES, which is estimated in a VAR(6). Shaded areas indicate 68 percent (dark) and 90 percent (light) credible sets.

risk responses are quantitatively more pronounced than in the panel VAR, even when controlling for the (normalized to 100 basis points) initial interest rate impact.

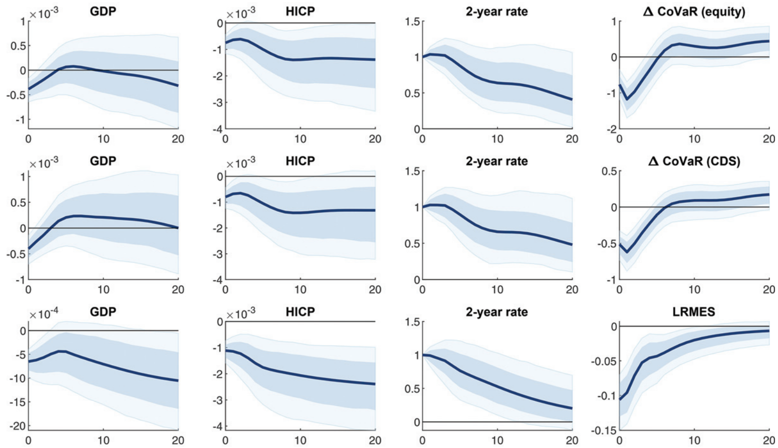
Figure 3 shows the same set of responses for the euro area. Also in this case, price or output puzzles are absent. Once again all three systemic risk measures decline. Quantitatively, the response of the risk metrics is even stronger for the euro area than in the U.S. model. This, however, results from the use of longer-term interest rates, which reflect innovations along a larger portion of the yield curve.[27]

3.2.5 Robustness and Extensions

Once again we check robustness along several dimensions also for the proxy VAR. First, figures A.5 and A.6 in online appendix A.2 show

[27]We verify this when harmonizing the shock cleansing procedure and then using longer-term interest rates for the U.S. model as well, which results in quantitatively very similar responses. See also section 4.

Figure 3. Euro-Area Proxy VAR



Notes: Impulse responses in monthly euro-area VAR(12) to a monetary policy shock identified using high-frequency market responses of one-year OIS rate (source: Altavilla, Brugnolini et al. 2019) around monetary policy announcements as external instruments (adjusted for information dissemination effects using stock price responses as in Jarocinski and Karadi 2020). Time sample: 1999:01–2016:12 for ΔCoVaR measures and 2000:06–2016:12 for LRMES, which is estimated in a VAR(6). Shaded areas indicate 68 percent (dark) and 90 percent (light) credible sets.

results when adding an excess bond premium and a stock market index to both models, as is often done in the literature. The response of systemic risk is slightly less persistent in the U.S. model, but otherwise hardly changed. Results remain robust when adding exchange rates or the VIX, when using flat priors and mostly when estimating the models over the pre-crisis sample (figures A.7 and A.8). Also, we verify our results when cleansing the U.S. shocks on our own (figure A.9) and when using alternative instrument data for the euro area (figure A.10). Finally, figures A.11 and A.12 show that our results remain robust even when we abstain from cleansing the surprise series and simply use interest rate changes around monetary policy meetings as instruments in the proxy VAR.

To sum up, the use of external instruments confirms and strengthens our evidence of an impact of monetary policy on systemic risk. This leads us to examine the role of policy spillovers across countries and the role of complementarities between monetary and macroprudential tools, which we do in sections 4 and 5, respectively. Before closing this section, however, we estimate two additional sets of specifications. First, we examine the response of a forward risk measure, namely forward-ΔCoVaR. Second, we include in our proxy VARs measures of bank leverage to see how much of the impact on systemic risk can be attributed to balance sheet rebalancing as opposed to changes in market valuations.

3.2.6 Forward-ΔCoVaR

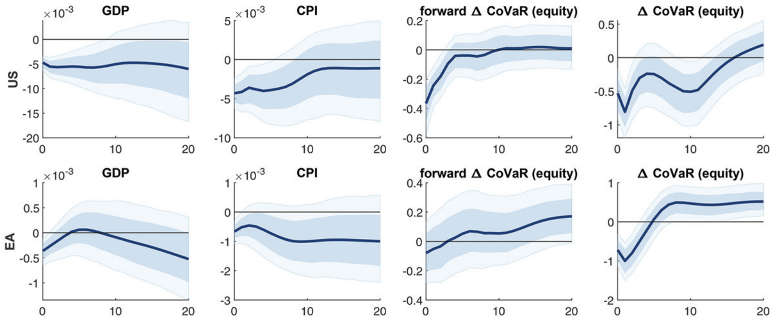
Generally speaking, monetary policy has an impact on both current variables and expectations, both with respect to inflation or measures of systemic risk. It is even more relevant in a case like the buildup of financial risk, as this likely takes place over extended periods of time. It is therefore instructive to add to our proxy VARs a forward measure of systemic risk. This is possible in the case of the ΔCoVaR metric, as Adrian and Brunnermeier (2016) provide both a real-time and a forward-ΔCoVaR. We follow their example and compute a two-year forward measure,[28] and then reestimate the proxy VAR for both the United States and the euro area. The VAR specification which we show includes both the ΔCoVaR and the forward forward-ΔCoVaR, though results remain robust when we only include the forward ΔCoVaR. The specification which includes both is akin to one in which an outcome variable and expectations of it are entered: in parallel with traditional monetary policy transmission channels, the latter could react differently depending on the expectation formation process. Results are shown in figure 4.

We see that the forward measures fall on impact, albeit significantly so only in the U.S. case.[29] But the most interesting aspect is the comparison of the response with the real-time systemic risk metric. For the United States, the latter falls and features a second decline after several months. On the contrary, the forward measure

[28] Details on the computation are provided in online appendix A.1.

[29] We note that these results depend to a larger extent on the particularities of computing the forward measure than is the case for the real-time metric, e.g., with respect to the forecast horizon. Also, we find the forward measure in the euro-area model to fall significantly when using German government yields instead of OIS rates in the construction of the instrument.

Figure 4. U.S. and Euro-Area Monetary Policy Shocks in Proxy VARs Including Forward-ΔCoVaR



Notes: Impulse responses to a monetary policy shock in U.S. (top) and euro-area (bottom) proxy VARs with forward-ΔCoVaR as additional variable. Remaining details as in figures 2 and 3, respectively.

falls only on impact. The delayed response of the real-time measure captures precisely the notion that the transmission of monetary policy to risk tends to materialize also at medium-term horizons, which the forward measure is meant to predict. For the euro area the impact of the policy rate on the forward measure is much milder, while the impact on the real-time measure does not show a second delayed decline. While it is not possible to draw conclusions with general validity from this particular exercise, we conjecture that the differences between the United States and the euro area are suggestive of different prudential and institutional backgrounds. It is generally true that the transmission of monetary policy to expectations can be strengthened or dampened by the particularities of agents' expectation formation processes, by country-specific institutions or actions of national policy bodies. Macroprudential policy, for instance, studied in more detail in section 5, is organized at the national level in Europe. With banks being residents in different countries, expectations and decisions of their executive managements might differ depending on the country-specific environment.

3.2.7 The Role of Bank Leverage

As mentioned earlier, an extensive literature has looked at the impact of low interest rates on banks' lending standards, at the individual bank level,[30] at the aggregate level,[31] or on banks' search for yield behavior.[32] In all those cases, atomistic banks take actions, which could be privately efficient, albeit failing to internalize the consequences of their decisions on others. In the aggregate, however, banks' individual decisions might cancel out. Changes in systemic risk would materialize either if banks' actions change the aggregate composition of the balance sheet, with excessive leverage, or if collectively they affect prices, thereby triggering changes in market valuation, or both. A priori, our analysis is agnostic on which of those two channels prevails and a complete separation of the two might be elusive, as changes in market valuations might trigger second-round portfolio rebalancing by banks. Still, it is instructive to provide suggestive evidence on which of the two channels seem to prevail in the data. To this purpose we rerun our proxy VAR for both the United States and the euro area and include bank book leverage.[33] This measure should, at least for some period, be immune to changes in market prices, and in general should be more directly linked to banks' active balance sheet adjustments in response to changes in interest rates. Our results (see figure 5) show that in response to a monetary tightening, book leverage tends to decline, albeit somewhat less significantly so than the systemic risk metrics.[34] Hence, banks individually and collectively tend to leverage less and to expose themselves less to liability risk. However, one observation that stands out is that the impact of monetary shocks on systemic risk is unaltered even when adding measures of banks' balance sheets that respond in line with the risk-taking channel. Further, we note that the response of book leverage is not sizable compared with the change observed in our systemic risk measures.

At last, it is plausible that the mild response of book leverage might be linked to the fact that this ratio is particularly highly

[30] See Dell'Ariccia, Laeven, and Marquez (2014) and Jiménez et al. (2014).

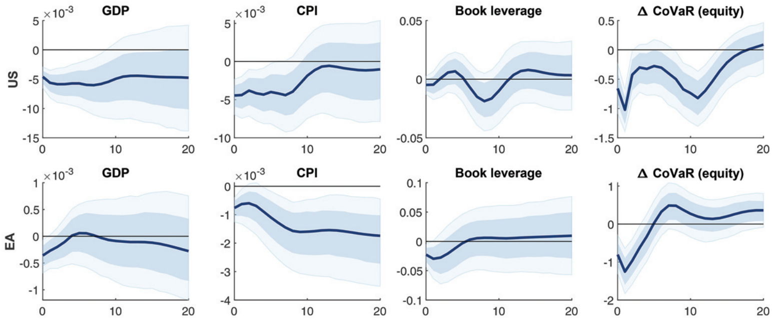
[31] See Neuenkirch and Nöckel (2018).

[32] See Becker and Ivashina (2015).

[33] Details on the computation are provided in online appendix A.1.

[34] Our results are in line with Miranda-Agrippino and Rey (2020), who also find some evidence that bank leverage of U.S. and European G-SIBs falls after contractionary U.S. monetary shocks. As in the case of the forward-ΔCoVaR, we observe that differences in measurement of the book leverage series, e.g., related to weighting, sometimes somewhat alter the responses.

Figure 5. U.S. and Euro-Area Monetary Policy Shocks in Proxy VARs Including Book Leverage



Notes: Impulse responses to a monetary policy shock in U.S. (top) and euro-area (bottom) proxy VARs with book leverage as additional variable. Remaining details as in figures 2 and 3, respectively.

regulated. We therefore also consider an alternative VAR specification which, instead of leverage, includes U.S. banks' short-term and wholesale funding ratio as an alternative balance sheet measure and find it to significantly fall in response to a monetary tightening.[35] The results indicate that part of the impact of monetary policy on systemic risk is plausibly channeled through adjustments in banks' balance sheet variables as well, on top of adjustment in market prices. Changes in short-term funding, however, indicate mainly a risk-taking channel on the liability side, as a fall in short-term funding corresponds to a decline in the risk of bank runs.

4. The Role of U.S. vs. Non-U.S. Monetary Policy

A growing literature stresses the importance of U.S. monetary policy in determining not only U.S. but also global monetary and financial conditions (Rey 2015; Miranda-Agrippino and Rey 2020). This notion stems primarily from the dominant role of the dollar in international markets. Since Bretton Woods, the U.S. currency has maintained a stable dominant role as vehicle and anchor currency.

[35] Results are shown in figure A.13 for U.S. G-SIBs, for which long-enough time series on short-term funding are available. Details on the data are given in online appendix A.1.

With the recent financial globalization, the dollar has established a dominant role also within the banking system. Several authors have argued that global banks in several countries seek liquidity and issue international deposits in dollars (Bruno and Shin 2015 or Gopinath and Stein 2018). If so, U.S. monetary policy in particular can play a role for risk of global banks, which are key contributors of systemic risk. Hence one of the most compelling questions relates to the assessment of whether U.S. monetary policy spills over or contributes to bank risk relatively more than domestic policy. Related to that is the relative impact of U.S. and euro-area monetary policy on other countries' systemic risk.

4.1 U.S. vs. National Shocks Based on the Panel VAR

Our goal in this section is to assess the role of U.S. monetary policy shocks relative to domestic shocks for the panel of countries in our sample. To accomplish this objective, we need an econometric specification that can include both types of shocks. We achieve that goal by extracting the identified structural shocks from our panel VAR and by including them in a local projection specification (Jordà 2005). Impulse responses from the panel VAR itself represent the average responses to each country's own monetary shocks. In contrast, using local projection methods with the extracted shocks allows us to easily compare the risk responses with U.S. and domestic monetary shocks.

The econometric specification reads as follows:

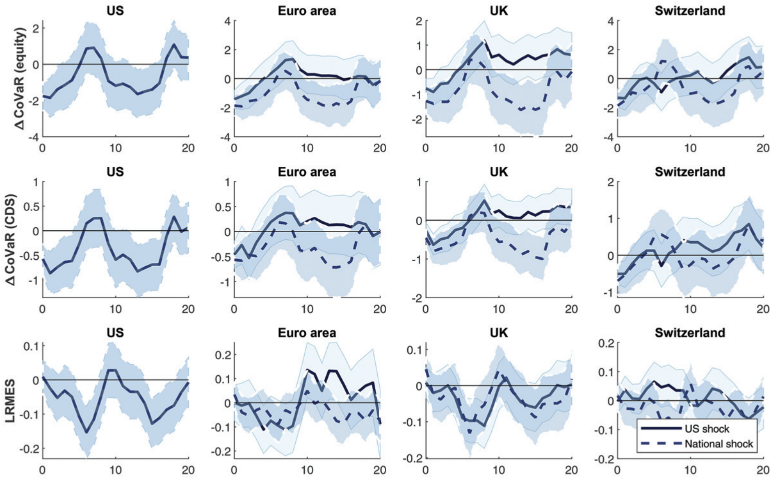
$$\begin{aligned}\mathbf{y}_{i,t+h} = \alpha_{i,h} + \beta_h \boldsymbol{\epsilon}_{s_t} + \sum_{j=1}^{p} (\gamma_h^y \mathbf{y}_{i,t-j} + \gamma_h^{\epsilon} \epsilon_{s,t-j} + \mathbf{X}_{i,t-j} \Gamma_h^X) \\ + \mathbf{e}_{i,t}, \quad h = 0, 1, \ldots H, \qquad (3)\end{aligned}$$

where $\boldsymbol{\epsilon}_{s,t}$, with $s \in (i, US)$, is the monetary policy shock; $\mathbf{y}_{i,t}$ indicates the risk measure; and $\mathbf{X}_{i,t}$ is a set of macroeconomic controls for country i.[36]

Figure 6 shows the estimated impulse responses to both U.S. and domestic shocks. Rows refer to each of the risk metrics, while

[36] We include each country's interest rate as well as logged GDP and CPI.

Figure 6. U.S. vs. Euro-Area Monetary Policy Shocks in Panel Local Projection



Notes: Impulse responses to U.S. (solid lines) and domestic (dashed lines) monetary policy shocks in panel local projection ($\{\beta_h\}_{h=0}^{H}$ in equation (3)). Shocks identified in the panel VAR as in figure 1. Time sample: 2000:06–2016:12. Shaded areas denote 90 percent confidence bands using cross-sectional system robust standard errors.

columns refer to the countries. First and foremost, all risk measures reliably fall following a monetary tightening. ΔCoVaR features a second decline after less than one year. Notably, this corresponds remarkably well to the results from the U.S. proxy VAR in section 3.2. Turning to the relative importance of monetary policy spillovers, U.S. policy shocks do spill over to other countries but do not bear the dominant responsibility of the impact on systemic risk. Indeed, for the euro area and the United Kingdom, national monetary policy sometimes has a more pronounced impact on risk. In other words, for some economies, the impact of U.S. monetary policy does not outweigh that of the national policies. This seems reasonable given the dominant role of the U.S. dollar in global banking and international deposits primarily in countries with unstable inflation and exchange rates, rather than in the advanced economies in our sample.[37]

[37] See, for instance, the ECB's (2019) report on the international role of the euro relative to the U.S. dollar.

Figure A.14 in online appendix A.2 reports *average* impulse responses to each country's own and U.S. shocks, respectively. Notwithstanding the heterogeneity uncovered so far, the average response to U.S. shocks is somewhat larger for the ΔCoVaR measures compared with domestic shocks.

4.2 U.S. vs. Euro-Area Shocks Based on the Proxy VARs

In parallel with the rest of the paper, we now test our results within the proxy VAR environment. Concretely, we add the risk variables of other countries to the U.S. and euro-area specifications and compare impulse responses. In order to ensure an accurate comparison, here we harmonize the two specifications. For the U.S. economy, we hence replace the shock series from Miranda-Agrippino and Ricco (2021) with one constructed following the procedure adopted for the euro-area proxy VAR.[38] Figure 7 shows impulse responses. Again, the systemic risk measures decline following both U.S. and the euro-area monetary policy shocks. Notably, the responses of LRMES are very heterogenous across countries, and in the euro area U.S. shocks have no significant effects on this measure.[39]

In sum, we conclude that Fed policy does not seem to be the only driver of the global financial cycle when it comes to systemic risk metrics among globally important banks. Also, there seems to be noticeable heterogeneity in the responses of systemic risk measures to shocks in different monetary areas. These might originate from institutional differences or stem from differences in (local or financial) proximity of the country in question.

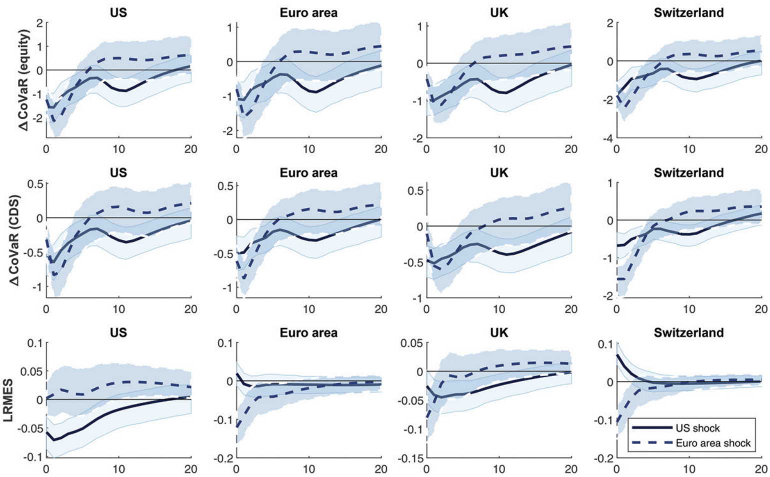
4.3 Robustness

As before, also in this case we perform robustness checks, mainly along the lines of shock identification and adding control variables. See online appendix A.2 for more details.

[38]Hence, we use the same identification as in figure A.9 in a robustness check of our main results.

[39]Note that impulse responses look smoother in this case due to the Bayesian estimation method and the recursivity of VAR impulse response functions.

Figure 7. U.S. vs. Euro-Area Monetary Policy Shocks in Proxy VARs



Notes: Impulse responses to a monetary policy shock in U.S. (solid lines) and euro-area (dashed lines) proxy VARs identified using high-frequency market responses of one-year rate (source: Cieslak and Schrimpf 2019 for United States, Altavilla, Brugnolini et al. 2019 for euro area) around monetary policy announcements as external instruments (adjusted for information dissemination effects using stock price responses as in Jarocinski and Karadi 2020). Time sample: 2000:06–2016:12. Shaded areas indicate 90 percent credible sets.

4.4 Discussion of Spillovers and the Role for Policy Coordination

Our results have important implications for a yet open debate on the extent of policy coordination for financial stability. Our data sample includes G-SIBs that operate in several countries. As ΔCoVaR by construction measures how distress of a particular institution affects the health of the other banks in the sample, in some sense already our results in section 3 could be interpreted as evidence of policy spillovers. For instance, a response of U.S. ΔCoVaR to U.S. monetary policy implies that Federal Reserve decisions affect the tail dependency of non-U.S. banks on U.S. G-SIBs. In this section, we have additionally established that there are spillovers of monetary policy to the risk metrics computed for global banks in other countries. With respect to ΔCoVaR we hence found that also, for instance, U.S. monetary policy shocks affect the tail dependency of U.S. banks on, say, European G-SIBs. With regard to the LRMES metric, the interpretation is somewhat more straightforward in that we find U.S. and euro-area monetary shocks to also affect the systemic exposure of G-SIBs domiciled in other countries.

One way these spillovers could come about is through funding in global wholesale markets, which has been growing particularly before the financial crisis. Bruno and Shin (2015) rationalize a risk-taking channel occurring through refinancing in repo markets. When global banks apply more lenient conditions on local banks in supplying wholesale funding, e.g., in response to a monetary easing, the local banks transmit these conditions to their borrowers through greater availability of local credit. Hence, global liquidity is transmitted through the interactions of global and local banks through bank risk-taking. What our analysis highlights is that monetary policy decisions not only affect particular global-local bank relations but also the interdependence of globally active banks at the heart of this mechanism. This seems to be the case for measures of both contagion and systemic exposure and is not limited to shocks emanating from the United States.

At the current juncture, monetary policymakers do not explicitly take into account spillovers from or to foreign banks when setting interest rates. At the same time, macroprudential policies are largely national. Our findings suggest that for domestic policymakers there may be value in both monitoring activity of global banks as well as coordinating policy responses across jurisdictions. To what extent national macroprudential measures are successful in mitigating the effects of monetary shocks on systemic risk is examined in the following section.

5. Complementarity of Monetary and Macroprudential Policies

As the evidence on the risk-taking channel kept growing, concerns were raised in policy and academic circles regarding the unintended consequences of recent monetary easing measures. Notwithstanding the need for substantial monetary accommodation in the wake of the 2007–08 financial and sovereign debt crises in the euro area, pundits have pointed to potentially detrimental effects of expansionary monetary policy on bank risk during boom phases. While monetary easing might stabilize the financial system following a crash, these measures, critics argue, might fuel future systemic banking crises. One response to those concerns has been that the effects on risk might be tamed by prudential policies. This view of policy complementarity entails that monetary policy should be concerned with its traditional role of price stability or demand stabilization, whereas in particular macroprudential policies should be devoted to deal with systemic risk.

This section tests this notion in our empirical time-series setup. First, we augment our baseline panel VAR with a macroprudential policy index by including an interaction term with the monetary policy measure. The objective is to examine how impulse responses to monetary policy vary when conditioning on "easy" or "tight" prudential regimes. Second, we again use extracted structural shocks in a local projections framework, which we augment with an interaction term of changes in macroprudential policy. Local projections are particularly well suited in this case since they easily accommodate the nonlinearities in the interaction of macroprudential and monetary policy that we wish to study. Furthermore, they allow us to quantify the impact on the monetary transmission of marginal changes in the prudential regime. We elaborate on this further below. Mirroring the two approaches used so far, we extract shocks from both panel and proxy VARs.

5.1 Interacted Panel VAR

To study policy complementarities in our panel of countries, we extend our VAR to include a macroprudential index as an interaction term with the interest rate measure. We use the *integrated macroprudential policy* (iMaPP) database recently released by the International Monetary Fund (IMF) (Alam et al. 2019). iMaPP represents the most detailed and comprehensive data set currently available and provides monthly information on changes in macroprudential measures of numerous countries in 17 different categories, such as capital and leverage requirements, loan loss provisions, liquidity regulation, various forms of borrowing limits, and reserve requirements.[40] Changes to these are reported in indicator form, which we sum to produce a cumulative index for each country.[41]

Our panel VAR specification now reads as follows:[42]

$$\mathbf{y}_{i,t} = \sum_{j=1}^{p} (\mathbf{B}_j \mathbf{y}_{i,t-j} + \mathbf{C}_j \mathbf{M}_{i,t-j-1} + \mathbf{D}_j \mathbf{y}_{i,t-j} \mathbf{M}_{i,t-j-1}) + \mathbf{u}_{i,t}, \quad (4)$$

where $\mathbf{M}_{i,t}$ is the macroprudential index for economy i at time t. We include this with a lag to address endogeneity concerns. $\mathbf{Y}_{i,t}\mathbf{M}_{i,t-1}$ is the interaction term between monetary and macroprudential policy. $\mathbf{C}_j$ is the coefficient vector on the index, and the $\mathbf{D}_j$ matrices contain the coefficients of the interaction terms. As we are primarily interested in the response to monetary shocks, we interact only the interest rate measure in the model with the macroprudential index.

In order to investigate whether the macroprudential regime alters the impact of monetary shocks on systemic risk, we compute impulse responses to a monetary policy shock conditional on an "easy" (low macroprudential index) and a "tight" (high macroprudential index) regime. We choose, respectively, the 20th and 80th percentile of the distribution of the index across countries in the sample and write the model as

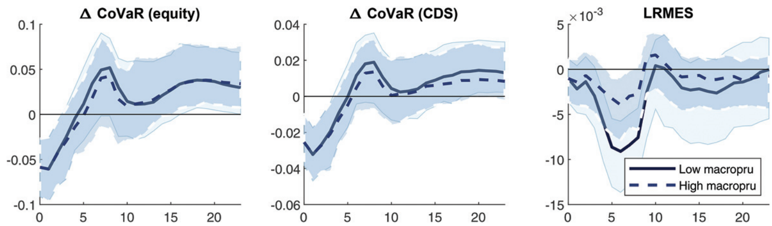
$$\begin{aligned}\mathbf{y}_{i,t}^{high} = \sum_{j=1}^{p} (&\hat{\mathbf{B}}_j^{high} \mathbf{y}_{i,t-j} + \hat{\mathbf{C}}_j^{high} \mathbf{M}_{i,t-j-1}^{high} \\ &+ \hat{\mathbf{D}}_j^{high} \mathbf{y}_{i,t-j} \mathbf{M}_{i,t-j-1}^{high}) + \hat{\mathbf{u}}_{i,t}, \qquad (5)\end{aligned}$$

[40] We use all categories except those related to reserve requirements, as it is often not clear whether these should be considered prudential or monetary policy measures.

[41] The indexes are depicted in figure A.1 in online appendix A.1.

[42] Our model specification builds on Towbin and Weber (2013) and Aastveit, Natvik, and Sola (2017). Note that we are not interested in identifying endogenous policy regimes, but rather in the response to monetary shocks conditional on the exogenous macroprudential environment. The parsimonious specification of the interacted VAR is best suited for this experiment.

Figure 8. Interacted Panel VAR with Macroprudential Index



Notes: Impulse responses to a monetary policy shock in the interacted panel VAR in "soft" (solid lines) and "tight" (dashed lines) macroprudential regimes. Shaded areas denote 90 percent confidence bands. Remaining details as in figure 1.

and

$$\mathbf{y}_{i,t}^{low} = \sum_{j=1}^{p}(\hat{\mathbf{B}}_j^{low}\mathbf{y}_{i,t-j} + \hat{\mathbf{C}}_j^{low}\mathbf{M}_{i,t-j-1}^{low} + \hat{\mathbf{D}}_j^{low}\mathbf{y}_{i,t-j}\mathbf{M}_{i,t-j-1}^{low}) + \hat{\mathbf{u}}_{i,t}. \quad (6)$$

Regime-conditional impulse responses are then obtained simply by adding the vector of interaction coefficients, at their low and high values, to that row in $\mathbf{A}_j$ that corresponds to the response of each endogenous variable to lagged interest rates. We then apply a standard Cholesky factorization to identify shocks recursively.

Figure 8 shows impulse responses for the risk metrics. In the "easy" macroprudential regime (solid lines), responses look very similar to the ones of the baseline panel VAR in figure 1. However, under tighter macroprudential policy (dashed lines), the LRMES responses are notably altered. The peak response is reduced by more than half. In contrast, for the ΔCoVaR metrics the tightness of the macroprudential regime does not seem to matter much.

So far results seem mixed. It is however possible that the role of policy complementarities is best captured within a model that more naturally lends itself to the study of nonlinearities. Moreover, the interacted panel VAR by construction allows us to study the response to monetary shocks conditional on the prudential regime, whereas the impact of prudential policy is perhaps most visible at the margin. In order to address these concerns, in the next section we repeat the analysis for the panel of countries by employing local projection methods, again extended to include macroprudential interaction terms. Not least, this lets us use the shocks from the proxy VAR based on more sophisticated instrumental-variable techniques.

5.2 Panel Interacted Local Projections

Technically, the local projection analysis with interacted policy tools is implemented as follows.[43] In a first step, we again extract structural shocks from our VARs and feed them into the following local projections:

$$\mathbf{y}_{i,t+h} = \alpha_{i,h} + \beta_h \boldsymbol{\epsilon}_{s_t} + \sum_{j=1}^{p} (\gamma_h^y \mathbf{y}_{i,t-j} + \gamma_h^{\epsilon} \boldsymbol{\epsilon}_{s,t-j} + \mathbf{X}_{i,t-j} \Gamma_h^X) + \mathbf{e}_{i,t}. \tag{7}$$

Second, the model is augmented with an interaction term between the structural shock and the marginal changes in the macroprudential regime:

$$\begin{aligned} \mathbf{y}_{i,t+h} = {} & \alpha_{i,h} + \beta_h \boldsymbol{\epsilon}_{s_t} + \delta_h \boldsymbol{\epsilon}_{s_t} \times \mathbf{M}_{it-1} + \gamma_h^M \mathbf{M}_{it-1} \\ & + \sum_{j=1}^{p} (\gamma_h^y \mathbf{y}_{i,t-j} + \gamma_h^{\epsilon} \boldsymbol{\epsilon}_{s,t-j} + \mathbf{X}_{i,t-j} \Gamma_h^X) + \mathbf{e}_{i,t}, \end{aligned} \tag{8}$$

where here $\mathbf{X}_{i,t}$ includes, next to the control variables in levels, also interaction terms with the macroprudential variable, $\mathbf{M}_{i,t-1}$. The latter takes a value of +1 under a macroprudential tightening, a value of −1 under an easing, and a value of 0 in the absence of changes in the preceding month in country i. Hence, in contrast to the interacted VAR in the previous section, this specification allows us to study the influence of marginal changes in the prudential regime. The coefficient of interest in (8) is δ_h. It measures the marginal contribution of changes in macroprudential policy to

[43] We adapt the procedure in Coman and Lloyd (2019), who study the role of macroprudential policies in mitigating spillovers of U.S. monetary policy on emerging market credit volumes.

the effect of monetary policy on risk. More concretely, whenever β_h in (7) is negative, a positive and statistically significantly δ_h implies that a change in macroprudential policy dampens the systemic risk response.

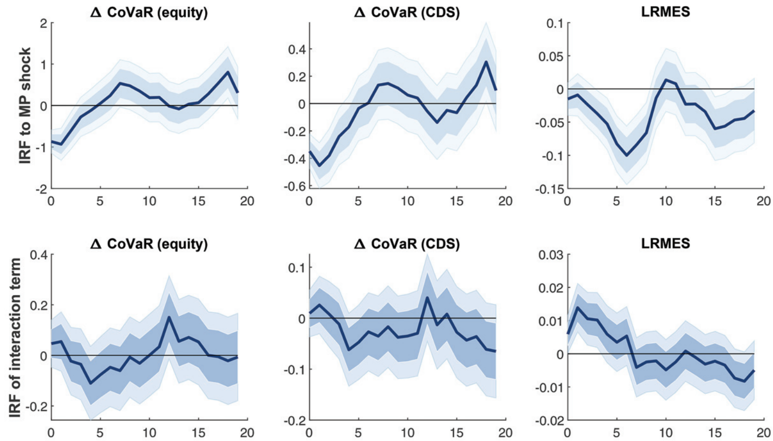
The methodology described lends itself to both panel and proxy VAR frameworks we have been using throughout. We check with both, for the reasons mentioned so far, namely having results robust to different identification schemes as well as being able to differentiate domestic from U.S. (and euro-area) shocks.

Figure 9 shows results for the first case in which the structural monetary shocks stem from the panel VAR, such that $s = i$ in (7) and (8). The upper panel depicts the sequence of coefficients $\{\beta_h\}_{h=0}^{H}$ in (7), hence implicitly for the case of no changes in the macroprudential regime, such that $\mathbf{M}_{i,t-1} = 0$. Reassuringly, these responses again look very similar to those in figure 1, in spite of the different methodologies. The lower panel of figure 9 shows the sequence of interaction coefficients $\{\delta_h\}_{h=0}^{H}$ in (8). For both ΔCoVaR measures the coefficients are mostly insignificant. In contrast, the LRMES coefficients clearly lie significantly above zero for some time. Hence again a tight macroprudential policy helps to mitigate the effects primarily on the LRMES measure.

Results so far are based on the panel VAR framework and therefore measure the effect of macroprudential measures to "one's own" monetary policy. In light of the sometimes notable differences in responses to U.S. and non-U.S. shocks uncovered in section 4, we are interested in testing the impact of macroprudential policy also in our proxy VAR setup. Not least, this seems desirable, as there we can identify structural monetary shocks particularly well. To that end, we extract the shocks from both proxy VAR models and feed them into (7) and (8), such that now $s = US$ and $s = EA$, respectively.[44] In figure 10, for the U.S. shocks, we again find that risk responses to monetary tightening shocks are significantly negative and look similar to before. More importantly, the lower panel reveals that macroprudential policy in this case mitigates the effects of monetary shocks both on the LRMES and on the ΔCoVaR measures.

[44] Extracting the structural shocks is slightly more involved than in the panel VAR with recursive identification since in the proxy VAR setting only one column of the impact matrix S is identified; see Piffer (2016).

Figure 9. Panel Local Projections with Macroprudential Interaction, with Shocks Identified in Panel VAR

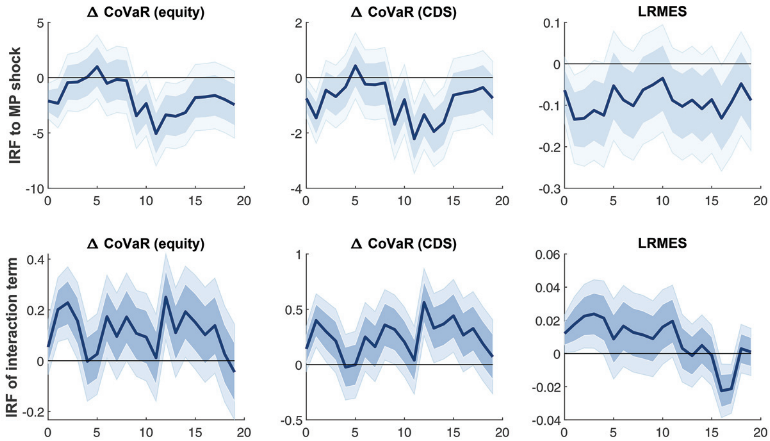


Notes: Upper panel: Impulse responses of monetary policy shock ($\{\beta_h\}_{h=0}^{H}$ in equation (7)). Lower panel: Impulse responses of interaction term of monetary and macroprudential policies ($\{\delta_h\}_{h=0}^{H}$ in equation (8)). Shocks extracted from panel VAR as in figure 1. Time sample: 1992:06–2016:12 for ΔCoVaR measures and 2000:06–2016:12 for LRMES. Shaded areas indicate 68 percent (dark) and 90 percent (light) confidence bands using cross-sectional system robust standard errors.

Finally, figure 11 shows results for the euro-area shocks. For this case again the mitigating effect seems to apply mainly to the LRMES measure. We conjecture that these differences might stem from the different concepts of systemic risk that the two metrics attempt to measure. Our results indicate that, for non-U.S. shocks, macroprudential policy seems to be primarily suited to shield banks from systemic distress, e.g., arising from pecuniary externalities. In contrast, macroprudential policy also seems to play a role in preventing contagion, e.g., arising from network effects, when it comes to U.S. shocks that drive funding conditions in global wholesale markets.

To sum up, we conclude from this section that macroprudential policy potentially plays a non-negligible role in mitigating the unintended consequences of monetary policy on systemic risk. While, in particular, U.S. policy seems to be mitigated significantly for all three risk measures, national and euro-area monetary shocks are

Figure 10. Panel Local Projections with Macroprudential Interaction, with Shocks Identified in U.S. Proxy VAR



Notes: Upper panel: Impulse responses of monetary policy shock ($\{\beta_h\}_{h=0}^{H}$ in equation (7)). Lower panel: Impulse responses of interaction term of monetary and macroprudential policies ($\{\delta_h\}_{h=0}^{H}$ in equation (8)). Shocks extracted from U.S. proxy VAR as in figure 2. Time sample: 1992:06–2016:12 for ΔCoVaR measures and 2000:06–2016:12 for LRMES. Shaded areas indicate 68 percent (dark) and 90 percent (light) confidence bands using cross-sectional system robust standard errors.

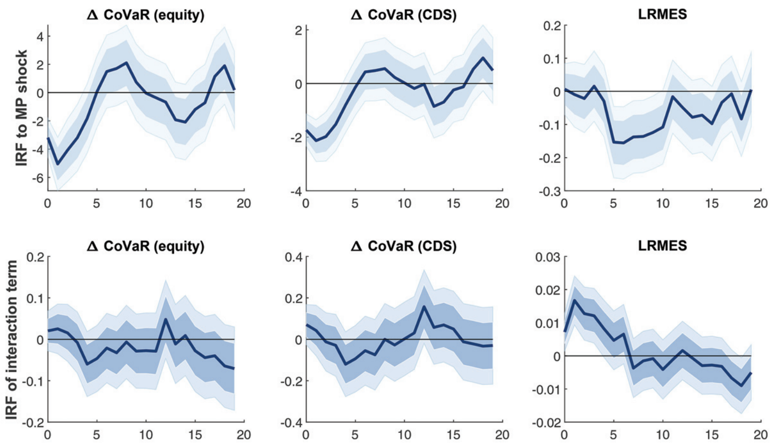
dampened, at least with respect to their effect on marginal shortfall measures.

6. Conclusion

Using both cross-country and time-series variation, we find novel and robust evidence that monetary policy shocks have an impact on systemic risk. So far the literature on the risk-taking channel of monetary policy focused on the bank-individual risk metrics and balance sheet variables. No evidence had been gathered on the potential systemwide consequences of monetary policy on risk, which can materialize through bank network connections or pecuniary externalities.

Given our findings, we examine implications for monetary policy spillovers across countries and for complementarities between

Figure 11. Panel Local Projections with Macroprudential Interaction, with Shocks Identified in Euro-Area Proxy VAR



Notes: Upper panel: Impulse responses of monetary policy shock ($\{\beta_h\}_{h=0}^{H}$ in equation (7)). Lower panel: Impulse responses of interaction term of monetary and macroprudential policies ($\{\delta_h\}_{h=0}^{H}$ in equation (8)). Shocks extracted from euro-area proxy VAR as in figure 3. Time sample: 1992:06–2016:12 for ΔCoVaR measures and 2000:06–2016:12 for LRMES. Shaded areas indicate 68 percent (dark) and 90 percent (light) confidence bands using cross-sectional system robust standard errors.

prudential and monetary tools. In light of the dominant role of the dollar, we quantify the impact of Fed policy, relative to domestic and euro-area shocks, in our panel of developed countries. It has indeed been argued that the Fed policy spillovers might be more pronounced due to the dominant international role of the dollar. We find that domestic shocks matter and that Fed and ECB policy spillovers are roughly at par. We conjecture that the reason lies with our panel of countries that comprises developed countries, while the U.S. dollar is relatively more predominant in the banking systems of countries with unstable inflation and exchange rates.

Finally, we examine whether macroprudential policies can tame the effects of monetary policy on systemic risk. We find that this is mostly the case for the LRMES metric, but we also find effects for our ΔCoVaR measures when considering U.S. shocks. Overall, we interpret our findings as evidence that macroprudential policy may indeed be able to alleviate at least some of the spillovers of monetary policy to systemic risk that we document.

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"Leaning against the Wind," Macroprudential Policy, and the Financial Cycle*

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Should monetary policy lean against financial stability risks? This has been a subject of fierce debate over the last decades. We contribute to the debate about "leaning against the wind" (LAW) along two lines. First, we extend the Svensson (2017) framework to address a critique that the framework does not consider the lower-frequency financial cycle. We then evaluate the costs and benefits of LAW in the extended framework for the euro area and find that the costs outweigh the benefits. Second, we assess the costs and benefits of monetary and macroprudential policy. We find that macroprudential policy has net marginal benefits in addressing risks to financial stability in the euro area, whereas monetary policy has net marginal costs. This would suggest that an active use of macroprudential policies targeting financial stability risks would alleviate the burden on monetary policy to "lean against the wind."

JEL Codes: E58, G01.

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1. Introduction

This article focuses on the long-running debate on whether and, if so, to what extent monetary policy should "lean against the wind" by addressing financial imbalances in addition to its inflation objectives.[1] In other words, it focuses on whether central banks should lean against the financial cycle by tightening monetary policy more than a pure inflation-targeting rule would prescribe in order to curtail asset prices and credit growth in economic upswings, and vice versa in downturns. Furthermore, it considers to what extent macroprudential policy, one of the key policy tools used more actively in the aftermath of the GFC, could help alter this tradeoff and potentially alleviate the need for monetary policy to "lean against the wind."

We contribute to this debate by analyzing the cost and benefits of monetary policy "leaning against the wind" in the euro area. Furthermore, we take the financial cycle into account in our assessment and, last but not least, we bring macroprudential policy into the picture. Our work is related to three different strands of the literature. First, it relates to the extensive literature on whether monetary policy should "lean against the wind." Second, it relates to the literature on financial crises, and third, to the literature on macroprudential policy.

The debate on whether to use monetary policy to address risks to financial stability, or to "lean against the wind," has been going on in policy and academic circles for at least two decades in two distinct stages. The first stage can be traced back to the empirical findings of Bernanke and Lown (1991) and Borio, Kennedy, and Prowse (1994), who documented a positive association between large fluctuations in equity and real estate prices and those in real economic activity. During this first stage, which lasted until the GFC, the prevailing view was that monetary policy should respond to fluctuations in asset

[1] See Taylor (2007) for a discussion of the implications of monetary policy for financial stability before the global financial crisis (GFC), and International Monetary Fund (2019) and Rajan (2013) highlighting the risks of low interest rates after the GFC.

prices only to the extent that they affect forecasts of inflation or the output gap.[2]

This view was based on two main arguments:[3] first, the early identification and precise measurement of price bubbles in real time was difficult, if not outright impossible; second, even if such price misalignments were observed, it was argued, monetary policy would not be able to deal with them adequately. This was because the interest rate adjustments necessary to contain asset price bubbles could, as a side effect, trigger bubbles in other asset classes and instabilities in aggregate demand.

This view was not shared by everyone. Cecchetti and others called for a more active role for monetary policy in addressing financial stability risks.[4] They argued that if expected inflation were to remain unaffected by an asset price bubble, which would be the case if the bubble did not last for too long, then reacting only to expected inflation would not prevent bubble-induced macroeconomic volatility.

Notably, in the pre-crisis stage, the debate neither centered on the role of excessive credit or risk-taking[5] in fueling asset price bubbles, nor did it consider the role of macroprudential policies.

This changed dramatically in the aftermath of the financial crisis, which ushered in the second stage of this debate. In this second stage, the focus first turned towards credit-fueled asset price bubbles.[6] These price misalignments are especially harmful because they generate feedback loops in financial markets that can considerably exacerbate systemic risk and financial instability.[7]

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[2] See, e.g., Bernanke and Gertler (1999, 2001) and Kohn (2006, 2008).

[3] See Constâncio (2018) and Filardo and Rungcharoenkitkul (2016).

[4] See Borio, English, and Filardo (2003); Borio and Lowe (2002b); Cecchetti et al. (2000); and Cechetti, Genberg, and Wadhwani (2002).

[5] Borio and Zhu (2012) highlighted the importance of bank risk-taking in the transmission of monetary policy. Di Maggio and Kacperczyk (2017) find evidence of risk-taking in a low interest rate environment for the U.S. money fund industry, and Lian, Ma, and Wang (2019) find that investors "reach for yield" when interest rates are low and propose mechanisms related to investor psychology.

[6] See Brunnermeier, Rother, and Schnabl (2017); Brunnermeier and Schnabel (2016); and Jordà, Schularick, and Taylor (2015a, 2015b) for the debate.

[7] Biljanovska, Gornicka, and Vardoulakis (2019) show that a rational bubble relaxes collateral constraints and, as a consequence, induces more borrowing and higher asset prices, and amplifies downturns. Models of boundedly rational

Second, the debate has focused on how to tackle such imbalances in the most effective manner. The severe consequences of credit-fueled asset price bubbles called for the development of new policy instruments tailored to containing systemic risk, i.e., macroprudential policy. A discussion has also emerged on whether monetary policy should coordinate with macroprudential policy to jointly safeguard financial stability. This coordination would be predicated on the strong mutual dependencies between the two policy functions and reflect uncertainty about whether macroprudential policy can fulfill all its objectives.

Broadly speaking, two opposing viewpoints have been put forward, calling for either (i) two separate policy functions, which would keep the pre-crisis, price-stability-oriented, monetary policy frameworks largely unchanged,[8] or (ii) fully merging monetary and macroprudential policy.[9]

The dominant view in the post-crisis stage still prescribes that monetary policy should not respond to financial stability concerns. The reason is now, however, different: the new macroprudential policies are deemed the most effective tool for ensuring financial stability, because they can directly restrain excessive leverage or risk-taking.[10]

According to Smets (2014), however, the need to incorporate to some extent financial stability concerns into monetary policy objectives hinges on (i) the effectiveness of macroprudential policies (e.g., the ability to manage the financial cycle); (ii) the extent to which monetary policy (including conventional and unconventional measures) can be a source of financial instability—for example, by incentivizing risk-taking; and (iii) the extent to which monetary policy

bubbles based on heterogeneous beliefs confirm the higher price volatility and the difficulty to predict them (Scheinkman and Xiong 2003; Xiong 2013). More recently, Schuler and Corrado (2019) analyzed policy in a model with boundedly rational bubbles and found that macroprudential policy is more effective in addressing the externality than monetary policy.

[8]See, e.g., Bean et al. (2010).

[9]See, e.g., Brunnermeier and Sannikov (2013).

[10]The following studies document the usefulness of macroprudential policies in moderating systemic risk and thus complementing monetary policy in the domain of financial stability: Angelini, Neri, and Panetta (2012); Angeloni and Faia (2013); Bean, Clerc, and Mojon (2012); Christensen, Meh, and Moran (2011); Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011); Korinek and Simsek (2016); and Lambertini, Mendicino, and Punzi (2013).

can remain independent from financial stability concerns, especially in crisis times.[11]

The strand of literature on model-based evaluations of LAW is most closely related to our contribution. On the one hand, Svensson (2017) finds that it is not advisable to use LAW. In the Svensson framework, assuming an inflation-targeting central bank, the cost of LAW is measured by the increase in unemployment following a monetary policy tightening, and benefits are related to a lower probability and severity of financial crises. Svensson argues that LAW not only has a cost in terms of a weaker economy if no crisis occurs but also substantial costs in terms of higher unemployment going into the crisis due to the policy. The empirical analysis of Svensson concludes that the marginal costs of LAW far exceed the benefits. In other words, the cost of higher unemployment as a result of the monetary policy tightening far outweighs the benefits of the reduced probability and severity of financial crises.

On the other hand, there are a range of studies exploring whether optimal policy should be "leaning against the wind." Most of them find small positive effects of LAW by monetary policy using small-scale models. In one of these studies, Gerdrup et al. (2017) base their analysis on a standard small New Keynesian model with regime switching. Debt dynamics are implemented ad hoc and the optimal rule is found by optimizing over the coefficients of the policy rule. Ajello et al. (2019) analyze the tradeoff in a stylized two-period model and find that the optimal monetary policy response to financial conditions is very small. Laséen, Pescatori, and Turunen (2017) use a New Keynesian framework with endogenous systemic risk to scrutinize optimal policy responses. They find that benefits from LAW are small and can also be negative in the case where the policy is implemented and the financial sector is in a fragile state.

Related to this, Svensson's conclusions have been criticized by the Bank for International Settlements (BIS) and others for not properly accounting for systemic risk and the persistence of the financial cycle, which risks ignoring the long-lasting effects on the

[11] An extended monetary policy mandate including financial stability concerns, as a complement to macroprudential policies, can help prevent the buildup of excessive debt overhangs in pre-crisis periods. Thereby, it could alleviate the need for monetary policy to engage in post-crisis resolution policies.

real economy that financial crises may have.[12] Accounting for these elements, it is argued, would create a case for a more active use of monetary policy to lean against the financial cycle. For instance, Filardo and Rungcharoenkitkul (2016) use a stylized model of the economy with a Markov-switching financial cycle and a macroeconomic block. Optimal monetary policy in this environment dampens the financial cycle.

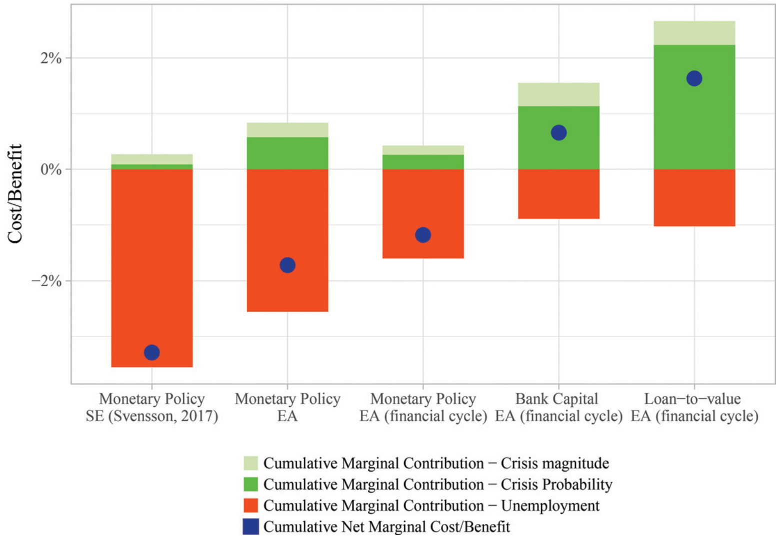
Contributing to this literature, we have recalibrated Svensson's model for the euro area. Furthermore, we account for the critique of the BIS by modifying the Svensson framework to take into account the financial cycle. We do this by making the probability of a crisis start dependent on a financial cycle early-warning indicator. To calibrate the Svensson model for the euro area and take into account the financial cycle, we change two parts of the framework. The dynamic stochastic general equilibrium (DSGE) model for the euro area of Darracq Pariés, Kok, and Rodriguez-Palenzuela (2011) is used to conduct the policy experiments, and the probability of crisis is estimated on the European financial crisis database by the European Systemic Risk Board (ESRB) (Lo Duca et al. 2017). Furthermore, we incorporate macroprudential policies into the framework to help assess whether such policies are more efficient for addressing financial stability risks than a LAW monetary policy.

Our findings suggest that (i) even when taking into account the more persistent financial cycle, LAW by monetary policy does not yield net benefits for the euro area, and (ii) the benefits of using macroprudential policies (in the form of capital and loan-to-value (LTV) ratio requirements) to address financial stability risks outweigh the costs.

These findings are summarized in figure 1. The figure shows that the recalibration of the model for the euro area and taking into account the financial cycle comes to the same conclusion as Svensson does for Sweden; namely, that LAW is associated with substantial net marginal costs (though slightly lower than the original Svensson result; see third bar from the left). Turning to macroprudential policy, we focus on two measures: a permanent 1 percentage point (pp)

[12]See, e.g., Adrian and Liang (2016); BIS (2016); Filardo and Rungcharoenkitkul (2016); Gourio, Kashyap, and Sim (2017).

Figure 1. Comparing the Cost and Benefits of Monetary and Macroprudential Policy "Leaning against the Wind"



increase in bank capital requirements and a permanent 1 pp tightening in LTV requirements. When modifying the model this way, we observe (fourth and fifth bar) that these measures are more effective in reducing the probability and severity of financial crises (marginal benefits) and that the negative impact on unemployment is lower (marginal costs) than a monetary policy that tries to address financial stability risks. Overall, the marginal benefits of macroprudential policy outweigh the marginal costs. These findings would suggest a meaningful role for macroprudential policies in complementing monetary policy and helping alleviate the burden on monetary policy to lean against financial stability risks.[13]

The article is structured as follows: Section 2 describes the Svensson framework underlying our analysis throughout. Section 3

[13]In the context of the euro area, the relative effectiveness of macroprudential policy to tackle the buildup of financial stability risks may be even more pronounced due to the fact that, in a monetary union, a single monetary policy is not well suited to deal with financial imbalances building up at the national level. Such imbalances are indeed better tackled with targeted national macroprudential measures (Darracq Pariès, Kok, and Rancoita 2019).

takes Svensson's analysis for monetary policy to the euro area and describes our extension of the Svensson model to consider the financial cycle. Section 4 analyzes macroprudential policy in the extended framework. Section 5 carries out robustness checks and section 6 discusses the results. Finally, section 7 concludes.

2. Svensson Framework

We base our calculations on the framework defined by Svensson (2017) and adapt it to the euro area. Before discussing the evaluation of the different policy options, we will explain in the following the underlying framework and the parameters used.

The Svensson framework is based on a quadratic loss function of unemployment. Assuming a monetary policy that stabilizes both the inflation rate around an inflation target and the unemployment rate around its long-run sustainable rate, we define u_t^* as the optimal unemployment rate under flexible inflation targeting when the possibility of a financial crisis is disregarded. The loss from the unemployment rate deviating from the benchmark unemployment rate, u_t^*, can be represented by the quadratic (indirect) loss function:

$$L_t = (\tilde{u}_t)^2,$$

with $\tilde{u}_t = u_t - u_t^*$ being the unemployment deviation.[14]

For the purpose of evaluating the costs and benefits of different policy options, we consider two states of the economy after period 1. With a probability p_t the economy is in a crisis state and the crisis unemployment deviation, $\tilde{u}_t^c$, is conditional on being in a crisis state. For the noncrisis state, which occurs with probability $1 - p_t$, the unemployment deviation is denoted by $\tilde{u}_t^n$.

The expected quarter-t loss conditional on information available in quarter 1 can be written as

$$\mathbb{E}_1 L_t = \mathbb{E}_1(\tilde{u}_t)^2 = (1 - p_t)\mathbb{E}_1(\tilde{u}_t^n)^2 + p_t\mathbb{E}_1(\tilde{u}_t^c)^2.$$

The crisis unemployment deviation, $\tilde{u}_t^c$, is composed of two components: a crisis increase in the unemployment rate net of any policy reaction during the crisis, Δu, and the noncrisis unemployment

[14] See appendix A of Svensson (2017) for further details on the quadratic loss function.

deviation, $\tilde{u}_t^n$. Therefore, we can rewrite the expected quarter-t loss as

$$\begin{aligned}\mathbb{E}_1 L_t &= (1-p_t)\mathbb{E}_1(\tilde{u}_t^n)^2 + p_t\mathbb{E}_1(\Delta u_t + \tilde{u}_t^n)^2, \\ &= \mathbb{E}_1(\tilde{u}_t^n)^2 + p_t\left(\mathbb{E}_1(\Delta u_t + \tilde{u}_t^n)^2 - \mathbb{E}_1(\tilde{u}_t^n)^2\right), \\ &= \mathbb{E}_1(\tilde{u}_t^n)^2 + p_t\big(\underbrace{\mathbb{E}_1(\Delta u_t)^2 + 2\mathbb{E}_1(\tilde{u}_t^n\Delta u_t)}_{cost\ \ of\ \ a\ \ crisis}\big).\end{aligned}$$

The second term in the last two expressions deserves further explanation. This term describes the cost of a crisis as being the crisis deviation less the noncrisis deviation.

A policy action in this setup is discretionary and not a reaction to a shock or the realization of the crisis state. Furthermore, the monetary policy in the underlying DSGE model interacts with the discretionary policy actions. In other words, policymakers systematically react ignoring the possibility of a crisis state, but they consider whether to intervene nonsystematically given the possibility of a crisis state. Their discretionary policy intervention might have benefits in the case that the crisis state materializes but also costs in both states.

Any policy will have an impact on the quarter-t loss and we define the net marginal cost, NMC_t, as the derivative of the quarter-t loss function with respect to the policy measure, $\mathfrak{p}_1^i$, implemented to address risks to financial stability:

$$\text{NMC}_t = \frac{d\mathbb{E}_1 L_t}{d\mathfrak{p}_1^i}.$$

Taking the partial derivatives for each component of the rewritten quarter-t loss function yields

$$\text{MC}_t = 2(\mathbb{E}_1\tilde{u}_t^n + p_t\mathbb{E}_1\Delta u_t)\frac{d\mathbb{E}_1 u_t^n}{d\mathfrak{p}_1^i}, \tag{1}$$

$$\text{MB}_t^p = -\left(\mathbb{E}_1(\Delta u_t)^2 + 2\mathbb{E}_1(\tilde{u}_t^n\Delta u_t)\right)\frac{dp_t}{d\mathfrak{p}_1^i}, \tag{2}$$

$$\text{MB}_t^{\Delta u} = -2p_t\mathbb{E}_1(\tilde{u}_t^n + \Delta u_t)\frac{d\mathbb{E}_1\Delta u_t}{d\mathfrak{p}_1^i}, \tag{3}$$

$$\text{NMC}_t = \text{MC}_t - (\text{MB}_t^p + \text{MB}_t^{\Delta u}), \tag{4}$$

with MC_t being the marginal cost related to the change in the unemployment rate, MB_t^p being the benefits from a lower probability of a crisis, and $\mathrm{MB}_t^{\Delta u}$ being the benefit of a reduced severity of a crisis.

For the purpose of assessing whether a policy is favorable, we look at the discounted cumulated net marginal cost:

$$\mathrm{NMC} = \sum_{t=1}^{\infty} \delta^{t-1}\mathrm{NMC}_t = \sum_{t=1}^{\infty} \delta^{t-1}\mathrm{MC}_t - \left(\sum_{t=1}^{\infty} \delta^{t-1}\mathrm{MB}_t^{\Delta u} + \sum_{t=1}^{\infty} \delta^{t-1}\mathrm{MB}_t^{p}\right),$$

with δ being the discount factor.

Here, we will look at the cumulated net marginal cost over time.

In order to evaluate policies in our framework, we need to define values of the static and dynamic components of the framework. Since we are taking partial derivatives, we need to define the constant values of the probability of a crisis, the noncrisis unemployment deviation, and the crisis increase in unemployment. For our analysis we rely on a calibration suitable for the euro area. Furthermore, we conduct a sensitivity analysis to the calibrated parameters (see table 1).

The probability of being in a crisis is determined, assuming a Markov process,[15] by the probability of a crisis start and the crisis duration. In order to calibrate the framework to the euro area, we assume the crisis duration to be eight quarters. This estimate, which coincides with the benchmark calibration of Svensson (2017), reflects the mean unfiltered peak-to-trough duration of the financial cycle in Europe as defined in Schüler, Hiebert, and Peltonen (2015).

As for the crisis increase in unemployment, Δu, we assume it to be 5 pp. This assumption rests on estimates from the International Monetary Fund (2015) and Sveriges Riksbank (2013) and is also used by Svensson in his analysis. A larger crisis increase in unemployment would lead to higher net marginal benefits because of the quadratic term in the marginal benefits of a lower probability of a crisis start (see equation (2)), and the otherwise linear influence of the crisis increase on the costs (see equation (1)).

[15] See appendix C in Svensson (2017) for further details on the Markov process.

Table 1. Sensitivity of Cost and Benefits of LAW by Monetary Policy Considering the Financial Cycle

Crisis Increase in Unemployment (pp)	Crisis Duration (Quarters)	Crisis Severity Coefficient on DTI Ratio	Discount Factor	Time Horizon	Cumulative Net Marginal Cost/Benefit
5	8	0.02	1.00	40	−1.46
1	8	0.02	1.00	40	−0.28
2	8	0.02	1.00	40	−0.56
3	8	0.02	1.00	40	−0.84
4	8	0.02	1.00	40	−1.13
5	8	0.02	1.00	40	−1.43
6	8	0.02	1.00	40	−1.73
7	8	0.02	1.00	40	−2.04
8	8	0.02	1.00	40	−2.35
9	8	0.02	1.00	40	−2.66
10	8	0.02	1.00	40	−2.99
5	**6**	0.02	1.00	40	−1.29
5	**7**	0.02	1.00	40	−1.36
5	**8**	0.02	1.00	40	−1.43
5	**9**	0.02	1.00	40	−1.48
5	**10**	0.02	1.00	40	−1.54
5	8	**0.01**	1.00	40	−1.47
5	8	**0.02**	1.00	40	−1.43
5	8	**0.03**	1.00	40	−1.38
5	8	**0.04**	1.00	40	−1.34
5	8	0.02	**0.95**	40	−1.12
5	8	0.02	**0.96**	40	−1.19
5	8	0.02	**0.97**	40	−1.26
5	8	0.02	**0.98**	40	−1.33
5	8	0.02	**0.99**	40	−1.39
5	8	0.02	**1.00**	40	−1.46
5	8	0.02	1.00	**20**	−2.23
5	8	0.02	1.00	**40**	−1.43
5	8	0.02	1.00	**50**	−1.71
5	8	0.02	1.00	**75**	−2.10
5	8	0.02	1.00	**100**	−2.35

With regard to the benefits of a less severe crisis, we rely on the conservative estimates found in Flodén (2014). These estimates, which Svensson uses in his framework, imply that the marginal benefit is equal to 0.02 times the policy effect on the household debt-to-income (DTI) ratio.

The marginal benefit of a lower probability of a crisis is the part we adapt in order to take into account the financial cycle (see section 3.1), and throughout our simulations we consider a discount factor of 1.[16]

All three parts rely on calibrated parameters, which we adjust to reflect the situation in the euro area wherever possible, and policy impulse responses. We also use Svensson's benchmark calibration in order to ensure comparability and because this calibration is very conservative and tilted in favor of LAW (see appendix A). The relevant policy impulse responses for marginal cost and severity of a crisis are unemployment [pp], and the DTI ratio [pp]. The relevant impulse response for the probability of a crisis will be explained along with the extensions we implemented to think about the financial cycle in the following section.

3. Calibrating the Model for the Euro Area and Incorporating the Financial Cycle

In order to calibrate the Svensson framework for the euro area, we employ the estimated closed-economy DSGE model of Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011).[17] This euro-area DSGE model is in regular use for monetary and macroprudential policy analysis at the European Central Bank (ECB). Moreover, in terms of macrofinancial propagation mechanisms, the model is consistent with other comparable macroeconomic models for the euro area (Cozzi et al. 2020). Focusing on the impact of monetary policy shocks on the unemployment rate, the Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) model produces broadly comparable, if slightly weaker, impulse responses to euro-area-based empirical (mainly vector autoregression (VAR)-based) studies. The impulse

[16] A discount factor of 1 implies no discounting. In our sensitivity analysis we also vary the discount factor (see table 1).

[17] See appendix B for a description of the model.

response of the unemployment rate to a 1 pp policy rate shock in Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) peaks at a slightly higher level but is less persistent compared with recent empirical studies on monetary policy transmission in the euro area (Laine 2019; Rubio 2019). Furthermore, it is broadly consistent with recent estimates based on the ECB's new multicountry model (ECB-BASE; see Angelini et al. 2019).

In line with Svensson's approach, the results for monetary policy "leaning against the wind" are achieved by assuming the policy rate to be 1 pp above the flexible inflation targeting implied equilibrium rate for four quarters and to move endogenously thereafter.[18]

3.1 Financial Cycle

A critique of the Svensson framework, which we address in this paper, is that it is unable to capture the effect of the financial cycle on the costs and benefits of LAW (see Adrian and Liang 2016; BIS 2016; Filardo and Rungcharoenkitkul 2016; Gourio, Kashyap, and Sim 2017). BIS (2016) underlines that the financial cycle has a much lower frequency and that risks build up gradually. These features are not captured in Svensson's framework because of the shorter time horizons.

We take this critique into account by changing how the policy experiments are translated into the probability of a crisis start. Svensson (2017) uses the household debt growth as the determinant of the probability of a crisis occurring based on regressions in Schularick and Taylor (2012). This approach uses credit as an indicator which is also widely used as a basis for early-warning indicators.[19] Furthermore, Schularick and Taylor (2012) include 17 developed countries from 1870 onwards on a yearly basis which are not representative of the euro area.[20] In order to have an approach which considers the longer time horizons of the financial cycle and

[18]We achieve this by extracting the monetary policy shocks from a conditional forecast on the policy rate being fixed for four quarters.

[19]See, e.g., Borio and Lowe (2002a, 2004); Drehmann (2013).

[20]The financial crisis database underlying their calculations can be found at http://www.macrohistory.net/data.

is more suitable for the euro area, we rely on an early-warning indicator combining a set of long-term growth rates and estimated on euro-area data.[21]

This early-warning indicator, called systemic risk indicator (SRI), is designed to capture cyclical systemic risk, uses data from the monthly European financial crisis database by Lo Duca et al. (2017), and consists of a weighted average of the following normed variables:[22]

- two-year change in bank credit-to-GDP ratio,
- two-year growth rate of real total credit,
- three-year change in residential real estate price-to-income ratio,
- two-year change in the debt-service ratio,
- three-year growth rate of real equity prices, and
- current account-to-GDP ratio.

Before regressing the SRI on the crisis start dates, we have to construct the SRI from the impulse response functions (IRFs) of the DSGE model. Since the Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) model does not include an external sector or equity markets, we cannot include the three-year growth rate of real equity prices and current account-to-GDP ratio in the calculation of the SRI. Therefore, we take a reduced version of the SRI based on the other four variables: the two-year change in bank credit-to-GDP ratio, the two-year growth rate of real total credit, the three-year change in residential real estate price-to-income ratio, and the two-year change in the debt-service ratio. Table 2 shows the weights used in constructing the SRI. These are chosen to optimize the early-warning properties of the SRI for systemic financial crisis, using a constrained least squares regression. The variables used in the regression are normalized with their mean and standard deviation across time and geographies.

[21] See Rünstler and Vlekke (2018) or Schüler, Hiebert, and Peltonen (2015) for an analysis of the financial cycle in the euro area.

[22] See Detken, Fahr, and Lang (2018) and Lang et al. (2019) for a detailed description of the methodology and an evaluation of the SRI as an early-warning indicator.

Table 2. Weights Used in Calculating SRI

	Weight
Two-Year Change in Bank Credit-to-GDP Ratio	0.62
Three-Year Change in Residential Real Estate Price-to-Income Ratio	0.28
Two-Year Growth Rate of Real Total Credit	0.05
Two-Year Change in the Debt-Service Ratio	0.05

Having constructed the four-variable SRI, we run the following regressions:

$$Pr(p_{i,t}) = b_{0,i} + b_1(L)SRI_{i,t} + b_2X_i + \varepsilon_{i,t},$$

with $b_1(L)$ being the lag polynomial of 0 up to 20 quarters, and X_i being country fixed effects. The left-hand-side variable is the probability of a crisis start in the respective quarter.

Given that the lags of the SRI are highly autocorrelated and therefore multicollinear, we resort to regularization techniques for variable selection. This problem is particularly suitable for the use of regularization techniques because we want to focus on predictive power and interpretability. In order to achieve this, we use an elastic net regression to identify the relevant lags.[23] First, we use the elastic net to identify the relevant lags, and then we use the OLS coefficient estimates to parameterize the linking function. Using cross-validation for selecting the hyperparameters of the elastic net, the regularization finds lags 7 to 10 to be relevant. Table 3 shows the result of the maximum-likelihood regression for the selected variables.

[23]The elastic net is a regularization and variable selection method which combines and nests the least absolute shrinkage and selection operator (LASSO) and Ridge regularization techniques. The LASSO (Ridge) regularization means that you add the sum of absolute values (square of the absolute values) of the coefficients to the cost function of an otherwise standard ordinary least squares (OLS) regression. The elastic net combines the strengths of both approaches, namely the improved prediction power of Ridge regressions and the sparsity, or automatic feature selection, of LASSO regressions. See Zou and Hastie (2005) for a detailed description of the elastic net regularization technique.

Table 3. Start of Financial Crisis Prediction: Logit Estimates

	Dependent Variable: $Pr(p_{i,t})$			
	(1)	**(2)**	**(3)**	**(4)**
L0 SRI	0.450	−0.969***	−0.021	
	(0.284)	(0.366)	(0.561)	
L4 SRI		1.703***	−0.227	
		(0.340)	(0.841)	
L7 SRI				0.471
				(1.808)
L8 SRI			1.414***	1.234
			(0.540)	(3.005)
L9 SRI				−0.909
				(3.079)
L10 SRI				0.528
				(1.853)
AUROC	0.64	0.86	0.84	0.84
Observations	1,599	1,519	1,439	1,400
Log Likelihood	−83.819	−73.682	−67.228	−66.276
AIC	171.638	153.365	142.455	142.552

Notes: Standard errors are clustered at country level. Significance levels: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

From left to right, we add lags in time steps of four quarters, starting with the contemporaneous effect of the SRI on the probability of a crisis start. Column 4 shows the regression on the variables selected by the elastic net. The area under receiver operating characteristic (AUROC) for the specification without time lags is relatively low at 0.64. When adding the four-quarter lag (see column 2), we see that the AUROC increases up to a value of 0.86, and adding the eight-quarter lag leads to a slightly lower AUROC of 0.84. In comparison, the full specification in Schularick and Taylor (2012), including lags up to five years, has a slightly higher AUROC but features country fixed effects. The elastic net excluded country fixed effects in our case. The variables selected by the elastic net yield an AUROC of 0.84 and have the lowest log likelihood (see column 4). Their Akaike information criterion (AIC) value is at about the same level as for the specification in column 3.

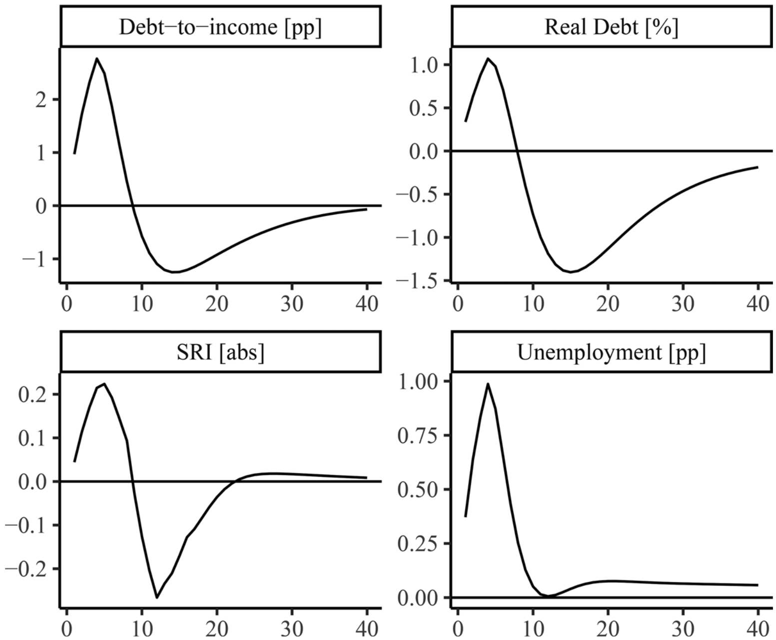
The functional form implies a quarterly probability of a crisis start of 0.5 percent versus the 0.8 percent used in Svensson's calculations. The difference is due to the different samples of the financial crisis databases used. Schularick and Taylor (2012) go back to 1870 and cover 17 developed countries, whereas Lo Duca et al. (2017) cover 22 European countries that experienced a financial crisis since 1970.

Coming back to the critique by the BIS and others, which was about monetary policy and its effect on the financial cycle, we will now discuss the results for "leaning against the wind" with our augmented version of the Svensson framework considering the financial cycle.

The IRFs for real GDP and real household and firm debt are then used to calculate the unemployment deviation (proxied by the GDP deviation times the Okun coefficient, with a value of 2), household debt growth, and the DTI ratio (total debt/GDP). These three series are used as inputs in the cost-benefit framework by Svensson (2017). The unemployment deviation drives the marginal costs, debt growth drives the probability of crisis, and the DTI ratio drives the severity of crisis.

Svensson's framework allows us to look at the cost over time. In order to establish whether a policy has net benefits or net costs, we look at the cumulative costs and benefits over 40 quarters.

Figure 2. Deviations from Steady State for a Temporary Monetary Policy Shock Using the Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) DSGE Model

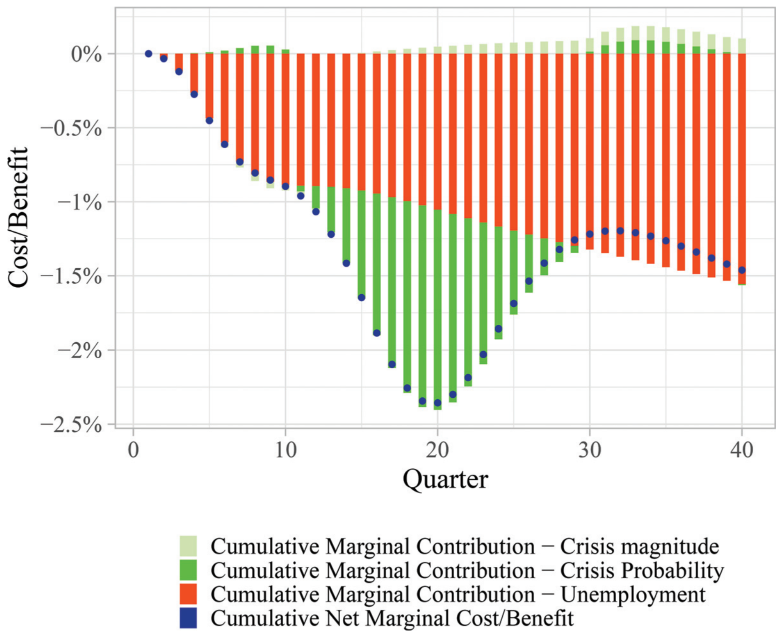


In the short run, an interest rate hike leads to an increase in debt levels (see figure 2). Such a short-term spike in debt levels is debatable, yet Gelain, Lansing, and Natvik (2018) and Korinek and Simsek (2016) confirm and explain how such a spike can come about.[24] Ultimately, the spike exacerbates the negative effects of monetary policy in the short run. Only in the medium turn does the DTI ratio decrease. The result of Svensson for "leaning against the wind" can be confirmed for the euro area, whereas the cumulated net marginal costs are slightly less negative.

We can see in figure 2 that monetary policy has a strong impact on the SRI. (See online version at http://www.ijcb.org for figures in

[24]An increase in interest rates can lead to a higher level of household debt, because higher interest rates also increase the debt service burden and lower the income of the borrowers, who then borrow more to smooth consumption.

Figure 3. Cumulative Net Marginal Cost/Benefit of LAW Considering the Financial Cycle



color.) It rises sharply in the beginning only to drop significantly to a low point after 2.5 years. The marginal benefits from a lower probability of a crisis are actually costs in the medium term because the SRI implies an increase in the probability of a crisis. Only towards the end of the 40-period horizon does the cumulated benefit of a lower probability of a crisis contribute to lowering the net cost. On top of this, there is a marginal cost in the form of the unemployment deviation. The marginal benefits of a less severe crisis are small compared with the marginal costs (see figure 3).

To conclude, even when considering the impact of monetary policy on the financial cycle, it is still inadvisable to use monetary policy to address financial stability risks. Nonetheless, the critique by the BIS is warranted in light of the results. The net marginal costs are lower when considering the financial cycle compared with the version without it, but the benefits of a lower probability of a crisis start are not enough to tip the balance.

4. Macroprudential Policy

Staying within the Svensson framework augmented to take into account the financial cycle, we next turn our attention to macroprudential policy. Are macroprudential policy instruments better able to address financial stability risks? Macroprudential policy interventions are represented here as an increase in banking-sector capital requirements[25] by 1 pp or a tightening in the LTV requirements[26] by 1 pp.[27]

We argue for one more additional change to the original framework to account for the financial cycle. We consider longer time horizons for which policy is activated to reflect the persistence and length of the financial cycle.[28] Furthermore, longer time horizons for the activation of macroprudential policy are more realistic, as they are usually implemented with a lag and are also typically adjusted more infrequently than monetary policy. The nature of the exercise implies that agents do not learn and are surprised every period again that the policymaker chooses to change macroprudential policy in a nonsystematic way. This assumption becomes more important the longer the time horizon we are considering.

Slight changes to the original DSGE model need to be incorporated for these simulations. For bank capital requirements, we

[25]Cozzi et al. (2020) provide an overview for different DSGE models of the impact on real GDP of a 1 pp change in bank capital requirements.

[26]The Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) model implies that a 1 pp decrease in the average LTV ratio would have a fourfold peak impact on GDP. Furthermore, changes in the LTV regulation are usually announced as caps on new loans. Therefore, a change in the average LTV translates into a much larger change in the LTV cap on new loans. This is because new loans are a relatively small share of the stock and caps are usually applied at the top quantiles of the new loan LTV distribution.

[27]The marginal effect should be seen in combination with the level of capital requirements or LTV requirements, respectively. The Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) DSGE model would imply that the effects are larger the higher (lower) the level of capital (LTV) requirements are. This is because both bank capital and collateral constraints are externalities with an optimal level of 0 in the case of bank capital and the absence of collateral constraints. Other models such as Mendicino et al. (2018) incorporate tradeoffs for bank capital and would allow a more informative analysis about the influence of the bank capital level.

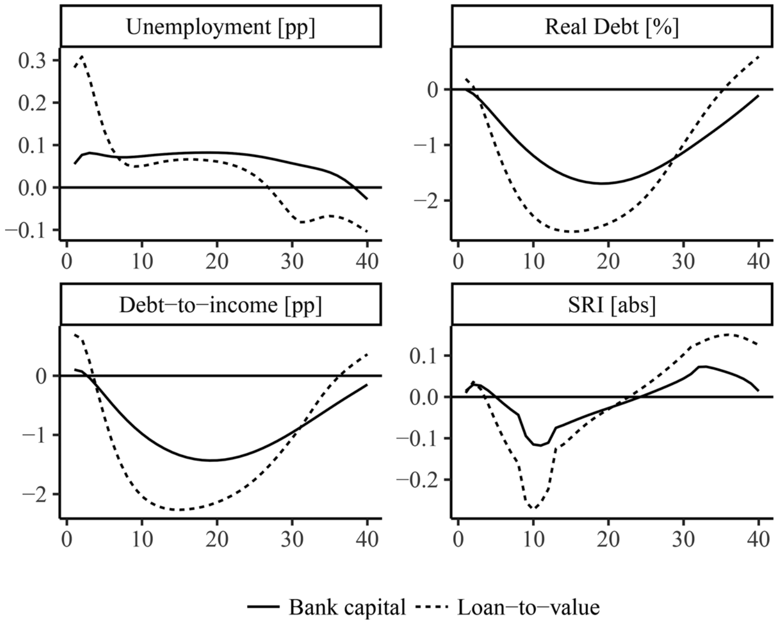
[28]The average length of the financial cycle in the euro area has been measured to 7.8 years; see Schüler, Hiebert, and Peltonen (2015).

assume an exogenous stationary AR(1) shock to the 11 percent bank capital requirements. With regard to the LTV requirements, we define LTV ratios for entrepreneurs and borrowing households as determined by a common LTV shock scaled to have the same absolute impact on both ratios. One has to bear in mind that a tightening of LTV requirements in the model does not fully represent how this tool is used in reality. In the model, we reduce the average LTV requirements, whereas in reality this tool is mostly used as a cap on LTV ratios. Therefore, a 1 pp reduction in average LTV corresponds to a lower cap of LTV ratios, depending on the distribution of LTV ratios.

Starting with bank capital requirements, we assume a 1 pp increase over the length of the financial cycle (7.8 years or 31 quarters). Figure 4 shows that the changes to debt levels are more pronounced and persistent than for LAW for four quarters. At the same time, the SRI is reduced significantly, reaching a low point 2.5 years after implementation of the policy. Unemployment increases slightly and goes down only towards the end of the 40 quarters considered here. These IRFs translate into considerable marginal costs (see figure 5). Nonetheless, the movements in the SRI are translated into marginal benefits outweighing the cost and tipping the balance in favor of using bank capital requirements to address financial stability risks. The benefits of a less severe crisis are not to be neglected either. The DTI ratio decreases significantly and translates into a significantly less severe crisis unemployment deviation.

Coming to LTV requirements, we find that decreasing the LTV requirements of both firms and households by 1 pp leads to a much stronger reaction of the macroeconomy than changing the bank capital requirements (see figure 4). Unemployment rises sharply and recedes to an elevated level. At the same time, debt and the DTI ratio decrease more, after an initial increase. Finally, the SRI reaches the bottom after 2.5 years but at a level more than twice as low as for the bank capital requirements. These IRFs imply a much higher marginal cost (see figure 6). Nevertheless, the benefits of a less severe crisis alone outweigh the marginal costs after 40 quarters. The probability of a crisis ultimately adds to the marginal benefits, although only slightly. In net cumulative terms, tightening the LTV requirements by 1 pp for 31 quarters is beneficial.

Figure 4. Deviations from Steady State for a 31-Quarter Activation of Macroprudential Policy Using the Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) DSGE Model



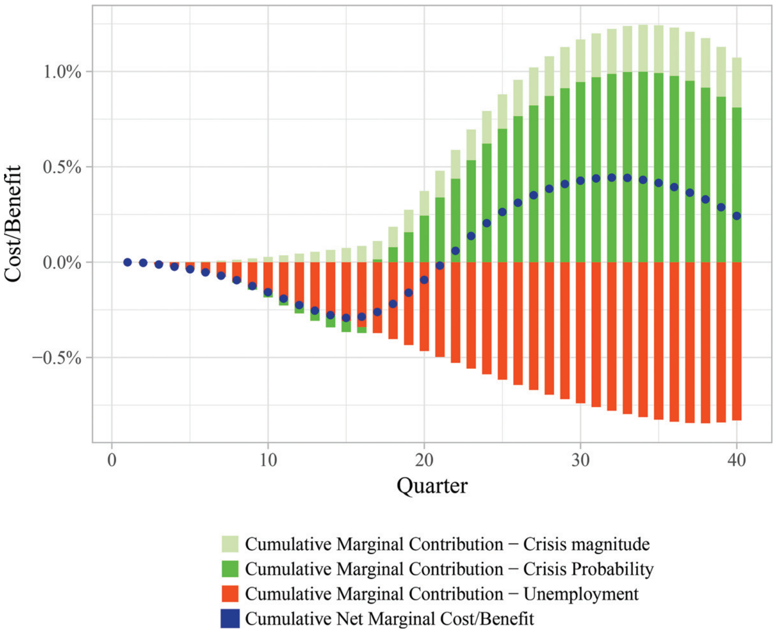
5. Robustness

5.1 Sensitivity to Calibrated Parameters

We calibrated the parameters so that they are suitable for the euro area. The results are of course conditional on the calibration we use. In order to underline the robustness of our results, we conduct a sensitivity test to the parameters. These parameters are the crisis increase in unemployment, crisis duration, crisis severity coefficient on DTI ratio, discount factor, and the time horizon. Table 1 shows the results for different calibrations, and we find that LAW by monetary policy considering the financial cycle has cumulated net marginal cost across all calibrations.

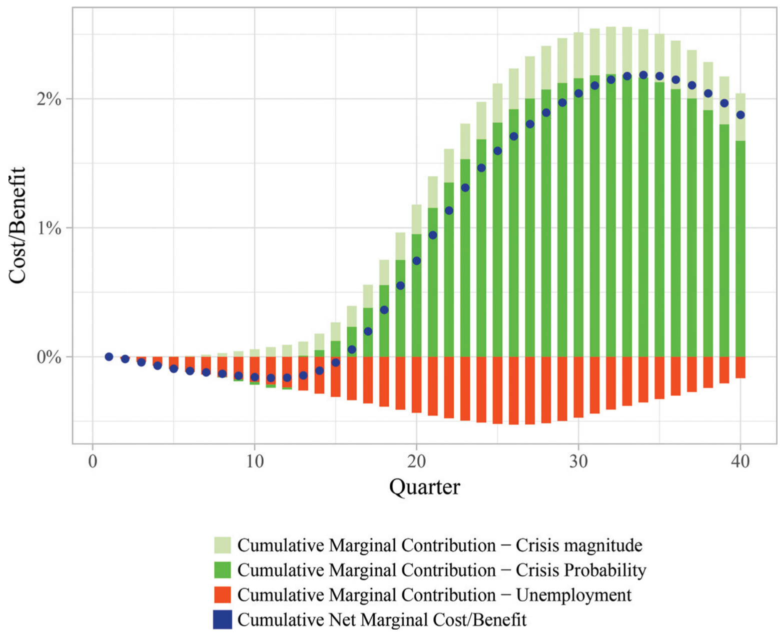
The parameter with the largest influence is the crisis increase in unemployment. We consider values from a 1 pp up to a 10 pp crisis

Figure 5. Cumulative Net Marginal Cost/ Benefit of Macroprudential Policy Considering the Financial Cycle (temporary increase of bank capital requirements—31 quarters)



increase in unemployment and find that the costs are larger for a higher crisis increase. This result is intuitive given the convex loss function. Regarding the crisis duration, we consider values between 6 and 10 quarters. Not surprisingly, we find that a longer crisis duration implies higher costs. Turning to the crisis severity coefficient on the DTI ratio, we consider values between 0.01 and 0.04. For this parameter a larger coefficient implies less cost. Given that the policy has net marginal benefits of reducing the crisis severity, this parameter amplifies the positive impact. For the discount factor we simulate values between 0.95 and 1 and find that a lower discount factor reduces the cumulated costs. Last but not least, we look at the time horizon and consider values between 20 and 100 quarters, and the costs outweigh the benefits across all time horizons with the least negative cost for a time horizon of 40 quarters.

Figure 6. Cumulative Net Marginal Cost/Benefit of Macroprudential Policy Considering the Financial Cycle (temporary increase of LTV requirements—31 quarters)

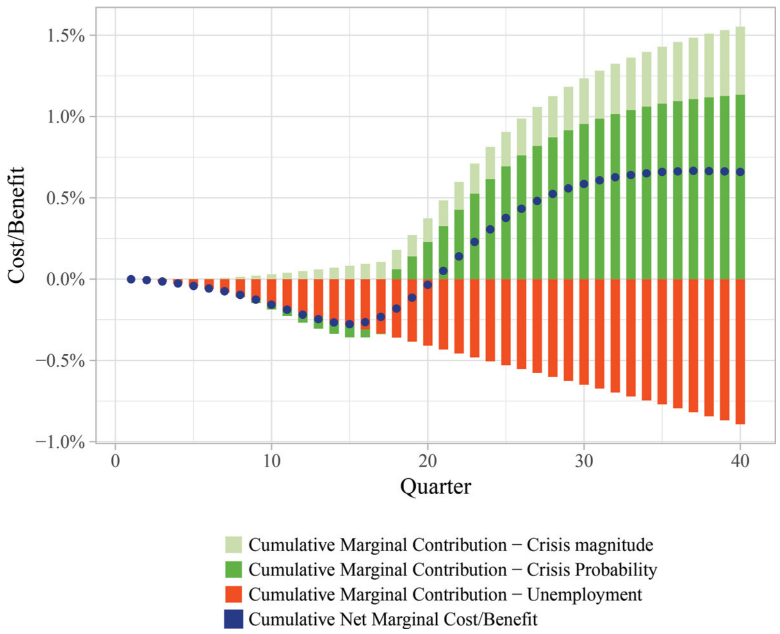


5.2 Permanent Policy Changes

It can be argued that in practice changes in macroprudential policy occur only quite infrequently. The contribution of the Svensson framework is that we can assess the cost and benefits of the *implementation* of a policy in contrast to a static level assessment. The DSGE model by Darracq Pariès, Kok, and Rodriguez-Palenquela (2011) is calibrated to reflect bank capital and LTV ratios in the euro area. Therefore, the investigation of whether a permanent change in bank capital or LTV requirements is advisable in order to tackle financial stability risks has merit.

Our results show that a permanent increase in bank capital requirements of 1 pp has net marginal benefits after 40 quarters (see figure 7). The results are driven by the permanent decrease in debt levels and a strong reduction in the SRI (see figure 8). The

Figure 7. Cumulative Net Marginal Cost/Benefit of Macroprudential Policy Considering the Financial Cycle (permanent increase of bank capital requirements)



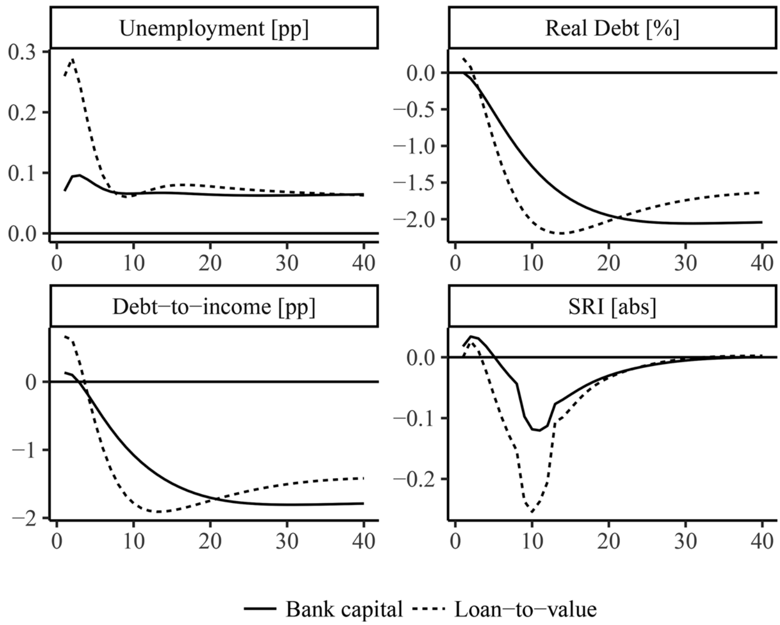
benefits outweigh the cost already after 23 quarters, and it is therefore advisable to use bank capital requirements in order to address financial stability concerns.

Similarly, a permanent decrease in the LTV requirements for entrepreneurs and borrowing households has net cumulated marginal benefits, outweighing marginal costs already after 18 quarters, and has cumulative net benefits after 40 quarters (see figure 9). These results are even more subject to the limitation that agents do not learn and are surprised every period about the macroprudential policy stance.

5.3 Short-Run Implementation of Macroprudential Policy

Having laid out in section 3.1 that a policy implementation over a longer horizon corresponds more naturally to the idea of the financial

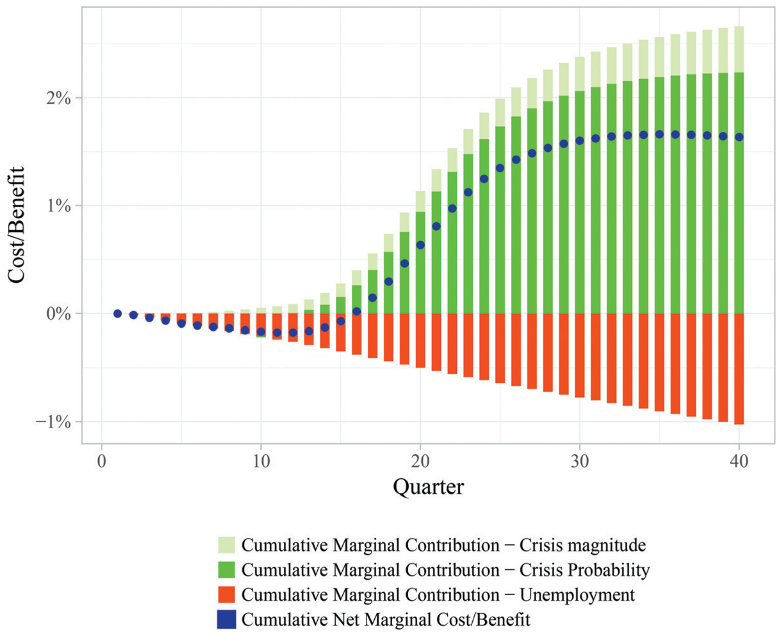
Figure 8. Deviations from Steady State for Permanent Macroprudential Policy Shocks Using the Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) DSGE Model



cycle, it is nonetheless worth exploring the results for shorter time spans of policy implementations.

As for monetary policy, we consider in the following a policy activation for four quarters. Starting with bank capital requirements, we find that a temporary increase in regulatory bank capital by 1 pp for four quarters has only marginal effects on the economy compared with LAW (see figure 10). Debt levels do go down and unemployment is slightly higher. The higher unemployment drives the marginal costs, which in this case dominate the cost-benefit analysis after 40 quarters (see figure 11). The erratic movement of the SRI in response to the policy leads to a cumulated cost of a higher probability of a crisis after around 20 quarters. In the end, the probability of a crisis has a cumulated benefit. The reduced debt levels only lead to comparatively very low cumulated marginal benefits due to a less severe crisis. In contrast to a longer time horizon of activation,

Figure 9. Cumulative Net Marginal Cost/Benefit of Macroprudential Policy Considering the Financial Cycle (permanent increase of LTV requirements)

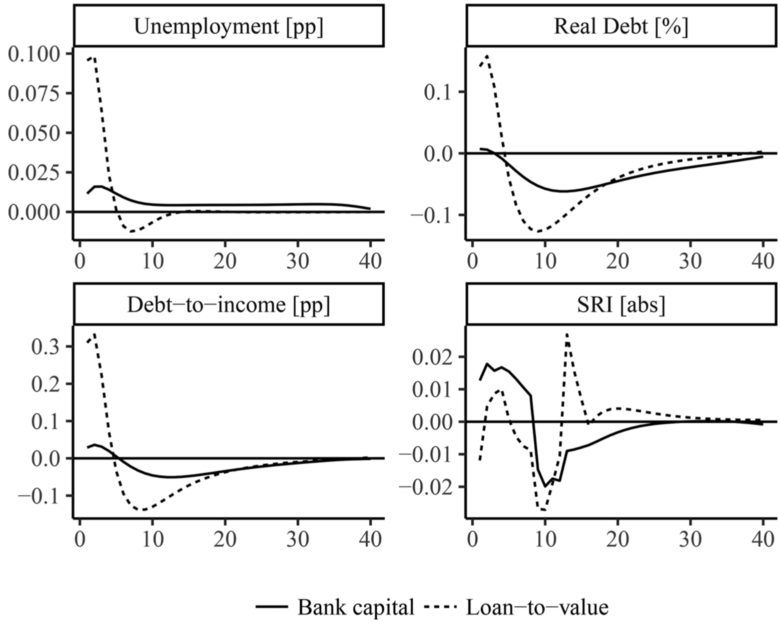


there are net marginal costs for the short-term use of bank capital requirements to address financial stability risks.

A four-quarter policy of a 1 pp tighter LTV requirement has a more persistent although weak effect on unemployment, debt levels, and the SRI (see figure 10). The benefits of a lower probability of a crisis start drive the results. In the short term, the cumulative costs outweigh the benefits, but after eight quarters the implementation has cumulated net marginal benefits (see figure 12). Therefore, even a short-term implementation of LTV requirements has net benefits in the long run, although the benefits are much larger for longer activation time spans.

We conclude that both macroprudential tools, if changed, should stay at their new respective levels in order to generate substantial benefits for the economy.

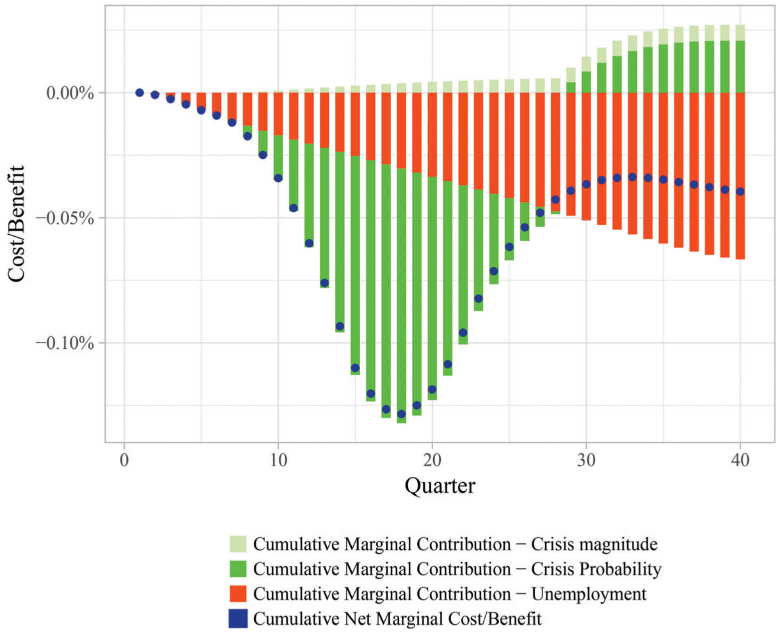
Figure 10. Deviations from Steady State for a Four-Quarter Activation of Macroprudential Policy Using the Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) DSGE Model



6. Discussion

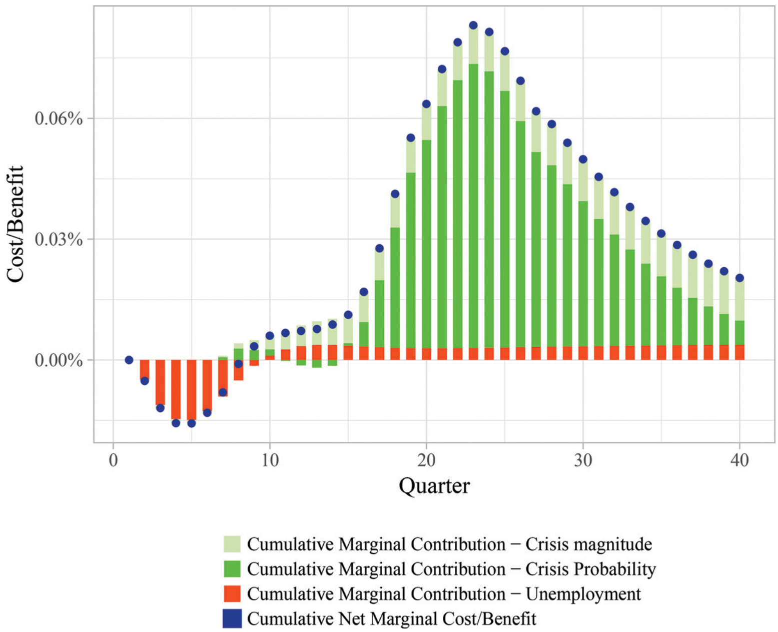
As already highlighted in the introduction, the finding that macroprudential policies are better suited to addressing financial stability risks than monetary policy is supported by a range of studies. This notwithstanding, our findings are obviously driven by the specific, and arguably simplistic, features of the Svensson framework. While we accommodate some of the criticism of the original Svensson approach (by studies such as Adrian and Liang 2016; Filardo and Rungcharoenkitkul 2016; and Gourio, Kashyap, and Sim 2017) by taking into account the longevity of financial cycles as compared with business cycle fluctuations, we acknowledge that further work is warranted to substantiate and improve the robustness of the finding that macroprudential policy is the preferred tool over monetary

Figure 11. Cumulative Net Marginal Cost/ Benefit of Macroprudential Policy Considering the Financial Cycle (temporary increase of bank capital requirements—four quarters)



policy to lean against the buildup of financial cycles. In particular, monetary policy is discretionary in the Svensson framework and imposes a cost in normal times by construction. A systematic policy response which takes into account the possibility of a crisis would be more balanced and consider the tradeoffs optimally. Gerdrup et al. (2017) highlight in a setting with endogenous crisis that a systematic (but not optimal) LAW policy rule is slightly beneficial. Nonetheless, the model they use lacks the level of sophistication regarding the debt dynamics featured in the model underlying our analysis. The debt dynamics are a crucial part of determining the benefits. The ideal experiment would consider endogenous crisis and optimal policy, but this is beyond the scope of this article. Another dimension we do not explore is systematic macroprudential policy

Figure 12. Cumulative Net Marginal Cost/Benefit of Macroprudential Policy Considering the Financial Cycle (temporary increase of LTV requirements—four quarters)



such as the countercyclical capital buffer (CCyB). Optimal macroprudential policy could further improve the benefits and reduce the costs over the discretionary policy. As for optimal monetary policy, optimal macroprudential policy also is out of the scope of this article.

As Jeremy Stein has observed, there may be situations where LAW is warranted, as it "gets into all the cracks" of the financial system.[29] In other words, in some circumstances, either due to the nature of financial stability risks or due to the potentially limited

[29]See "Overheating in Credit Markets: Origins, Measurement, and Policy Responses," speech by U.S. Federal Reserve Governor Jeremy C. Stein at the "Restoring Household Financial Stability after the Great Recession: Why Household Balance Sheets Matter" research symposium sponsored by the Federal Reserve Bank of St. Louis, St. Louis, Missouri, February 7, 2013.

effectiveness of the targeted macroprudential tools, some LAW may improve welfare.[30]

Furthermore, it has to be kept in mind that macroprudential policy and monetary policy are to a large extent interdependent. These interdependencies imply the potential for a tradeoff between the two policy functions, as the transmission of macroprudential instruments is likely to affect the monetary policy transmission mechanism. It is to be expected that a monetary policy change will often affect the macroprudential policy stance (e.g., through its effect on bank profitability and risk-taking behavior in the economy). Vice versa, changes in macroprudential policy, such as an adjustment of capital buffer requirements or changes to borrower-based measures (e.g., LTV ratios), are likely to affect general economic activity (via credit provisioning, asset prices, and the impact of economic activity on overall financing conditions) and thus may influence the monetary policy stance. As highlighted by inter alia Carboni, Darracq Pariès, and Kok (2013), price stability and financial stability are complementary and will often be mutually reinforcing.[31] In general, it is thus likely that in many instances there will be strategic complementarities between the two policy functions and that actions in one area will be supportive of the other policy area. However, there can also be potential for conflict between monetary and macroprudential policies; for instance, there can be situations where monetary policy would be too loose and risk creating financial imbalances, whereas macroprudential policy can be too restrictive, hampering the smooth transmission of monetary policy. Overall, while these considerations do not contradict the findings of this paper suggesting that targeted macroprudential policies are preferable to LAW, these considerations still underline the need to ensure an appropriate institutional framework with effective coordination mechanisms among the different policy functions, with clear delineations of responsibility.

[30]See also Smets (2014).

[31]See Angelini, Nicoletti-Altimari, and Visco (2012), Goodhart et al. (2007), and IMF (2015).

7. Conclusion

This paper analyzes the cost and benefits of monetary and macroprudential policy in addressing risks to financial stability for the euro area. This question is especially relevant today given the risk that the prolonged period of very accommodative monetary policy increases systemic risk.

In a first step we extend the Svensson framework to take into account the financial cycle and evaluate LAW by monetary policy in the euro area. We find that monetary policy has cumulated net marginal costs in addressing risks to financial stability. For the extended framework we reestimate the probability of a crisis start making use of the SRI, and determine with these estimates the benefits of a given policy in reducing the probability of a crisis. Thereby, we can answer one of the critiques of the BIS that the original Svensson framework does not consider the financial cycle and confirm the result by Svensson regarding LAW.

Turning to macroprudential policy, we argue for longer time horizons for which policy is activated and find that both a 1 pp increase in bank capital requirements and a 1 pp decrease in LTV requirements has cumulated net marginal benefits after 40 quarters. Furthermore, we assess permanent changes in macroprudential policy and find that the benefits are even greater. As a robustness check, we conduct the analysis for short-term implementation of macroprudential policies and find that these policies are less beneficial and show cumulative marginal costs in the case of an increase in bank capital requirements for four quarters.

To conclude, our analysis suggests that macroprudential policy is better suited to addressing risks to financial stability. The benefits outweigh the costs to a large degree for policy implementation with a longer time horizon.

Appendix A. Monetary Policy "Leaning against the Wind" in the Euro Area

In the following we will explain in detail which parts of the model are driven by which parameters and go step by step through the original Svensson framework applied to the euro area.

We conduct the policy evaluation in the Svensson framework with only minimal changes in order to compare the results for Sweden and the euro area. After all, Sweden is a small open economy and the euro area is large enough to be modeled as a closed economy. Therefore, monetary policy will have different effects on the macroeconomy.

The policy experiment in Svensson (2017) is conducted using the RAMSES DSGE model for Sweden.[32] The IRFs for real GDP and real household and firm debt are then used to calculate the unemployment deviation (proxied by the GDP deviation times the Okun coefficient, with a value of 2), household debt growth, and the DTI ratio (total debt/GDP). These three series are used as inputs in the cost-benefit framework by Svensson (2017). The unemployment deviation drives the marginal costs, debt growth drives the probability of crisis, and the DTI ratio drives the severity of crisis.

We contrast the results of Svensson with those of the euro area using the same calibration. The quarterly probability of a crisis start is assumed to be $q_t = 0.8\%$ and based on estimates from Schularick and Taylor (2012). Using a simple linear approximation,[33] these values imply a steady-state probability of being in a crisis of around $p_t = 6\%$.

With regard to the benefits of a less severe crisis, we rely on the conservative estimates found in Sveriges Riksbank (2014). These estimates, which Svensson uses in his framework, imply that the marginal benefit is equal to 0.02 times the policy effect on the household DTI ratio. The change in the crisis severity is to be seen in conjunction with the baseline crisis severity of an increase in unemployment of 5 pp. Taken together with the eight quarters crisis duration, 10 pp-years of unemployment deviation determine the severity of the crisis in the model without policy intervention.

Underlying the quarterly probability of a crisis start is a logistic function that links the policy impact via debt growth to the probability of a crisis.[34] The constant crisis probability is therefore

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[32] See Adolfson et al. (2013).

[33] The linear approximation is the sum of the quarterly probabilities of a crisis start over eight quarters: $p_t \approx \sum_{i=0}^{n-1} q_{t-i}$.

[34] The function is taken from the estimates found in Schularick and Taylor (2012).

dependent on the steady-state growth of debt. Again we rely on the benchmark calibration and assume a 5 percent per annum growth in debt. In a first step the trend growth is added to the IRF from the DSGE model and then the transformed growth is the input for the logistic function linking debt growth and the probability of a crisis start:

$$X_t = -3.89 - 0.398 \cdot g_{t-4} + 7.138 \cdot g_{t-8} + 0.888 \cdot g_{t-12} \\ + 0.203 \cdot g_{t-16} + 1.867 \cdot g_{t-20}, \tag{A.1}$$

with X_t being the annual probability of a crisis start and g_{t-i} being the annual growth rate of (average annual) real debt lagged by i quarters. The real debt growth rate is a transformation of the IRF of real household and firm debt. First, the trend growth is added to the IRF and second the growth rate is calculated according to $g_t = log(\sum_{i=0}^{3} d_{t-i}/4) - log(\sum_{i=0}^{3} d_{t-4-i}/4)$, with d_t being the IRF of real household and firm debt including the trend growth of 5 percent. The annual probability is then transformed into the quarterly probability: $q_t = \frac{1}{4 \cdot (1+exp(-X_t))}$. The probability of being in a crisis and the change in the probability of being in a crisis due to policy can be calculated using a Markov process.[35]

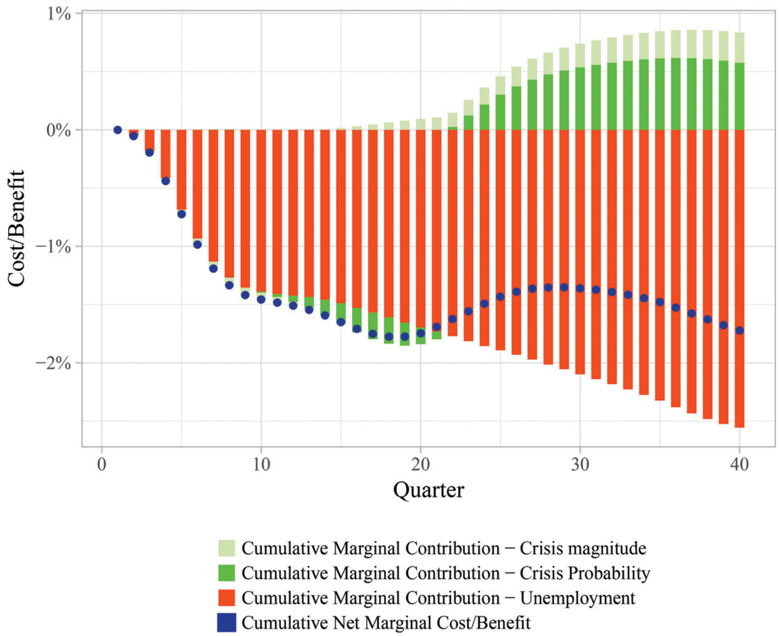
We use as before the IRFs from Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) as inputs to the Svensson framework. Now we are using the original calibration and therefore we do not use the SRI as an input but debt growth drives the probability of crisis.

Svensson's framework allows us to look at the cost over time. In order to establish whether a policy has net benefits or net costs, we look at the cumulative discounted costs and benefits over 40 quarters. We apply a discount factor of 1, relying on the benchmark calibration of Svensson. Equations (1), (2), and (3) determine the benefits and cost of the policy.

For monetary policy we can see that the marginal costs are driving the results (see figure A.1). Monetary policy has a relatively strong impact on the real economy, and the benefits are not sufficient to outweigh these high costs over time. An interest rate increase

[35] See appendix C in Svensson (2017) for a detailed explanation of the Markov process.

Figure A.1. Cumulative Net Marginal Cost/Benefit of LAW



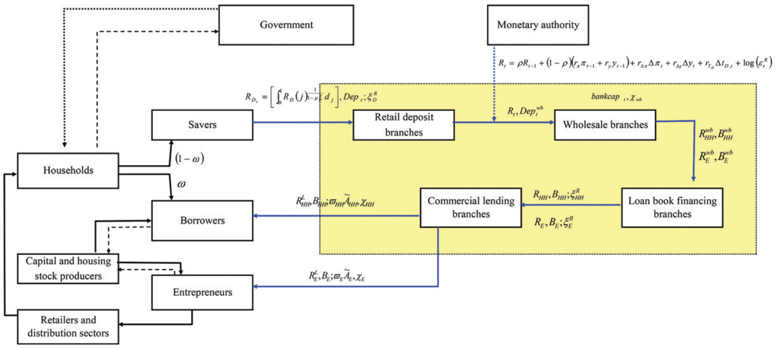
does lower debt and DTI in the long term but not enough to tip the balance between costs and benefits over the horizon of 40 quarters (see figure 2).

Appendix B. Euro-Area DSGE Model

In this section we describe the model found in Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011).

The real side of the economy is modeled as a three-agent, two-sector economy, producing residential and nonresidential goods. Residential goods are treated here as *durable* goods. A continuum of entrepreneurs, with unit mass, produce nonresidential and residential intermediate goods under perfect competition and face financing constraints. Retailers differentiate the intermediate goods under imperfect competition and staggered price setting, while competitive distribution sectors serve final nonresidential consumption as well as

Figure B.1. Structure of the Model



residential and nonresidential investments. A continuum of infinitely lived households, with unit mass, is composed of two types, differing in their relative intertemporal discount factor. A fraction $(1-\omega)$ of households are relatively *patient*, the remaining fraction ω being *impatient*. Households receive utility from consuming both nonresidential and residential goods, and disutility from labor. Impatient households are financially constrained. The labor market structure is characterized by homogeneous labor supply and monopolistically competitive unions, which gives rise to staggered wage setting.

The banking sector collects deposits from patient households and provides funds to entrepreneurs and impatient households. Three layers of frictions affect financial intermediaries. First, wholesale banking branches face capital requirements (which can be risk insensitive or risk sensitive) as well as adjustment costs related to their capital structure. Second, some degree of nominal stickiness generates some imperfect pass-through of market rates to bank deposit and lending rates. Finally, due to asymmetric information and monitoring cost in the presence of idiosyncratic shocks, the credit contracts proposed to entrepreneurs and impatient households factor in external financing premiums which depend indirectly on the borrower's leverage. Figure B.1 provides an overview of the financial contracts linking the banking sector to the real economy.

Finally, a government sector collecting taxes and providing lump-sum fiscal transfers and a monetary authority applying a standard Taylor-rule close the model.

B.1 Households

B.1.1 The Saver's Program

The patient agents, $s \in [\omega, 1]$, are characterized by a higher intertemporal discount factor than the borrowers, and thus act as net lenders in equilibrium. They own the productive capacities of the economy. Each patient agent receives instantaneous utility from the following instantaneous utility function:

$$\mathcal{W}_t^s = \mathbb{E}_t \left\{ \sum_{j \geq 0} \gamma^j \left[\begin{array}{c} \frac{1}{1-\sigma_X} \left(X_{t+j}^s \right)^{1-\sigma_X} - \frac{\varepsilon_{t+j}^L \overline{L}_{S,C}}{1+\sigma_{LC}} \left(N_{Ct+j}^s \right)^{1+\sigma_{LC}} \\ - \frac{\varepsilon_{t+j}^L \overline{L}_{S,D}}{1+\sigma_{LD}} \left(N_{Dt+j}^s \right)^{1+\sigma_{LD}} \end{array} \right] \varepsilon_{t+j}^{\beta} \right\},$$

where X_t^s is an index of consumption services derived from nonresidential final goods (C^s) and residential stock (D^s), respectively.

$$X_t^s \equiv \left[\left(1 - \varepsilon_t^D \omega_D \right)^{\frac{1}{\eta_D}} \left(C_t^s - h_S C_{t-1}^s \right)^{\frac{\eta_D - 1}{\eta_D}} + \varepsilon_t^D \omega_D^{\frac{1}{\eta_D}} \left(D_t^s \right)^{\frac{\eta_D - 1}{\eta_D}} \right]^{\frac{\eta_D}{\eta_D - 1}},$$

with the parameter h_S capturing habit formation in consumption of nonresidential goods. We introduce three stochastic terms in the utility function: a preference shock ε_t^{β}, a labor supply shock ε_t^L (common across sectors), and a housing preference shock, ε_t^D. The latter affects the relative share of residential stock, ω_D, and modifies the marginal rate of substitution between nonresidential and residential goods consumption. All the shocks are assumed to follow stationary AR(1) processes.

Households receive disutility from their supply of homogeneous labor services to each sector, $N_{C,t}^s$ and $N_{D,t}^s$. The real compensation of hours worked in each sector are denoted $w_{C,t}^s$ and $w_{D,t}^s$. The specification of labor supply assumes that households have preferences over providing labor services across different sectors. In particular, the specific functional form adopted implies that hours worked are perfectly substitutable across sectors. $\overline{L}_C$ and $\overline{L}_D$ are level-shift terms needed to ensure that the patient agent's labor supply is equal to one in steady state.

The saver maximizes its utility function subject to an infinite sequence of the following budget constraint:

$$\begin{aligned} & C_t^s + Q_{D,t}T_{D,t}\left(D_t^s - (1-\delta)\,D_{t-1}^s\right) + Dep_t^s \\ & \quad = \frac{(1+R_{D,t-1})}{(1+\pi_t)}Dep_{t-1}^s + (1-\tau_{w,t})\,(w_{C,t}^s N_{C,t}^s + w_{D,t}^s N_{D,t}^s) \\ & \qquad + \Pi_t^s + TT_t^s, \end{aligned}$$

where $Q_{D,t}T_{D,t}$ is real price of housing stock in terms of nonresidential goods, TT_t^s are real government transfers, and Π_t^s are real distributed profits. $\delta \in (0,1)$ is the residential good depreciation rate. π_t is the nonresidential good inflation rate. $R_{D,t-1}$ is the nominal interest rate paid on the one-period real deposits Dep_t^s.

In equilibrium, all savers have identical consumption plans. Therefore, we can drop superscripts s. We also allow for a time-varying labor income tax, given by $1-\tau_{w,t} = \left(1-\overline{\overline{\tau}}_w\right)\varepsilon_t^W$.

B.1.2 The Borrower's Program

Each impatient agent $b \in [0,\omega]$ receives utility from the same type of function as in the case of patient households but with a lower discount factor $\beta < \gamma$:[36]

$$\mathcal{W}_t^b = \mathbb{E}_t\left\{\sum_{j\geq 0}\beta^j\left[\begin{array}{c} \frac{1}{1-\sigma_X}\left(\widetilde{X}_{t+j}^b\right)^{1-\sigma_X} - \frac{\varepsilon_{t+j}^L \overline{L}_{B,C}}{1+\sigma_{LC}}\left(N_{C,t+j}^b\right)^{1+\sigma_{LC}} \\ -\frac{\varepsilon_{t+j}^L \overline{L}_{B,D}}{1+\sigma_{LD}}\left(N_{D,t+j}^b\right)^{1+\sigma_{LD}} \end{array}\right]\varepsilon_{t+j}^\beta\right\},$$

where $\widetilde{X}_t^b$ is given by

$$\widetilde{X}_t^b \equiv \left[\left(1-\varepsilon_t^D\omega_D\right)^{\frac{1}{\eta_D}}\left(\widetilde{C}_t^b - h_B\widetilde{C}_{t-1}^b\right)^{\frac{\eta_D-1}{\eta_D}} + \varepsilon_t^D\omega_D^{\frac{1}{\eta_D}}\left(\widetilde{D}_t^b\right)^{\frac{\eta_D-1}{\eta_D}}\right]^{\frac{\eta_D}{\eta_D-1}}.$$

As regards savers, $\overline{L}_{B,C}$ and $\overline{L}_{B,D}$ are level-shift terms needed to ensure that the impatient agent's labor supply equals one in steady state.

[36]Variables related to the saver are denoted with a superscript b, as opposed to s, used for the savers.

Borrowers' incomes and housing stock values are subject to common idiosyncratic shocks $\varpi_{HH,t}$ that are iid across borrowers and across time. $\varpi_{HH,t}$ has a log-normal cumulative distribution function (CDF) $F(\varpi)$ with $F'(\varpi) = f(\varpi)$, and a mean of $E(\varpi) = 1$. The variance of the idiosyncratic shock $\sigma_{HH,t}$ is time varying. The value of the borrower's house is given by

$$\varpi_{HH,t}\widetilde{Q}_{D,t}T_{D,t}(1-\delta)\widetilde{D}^{b}_{t-1}.$$

Lending in this economy is only possible through one-period state-contingent debt contracts that require a constant repayment of $\frac{\left(1+R^L_{HH,t}\right)}{1+\pi_t}B_{HH,t-1}$ independent of $\varpi_{HH,t}$ if the borrower is to avoid costly loan monitoring or enforcement, where $R^L_{HH,t}$ is the nominal lending rate.

The borrower can default and refuse to repay the debt. Savers cannot force borrowers to repay. Instead lending must be intermediated by commercial banks that have a loan enforcement technology allowing them to seize collateral expressed in real terms,

$$\varpi_{HH,t}\tilde{A}^{b}_{HH,t} = (1-\chi_{HH})\varpi_{HH,t}\widetilde{Q}_{D,t}T_{D,t}(1-\delta)\widetilde{D}^{b}_{t-1},$$

at a proportional cost $\mu_{HH}\varpi_{HH,t}\tilde{A}_{HH,t}$ when the borrower defaults.

$\mu_{HH} \in (0,1)$ determines the deadweight cost of default; $0 < \chi_{HH} \leq 1$ represents housing exemptions. It defines the maximum loan-to-collateral ratio (often called the loan-to-value ratio) that the bank is willing to grant against each component of the collateral. Conditional on enforcement, the law cannot prevent the bank from seizing $\varpi_{HH,t}\tilde{A}_{HH,t}$. Suppose first that the borrower does not have access to any insurance against the $\varpi_{HH,t}$ shock. Whenever $\varpi_{HH,t} < \overline{\varpi}_{HH,t}$, the borrower prefers to default and lose

$$\varpi_{HH,t}\tilde{A}^{b}_{HH,t} < \frac{\left(1+R^L_{HH,t}\right)}{1+\pi_t}B_{HH,t-1} = \overline{\varpi}_{HH,t}\tilde{A}^{b}_{HH,t}$$

when the bank enforces the contract. On the other hand, when $\varpi_{HH,t} \geq \overline{\varpi}_{HH,t}$, the borrower prefers to pay $\frac{\left(1+R^L_{HH,t}\right)}{1+\pi_t}B_{HH,t-1}$ rather than lose $\varpi_{HH,t}\tilde{A}_{HH,t} \geq \frac{\left(1+R^L_{HH,t}\right)}{1+\pi_t}B_{HH,t-1}$.

To be able to use a representative-agent framework while maintaining the intuition of the default rule above, we assume that borrowers belong to a large family that can pool their assets and diversify away the risk related to $\varpi_{HH,t}$ after loan repayments are made. As in Lucas (1990) and Shi (1997), the family maximizes the expected lifetime utility of borrowers with an equal welfare weight for each borrower. The payments from the insurance scheme cannot be seized by the bank. As a result, despite the insurance, the bank cannot force the borrower to repay $\frac{(1+R^L_{HH,t})}{1+\pi_t}B_{HH,t-1}$ when $\varpi_{HH,t} < \overline{\varpi}_{HH,t}$. Like the individual borrowers, the family cannot commit to always repay the loan (or make up for any lack of payment by a borrower), even though from an ex ante perspective it is optimal to do so. Ex post, from the perspective of maximizing the expected welfare of the borrowers, for any given $R^L_{HH,t}$ it is optimal to have borrowers with $\varpi_{HH,t} < \overline{\varpi}_{HH,t}$ default and borrowers with $\varpi_{HH,t} \geq \overline{\varpi}_{HH,t}$ repay $\frac{(1+R^L_{HH,t})}{1+\pi_t}B_{HH,t-1}$.

Given the large family assumption in particular, households' decisions are the same in equilibrium. Therefore, we can drop the superscript b.

By pooling the borrowers' resources, the representative family has the following aggregate repayments and defaults on its outstanding loan:

$$H(\overline{\varpi}_{HH,t})\tilde{A}_{HH,t} = \left[(1 - F_t(\overline{\varpi}_{HH,t}))\overline{\varpi}_{HH,t} + \int_0^{\overline{\varpi}_{HH,t}} \varpi dF_t\right]\tilde{A}_{HH,t}.$$

On the commercial lending bank side, the profit made on the credit allocation is given by

$$G(\overline{\varpi}_{HH,t})\tilde{A}_{HH,t} - \frac{(1 + R_{HH,t-1})}{1 + \pi_t}B_{HH,t-1} \geq 0$$

with

$$G(\overline{\varpi}_{HH,t}) = (1 - F_t(\overline{\varpi}_{HH,t}))\overline{\varpi}_{HH,t} + (1 - \mu_{HH})\int_0^{\overline{\varpi}_{HH,t}} \varpi dF_t.$$

$R_{HH,t-1}$ is the interest rate at which the commercial lending bank gets financing every period, while $R^L_{HH,t}$ is the state-contingent lending rate. Competition among banks will ensure that profits are null in equilibrium. The zero-profit condition could also be seen as the borrowing constraint in this model. Notice that this constraint always binds as long as it can be satisfied.[37] In contrast, the hard borrowing constraint in Iacoviello (2005) or Kiyotaki and Moore (1997) may not bind, even though authors using that framework assume it always binds to allow the use of perturbation methods.[38] The caveat is that if a new shock significantly lowers the value of $\widetilde{A}_{HH,t}$, it may be impossible to find a default threshold that allows the bank to break even on the loan with the risk-free rate. This should not be a major concern except for very low aggregate shock values.[39]

With the assumption of perfectly competitive banks, we can represent the problem of borrowers as if they choose default thresholds as a function of the aggregate states directly, subject to the bank's participation constraints.

Each borrower maximizes utility function with respect to $\widetilde{C}_t$, $\widetilde{D}_t$, $B_{HH,t}$, $\overline{\varpi}_{HH,t}$, $N_{C,t}$, $N_{D,t}$, subject to an infinite sequence of real budget constraints:[40]

$$\begin{aligned}&\widetilde{C}_t + \widetilde{Q}_{D,t} T_{D,t} \left(\widetilde{D}_t - (1-\delta)\, \widetilde{D}_{t-1} \right) + H(\overline{\varpi}_{HH,t}) \tilde{A}_{HH,t} \\ &\quad = B_{HH,t} + \widetilde{TT}_t + \widetilde{w}_{C,t} \widetilde{N}_{C,t} + \widetilde{w}_{D,t} \widetilde{N}_{D,t}\end{aligned}$$

and the zero-profit condition for the commercial lending banks.

B.2 Labor Supply and Wage Setting

The labor market structure is modeled following Schmitt-Grohe and Uribe (2006). In both countries, households of each type (patient, impatient) provide homogeneous labor services, which are transformed by monopolistically competitive unions into differentiated labor inputs. As a result, all household of the same type supply the same amount of hours worked in each sector, in equilibrium.

[37] If the constraint were slack, the lender could always reduce the borrower's expected repayments while still respecting the constraint by reducing $\overline{\varpi}_{HH,t}$.

[38] This may be a reasonable assumption for small shocks, but it can be a bad approximation for larger shocks that may be of concern to policymakers.

[39] In our calibrations, the balanced growth path value of the LTV $G(\overline{\varpi}_{HH,t})$ is around 0.5. This suggests that we would need shocks that cause extremely large movements in the LTV on impact before we violate the upper bound on the LTV. See the appendix in Bernanke, Gertler, and Gilchrist (1999) for a discussion of the same issue in their model.

[40] We use the nonresidential goods price level as a deflator.

We assume that in each sector $j \in \{C, D\}$ there exist monopolistically competitive labor unions indexed representing the patient and impatient households. Unions differentiate the homogeneous labor provided by households, N_{jt} from savers and $\widetilde{N}_{jt}$ from borrowers, creating a continuum of measure one of labor services (indexed by $z \in [0, 1]$) which are sold to labor packers.

Then perfectly competitive labor packers buy the differentiated labor input and aggregate them through a constant elasticity of substitution (CES) technology into one labor input per sector and households type. Finally, the labor inputs are further combined using a Cobb-Douglas technology to produce the aggregate labor resource $L_{C,t}$ and $L_{D,t}$ that enters the production functions of entrepreneurs (see later). We specify the details of the labor packers' profit-maximization problem below.

For $i \in \{B, S\}$, $L_{j,i,t}$ measures aggregate labor input for household type i and sector j,

$$L_{j,i,t} = \left[\int_0^1 L_{j,i,t}(z)^{\frac{1}{\mu_w}} \mathrm{d}z \right]^{\mu_w},$$

while $W_{j,i,t}$ denotes the aggregate nominal wage for type i and sector j,

$$W_{j,i,t} = \left[\int_0^1 W_{j,i,t}(z)^{\frac{1}{1-\mu_w}} \mathrm{d}z \right]^{1-\mu_w}.$$

Each union thus faces the following labor demand (originating from sector-specific labor packers):

$$L_{j,i,t}(z) = \left(\frac{W_{j,i,t}(z)}{W_{j,i,t}} \right)^{-\frac{\mu_w}{\mu_w - 1}} L_{j,i,t},$$

where $z \in [0, 1], \mu_w = \frac{\theta_w}{\theta_w - 1}$ and $\theta_w > 1$ is the elasticity of substitution between differentiated labor services, which we assume to be constant across types and sectors. Clearly, our structure gives rise to four different wages in equilibrium, each corresponding to a specific worker type (patient, impatient) in a specific sector (C, D). Unions set wages on a staggered basis. Every period, each union faces a constant probability $1 - \alpha_{wji}$ of being able to adjust its nominal wage.

If the union is not allowed to reoptimize, wages are indexed to past and steady-state inflation according to the following rule:

$$W_{j,i,t}(z) = [\Pi_{t-1}]^{\gamma_w^{j,i}} \left[\overline{\Pi}\right]^{1-\gamma_w^{j,i}} W_{j,i,t-1}(z),$$

where $\Pi_t = \frac{P_t}{P_{t-1}}$ and $\gamma_w^{j,i}$ denotes the degree of indexation in each sector, for each type. Taking into account that unions might not be able to choose their nominal wage optimally in the future, the optimal nominal wage $\widehat{W}_{j,i,t}(z)$ is chosen to maximize intertemporal utility under the budget constraint and the labor demand function.

B.3 Nonfinancial Corporate Sectors

B.3.1 Entrepreneurs

Entrepreneurs are also more impatient than household savers and have a discount factor $\beta_E < \beta$. They receive utility from their consumption of nonresidential goods. They are in charge of the production of intermediate residential and nonresidential goods, and operate in a perfectly competitive environment. They do not supply labor services. Their intertemporal utility function is given by

$$\mathcal{W}_t^E = \mathbb{E}_t \left\{ \sum_{j \geq 0} (\beta_E)^j \frac{\left(C_{t+j}^E - h_E C_{t+j-1}^E\right)^{1-\sigma_{CE}}}{1-\sigma_{CE}} \varepsilon_{t+j}^{\beta} \right\}.$$

Nonresidential intermediate goods are produced with capital and labor, while residential intermediate goods combine capital, labor, and land. In every period of time, savers are endowed with a given amount of land, which they sell to the entrepreneurs in a fixed quantity. We assume that the supply of land is exogenously fixed and that each entrepreneur takes the price of land as given in its decision problem. Entrepreneurs make use of Cobb-Douglas technology as follows:

$$Z_t(e) = \varepsilon_t^A \left(u_t^C(e) K_{t-1}^C(e)\right)^{\alpha_C} L_t^C(e)^{1-\alpha_C} - \Omega_C \qquad \forall e \in [0,1]$$

$$Z_{D,t}(e) = \varepsilon_t^{A_D} \left(u_t^D(e) K_{t-1}^D(e)\right)^{\alpha_D} L_t^D(e)^{1-\alpha_D-\alpha_{\mathcal{L}}} \mathcal{L}_t(e)^{\alpha_{\mathcal{L}}} - \Omega_D,$$

where ε_t^A and $\varepsilon_t^{A_D}$ are exogenous technology shocks and $\mathcal{L}_t(e)$ denotes the endowment of land used by entrepreneur e at time t.

Capital is sector specific and is augmented by a variable capacity utilization rate u_t. MC_t and $MC_{D,t}$ denote the selling prices for intermediate nonresidential and residential products.

Entrepreneurs' fixed capital is subject to common multiplicative idiosyncratic shocks $\varpi_{E,t}$. As for households, these shocks are independent and identically distributed across time and across entrepreneurs with $E(\varpi_{E,t}) = 1$, and a log-normal CDF $F^E(\varpi_{E,t})$. Here again, the variance of the idiosyncratic shock $\sigma_{E,t}$ is time varying.

As for borrowers, entrepreneurs only use debt contracts in which the loan rates can be made contingent on aggregate shocks but not on the idiosyncratic shock $\varpi_{E,t}$. Entrepreneurs belong to a large family that can diversify the idiosyncratic risk after loan contracts are settled, but cannot commit to sharing the proceeds of this insurance with banks. Banks can seize collateral $\varpi_{E,t}\tilde{A}_{E,t}$ when the entrepreneur refuses to pay at a cost of $\mu_E\varpi_{E,t}\tilde{A}_{E,t}$. The value of the collateral that the bank can seize is

$$\varpi_{E,t}\tilde{A}_{E,t} = \varpi_{E,t}(1-\chi_E)(1-\delta_K)(Q_t^C K_{t-1}^C + Q_t^D K_{t-1}^D).$$

We assume that the capital utilization rate is predetermined with respect to the idiosyncratic shock to facilitate aggregation. χ_E reflects the ability to collateralize capital. This specification relates to models where only capital serves as collateral as in Gerali et al. (2010) or Kobayashi, Nakajima, and Inaba (2007).

Aggregate repayments or defaults on outstanding loan to entrepreneurs are

$$H^E(\overline{\varpi}_{E,t})\tilde{A}_{E,t} = \left[(1-F_t^E(\overline{\varpi}_{E,t}))\overline{\varpi}_{E,t} + \int_0^{\overline{\varpi}_{E,t}} \overline{\varpi} dF_t^E\right]\tilde{A}_{E,t}.$$

On the commercial lending bank side, the profit made on the credit allocation is given by

$$G^E(\overline{\varpi}_{E,t})\tilde{A}_{E,t} - \frac{(1+R_{E,t-1})}{1+\pi_t}B_{E,t-1} \geq 0$$

with

$$G^E(\overline{\varpi}_{E,t}) = (1-F_t^E(\overline{\varpi}_{E,t}))\overline{\varpi}_{E,t} + (1-\mu_E)\int_0^{\overline{\varpi}_{E,t}} \overline{\varpi} dF_t^E.$$

$R_{E,t-1}$ is the interest rate at which the commercial lending bank gets financing every period, while $R^L_{E,t}$ is the state-contingent lending rate to entrepreneurs.

Overall, each entrepreneur maximizes its utility function with respect to C^E_t, K^C_t, K^D_t, u^C_t, u^D_t, B^E_t, $\overline{\varpi}_{E,t}$, $L_{C,t}$, $L_{D,t}$, subject to an infinite sequence of real budget constraints

$$\begin{aligned} & C^E_t + Q^C_t(K^C_t - (1-\delta_K)K^C_{t-1}) \\ & \quad + Q^D_t(K^D_t - (1-\delta_K)K^D_{t-1}) + H^E(\overline{\varpi}_{E,t})\tilde{A}_{E,t} \\ = {} & B_{E,t} + MC_tZ_t + MC_{D,t}Z_{D,t} - W^r_{C,t}L_{C,t} - W^r_{D,t}L_{D,t} - p_{lt}\mathcal{L}_t \\ & - \Phi\left(u^C_t\right)K^C_{t-1} - \Phi\left(u^D_t\right)K^D_{t-1} + TT^E_t \end{aligned}$$

together with the participation constraints for the banks. We assume the following functional form for the adjustment costs on capacity utilization: $\Phi(X) = \frac{\overline{\overline{R^k}}(1-\varphi)}{\varphi}\left(\exp\left[\frac{\varphi}{1-\varphi}(X-1)\right]-1\right)$. Following Smets and Wouters (2007), the cost of capacity utilization is zero when capacity is fully used ($\Phi(1) = 0$). p_{lt} denotes the relative price of land deflated by nonresidential goods price.

B.3.2 Retailers and Distribution Sectors

Retailers differentiate the residential and nonresidential goods produced by the entrepreneurs and operate under monopolistic competition. They sell their output to the perfectly competitive distribution sectors, which aggregate the continuum of differentiated goods. The elementary differentiated goods are imperfect substitutes with elasticity of substitution denoted $\frac{\mu_D}{\mu_D-1}$ and $\frac{\mu}{\mu-1}$ for the residential and the nonresidential sectors, respectively. The distributed goods are then produced with the following technology: $Y_D = \left[\int_0^1 Z_D(d)^{\frac{1}{\mu_D}}\mathrm{d}d\right]^{\mu_D}$ and $Y = \left[\int_0^1 Z(c)^{\frac{1}{\mu}}\mathrm{d}c\right]^{\mu}$. The corresponding aggregate price indexes are defined as $P_D = \left[\int_0^1 p_D(d)^{\frac{1}{1-\mu_D}}\mathrm{d}d\right]^{1-\mu_D}$ for the residential sector and $P = \left[\int_0^1 p(c)^{\frac{1}{1-\mu}}\mathrm{d}c\right]^{1-\mu}$ for the nonresidential sector. The distribution goods serve as final consumption goods for households and are used by capital and housing stock producers.

Retailers are monopolistic competitors which buy the homogeneous intermediate products of the entrepreneurs at prices MC_t for the nonresidential intermediate goods and $MC_{D,t}$ for the residential intermediate goods. The intermediate products are then differentiated and sold back to the distributors. Retailers set their prices on a staggered basis à la Calvo (1983). In each period, a retailer in the nonresidential sector faces a constant probability $1 - \xi_C$ (resp. $1 - \xi_D$ in the residential sector) of being able to reoptimize its nominal price. The demand curves that retailers face in each sector follow $Z_D(d) = \left(\frac{p_D(d)}{P_D}\right)^{-\frac{\mu_D}{\mu_D - 1}} Y_D$ and $Z(c) = \left(\frac{p(c)}{P}\right)^{-\frac{\mu}{\mu - 1}} Y$.

B.3.3 Capital and Housing Stock Producers

Using distributed residential and nonresidential goods, a segment of perfectly competitive firms, owned by the patient households, produce a stock of housing and fixed capital. At the beginning of period t, those firms buy back the depreciated housing stocks from both household types $(1 - \delta)D_{t-1}$ and $(1 - \delta)\widetilde{D}_{t-1}$ as well as the depreciated capital stocks $(1 - \delta_K)K^C_{t-1}$, $(1 - \delta_K)K^D_{t-1}$ at real prices (in terms of consumption goods) $Q_{D,t}T_{D,t}$, $\widetilde{Q}_{D,t}T_{D,t}$, Q^D_t, Q^C_t, respectively. Then they augment the various stocks using distributed goods and facing adjustment costs. The augmented stocks are sold back to entrepreneurs and households at the end of the period at the same prices.

B.4 The Banking Sector

The banking sector is owned by the patient households and is segmented in three parts. Following Gerali et al. (2010), each banking group is first composed of a wholesale branch which gets financing in the money market and allocates funds to the rest of the group, facing an adjustment cost on the overall capital ratio of the group. The wholesale branch takes the bank capital and the dividend policy as given in its decision problem and operates under perfect competition. The second segment of the banking group comprises a deposit branch, which collects savings from the patient households and places them in the money markets, as well as two loan book financing branches, which receive funding from the wholesale branch and allocate those funds to the commercial lending branches. In this second segment, banks operate under monopolistic competition and face nominal rigidity in their interest rate settings. The third segment of the banking group is formed by two commercial lending branches which provide loan contracts to impatient households and entrepreneurs. The commercial lending branches are zero-profit competitive firms.

B.4.1 Wholesale Branch

The perfectly competitive wholesale branches receive deposits Dep_t^{wb}, from the retail deposit banks, with an interest rate set at the policy rate R_t. Taking as given the bank capital $Bankcap_t$ in real terms, they provide loans $B_{E,t}^{wb}$ and $B_{HH,t}^{wb}$ at interest rates $R_{E,t}^{wb}$ and $R_{HH,t}^{wb}$ to the loan book financing branches for lending to entrepreneurs and households, respectively. When deciding on deposits and loans, the wholesale banks are constrained by an adjustment cost on bank's leverage. This friction is meant to capture the capital requirement pressures on the bank's behavior. For this reason, we assume that wholesale banks target a capital ratio of 11 percent and the quadratic cost is supposed to illustrate the various interactions between banks' balance sheet structure, market disciplining forces, and the regulatory framework.[41] On the one hand, this reflects that, due to pecuniary and reputational costs, banks are keen to avoid getting too close to the regulatory minimum capital requirement and hence tend to operate with a substantial buffer over that minimum capital ratio.[42] On the other hand, bank capital is costly relative to other sources of financing (like deposits and bond issuance), implying that banks tend to economize on the amount of capital they hold.[43]

[41]The 11 percent capital ratio target corresponds to the average (risk-adjusted) total capital ratio of the around 100 largest euro-area banks for the period 1999–2008, according to Datastream (Worldscope).

[42]There is a rich literature providing evidence that banks operate with substantial capital buffers; for some recent studies see, e.g., Ayuso, Pérez, and Saurina (2004), Berger et al. (2008), Bikker and Metzemakers (2004), Gropp and Heider (2010), and Stolz and Wedow (2005).

[43]For example, ECB estimates of the cost of equity, the cost of market-based debt (i.e., bond issuance), and the cost of deposits for euro-area banks show that the former was on average around 6.7 percent in the period 2003–09. During

Under the Basel I-like capital requirement regime, the bank's static profit-maximization problem can be formulated as follows where all quantities are expressed in real terms:

$$\max_{B_t^w, Dep_t^w} R_{HH,t}^{wb} B_{HH,t}^{wb} + R_{E,t}^{wb} B_{E,t}^{wb} - R_t Dep_t^{wb}$$
$$- \frac{\chi_{wb}}{2} \left(\frac{Bankcap_t}{0.5 B_{HH,t}^{wb} + B_{E,t}^{wb}} - 0.11 \right)^2 Bankcap_t$$

subject to the balance sheet identity

$$B_{HH,t}^{wb} + B_{E,t}^{wb} = Dep_t^{wb} + Bankcap_t.$$

As in Gerali et al. (2010) the derived lending spreads emphasize "the role of bank capital in determining loan supply conditions." For example, if the spread between the lending rate and the policy rate is positive, the bank would have an incentive to increase profits by raising loan volumes. But expanding lending would increase its leverage, which is penalized by regulatory rules and market disciplining forces. In the model, these penalties take the form of a cost to the bank which increases as the capital ratio moves away from its target. The bank's decision problem is therefore finely balanced between boosting its profits via increased leverage and retaining control of its capital structure. Moreover, a key point to notice for our Basel I-type specification is that the bank's target capital ratio is insensitive to changes in borrower risk over time. In addition, reflecting the risk weighting of the Basel I regulatory framework, household loans are given a (fixed) risk weight of 50 percent whereas the risk weight attached to corporate loans is 100 percent.

The decision problem of the wholesale bank leads to the following condition on the spread between the lending rate and the policy rate:

$$R_{HH,t}^{wb} - R_t$$
$$= -\chi_{wb} \left(\frac{Bankcap_t}{0.5 B_{HH,t}^{wb} + B_{E,t}^{wb}} - 0.11 \right) \left(\frac{Bankcap_t}{0.5 B_{HH,t}^{wb} + B_{E,t}^{wb}} \right)^2 0.5$$

the same period, banks' cost of raising debt in the capital markets was around 5 percent, while their average cost of deposit funding was close to 2 percent.

$$R^{wb}_{E,t} - R_t$$
$$= -\chi_{wb}\left(\frac{Bankcap_t}{0.5B^{wb}_{HH,t} + B^{wb}_{E,t}} - 0.11\right)\left(\frac{Bankcap_t}{0.5B^{wb}_{HH,t} + B^{wb}_{E,t}}\right)^2.$$

When the leverage of the bank increases beyond the targeted level, banks increase their loan-deposit margins.

The capital base of the wholesale branch is accumulated out of retained earnings from the bank group profits

$$Bankcap_t = (1 - \delta^{wb})Bankcap_{t-1} + \nu^b \Pi^b_t,$$

where δ^{wb} represents the resources used in managing bank capital, Π^b_t is the overall profit of the bank group, and ν^b is the share of profits not distributed to the patient households.

B.4.2 Imperfect Pass-Through of Policy Rate on Bank Lending Rates

The retail deposit branch and the loan book financing branches are monopolistic competitors and set their interest rates on a staggered basis with some degree of nominal rigidity à la Calvo (1983).

Retail Deposit Branch. The deposits offered to patient households are a CES aggregation of the differentiated deposits provided by the retail deposit branches: $Dep = \left[\int_0^1 Dep(j)^{\frac{1}{\mu^R_D}} \mathrm{d}j\right]^{\mu^R_D}$, expressed in real terms. Retail deposits are imperfect substitutes with elasticity of substitution $\frac{\mu^R_D}{\mu^R_D - 1} < -1$. The corresponding average interest rate offered on deposits is $R_D = \left[\int_0^1 R_D(j)^{\frac{1}{1-\mu^R_D}} \mathrm{d}j\right]^{1-\mu^R_D}$.

Retail deposit branches are monopolistic competitors which collect deposits from savers and place them in the money market. Deposit branches set interest rates on a staggered basis à la Calvo (1983), facing each period a constant probability $1 - \xi^R_D$ of being able to reoptimize their nominal interest rate. When a retail deposit branch cannot reoptimize its interest rate, the interest rate is left at its previous period level:

$$R_{D,t}(j) = R_{D,t-1}(j).$$

The retail deposit branch j chooses $\hat{R}_{D,t}(j)$ to maximize its intertemporal profit.

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} \left(\gamma \xi_D^R\right)^k \frac{\Lambda_{t+k}}{\Lambda_t} \left(R_{t+k} Dep_{t+k}(j) - \hat{R}_{t,D}(j) Dep_{t+k}(j) \right) \right],$$

where $Dep_{t+k}(j) = \left(\frac{\hat{R}_{D,t}(j)}{R_{D,t}}\right)^{-\frac{\mu_D^R}{\mu_D^R - 1}} \left(\frac{R_{D,t}}{R_{D,t+k}}\right)^{-\frac{\mu_D^R}{\mu_D^R - 1}} Dep_{t+k}$ and Λ_t is the marginal value of nonresidential consumption for the households savers.

A markup shock $\varepsilon_{D,t}^R$ is introduced on the interest rate setting.

Loan Book Financing Branches. As for the retail deposit branches, loan book financing branches provide funds to the commercial lending branches, which obtain overall financing through a CES aggregation of the differentiated loans: $B_{E,t} = \left[\int_0^1 B_{E,t}(j)^{\frac{1}{\mu_E^R}} \mathrm{d}j\right]^{\mu_E^R}$ as regards commercial loans to entrepreneurs and $B_{HH,t} = \left[\int_0^1 B_{HH,t}(j)^{\frac{1}{\mu_{HH}^R}} \mathrm{d}j\right]^{\mu_{HH}^R}$ as regards commercial loans to households. Loans from loan book financing branches are imperfect substitutes with elasticity of substitution $\frac{\mu_E^R}{\mu_E^R - 1}$ and $\frac{\mu_{HH}^R}{\mu_{HH}^R - 1} > 1$. The corresponding average lending rate is

$$R_E = \left[\int_0^1 R_E(j)^{\frac{1}{1-\mu_E^R}} \mathrm{d}j\right]^{1-\mu_E^R} \text{ and}$$

$$R_{HH} = \left[\int_0^1 R_{HH}(j)^{\frac{1}{1-\mu_{HH}^R}} \mathrm{d}j\right]^{1-\mu_{HH}^R}.$$

Loan book financing branches for each segment of the credit market are monopolistic competitors which levy funds from the wholesale branches and set interest rates on a staggered basis à la Calvo (1983), facing each period a constant probability $1 - \xi_E^R$ and $1 - \xi_{HH}^R$ of being able to reoptimize their nominal interest rate. If a loan book financing branch cannot reoptimize its interest rate, the interest rate is left at its previous-period level:

$$R_{HH,t}(j) = R_{HH,t-1}(j)$$
$$R_{E,t}(j) = R_{E,t-1}(j).$$

In each sector $i \in \{E, HH\}$, the loan book financing branch j chooses $\hat{R}_{i,t}(j)$ to maximize its intertemporal profit.

$$\mathbb{E}_t \left[\sum_{k=0}^{\infty} \left(\gamma \xi_i^R\right)^k \frac{\Lambda_{t+k}}{\Lambda_t} \left(\hat{R}_{i,t}(j) B_{i,t+k}(j) - R_{i,t}^{wb}(j) B_{i,t+k}(j) \right) \right],$$

where $B_{i,t+k}(j) = \left(\frac{\hat{R}_{i,t}(j)}{R_{i,t}}\right)^{-\frac{\mu_i^R}{\mu_i^R - 1}} \left(\frac{R_{i,t}}{R_{i,t+k}}\right)^{-\frac{\mu_i^R}{\mu_i^R - 1}} B_{i,t+k}$.

As for deposit rates, we add markup shocks $\varepsilon_{HH,t}^R$ and $\varepsilon_{E,t}^R$ to the staggered nominal lending rate settings.

Commercial Lending Branches. Commercial lending branches are delivering credit contracts for entrepreneurs and household borrowers. Those branches are perfectly competitive and in equilibrium have zero profits. Details on the credit contract and the decision problems for the commercial lending branches are provided in the sections on entrepreneurs and household borrowers.

B.5 Government and Monetary Authority

Public expenditures $\overline{\overline{G}}$ are subject to random shocks ε_t^G. The government finances public spending with lump-sum transfers.

Monetary policy is specified in terms of an interest rate rule targeting inflation, output, and their first difference as well as changes in the relative price of housing. Written in deviation from the steady state, the interest rate rule used has the following form:

$$\begin{aligned} r_t = {} & \rho r_{t-1} + (1-\rho)\left(r_\pi \pi_{t-1} + r_y y_{t-1}\right) \\ & + r_{\Delta\pi} \Delta\pi_t + r_{\Delta y} \Delta y_t + r_{T_D} \Delta t_{D,t} + \log\left(\varepsilon_t^R\right), \end{aligned}$$

where lowercase letters denote log-deviations of a variable from its deterministic steady state.

B.6 Comparing RAMSES Model for Sweden and the Euro-Area Model

The main differences between the DSGE model used for our euro-area calculations and the model used by Svensson for Sweden are the banking sector, labor market, housing sector, and the open economy. Darracq Pariès, Kok, and Rodriguez-Palenzuela (2011) feature a well-developed banking sector which intermediates deposits from patient households to firms and impatient households. Furthermore, loans to households are backed by housing. RAMSES features an open economy, has more sophisticated labor market dynamics featuring unemployment, and only incorporates risky loans between firms and households.

Appendix C. Acronyms

AIC	Akaike information criterion
AUROC	area under receiver operating characteristic
BIS	Bank for International Settlements
CCyB	countercyclical capital buffer
CDF	cumulative distribution function
CES	constant elasticity of substitution
DSGE	dynamic stochastic general equilibrium
DTI	debt-to-income
ECB	European Central Bank
ESRB	European Systemic Risk Board
GDP	gross domestic product
GFC	global financial crisis
IRF	impulse response function
LASSO	least absolute shrinkage and selection operator
LAW	"leaning against the wind"
LTV	loan-to-value
OLS	ordinary least squares
pp	percentage point
SRI	systemic risk indicator
VAR	vector autoregression

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Monetary Policy and the Top 1%: Evidence from a Century of Modern Economic History*

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This paper examines the distributional effects of monetary policy in 12 OECD economies between 1920 and 2016. We exploit the implications of the macroeconomic policy trilemma with an external instrument approach to analyze how top income shares respond to monetary policy shocks. The results indicate that monetary tightening strongly decreases the share of national income held by the top 1 percent and vice versa for a monetary expansion, irrespective of the position of the economy. This effect (i) holds for the top percentile and the ultra-rich (top 0.1 percent and 0.01 percent income shares), while (ii) it does not necessarily induce a decrease in income inequality when considering the entire income distribution. Our findings also suggest that the effect of monetary policy on top income shares is likely to be channeled via real asset returns.

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1. Introduction

The global financial crisis and subsequent central bank measures raised important questions about the side effects of accommodative monetary policies. In a context already marked by rising income and wealth inequality, the distributional effects of monetary policy have become an increasingly popular topic in policymaking circles. This is unusual because it is widely accepted that central banks should not be concerned about inequality: they are independent of the political process, and dealing with distributional matters goes beyond their mandate. Nevertheless, the combination of an ultra-low interest rate environment and large asset purchase programs is argued to have reduced modest household savings and driven up prices of assets, which are mainly held by rich households. Are these effects only linked to the context of unconventional measures, or do they constitute a structural feature of monetary policy?

This paper presents new empirical evidence regarding the distributional consequences of monetary policy using annual data from 12 OECD economies over the period 1920–2016.[1] The pre-tax national income share held by the top 1 percent (P1) is used as a benchmark top income measure.[2] The adopted identification scheme of monetary policy shocks particularly relates to the historical context of this study and uses a quasi-natural experiment approach to estimate how exogenous changes in monetary conditions affect the top 1 percent. To understand how monetary policy interacts with the rest of the income distribution, we draw on different distributional measures of the top decile and standard indicators of income inequality. Furthermore, we exploit the importance of financial assets and capital returns for top income households to provide insights into some of the underlying transmission mechanisms of monetary policy. Finally, state-dependent effects of interest rate shocks are estimated to study the nonlinear effects of monetary policy on top incomes.

[1]The 12-country panel includes Australia, Canada, Denmark, France, Germany, Italy, Japan, the Netherlands, Norway, Sweden, the United Kingdom, and the United States.

[2]Our interest in top incomes and the top 1 percent in particular stems from the fact that they have largely contributed, since the 1980s, to the rising inequality in the developed world (see, e.g., Alvaredo et al. 2013).

Our empirical methodology primarily relies on local projections (LPs) à la Jordà (2005). The latter generates dynamic responses of top income shares to an exogenous perturbation in the short-term interest rate. The identification of such shocks is based on the approach recently proposed by Jordà, Schularick, and Taylor (2020), which responds to the fact that the short-term interest rate and top income shares are potentially influenced by common unobserved factors, biasing the empirical effect of interest. Precisely, our approach exploits an instrumental variable in the context of a local projection-instrumental variable (LP-IV) framework (see Jordà, Schularick, and Taylor 2015, 2020; Ramey and Zubairy 2018) to isolate exogenous fluctuations in the short-term interest rate, which are drawn from the well-known macroeconomic policy trilemma. The trilemma states that movements in the base country's short-term interest rate provide exogenous variations in the domestic short-term rate for an open peg. As a result, policy choices regarding capital mobility, exchange rates, and interest rates provide a natural experiment to analyze the effect of monetary policy on top income shares. Finally, because LPs easily accommodate nonlinearities, we test our model in a state-dependent setting, where we allow the response of top income shares to depend on the regime of a specific variable (i.e., business cycle, the inflation regime, credit cycles, stock return cycles, and monetary policy stance).

The empirical literature on the effects of monetary policy on the income distribution is growing rapidly but remains inconclusive. Country-level studies using household-level data suggest that conventional monetary tightening increases income and consumption inequality (see Coibion et al. 2017 for the United States and Mumtaz and Theophilopoulou 2017 for the United Kingdom). Cross-country evidence by Furceri, Loungani, and Zdzienicka (2018) documents a similar effect while stressing that its magnitude depends on the share of labor income and extent of redistribution policies. Other studies argue that expansionary monetary policy may also have negative distributional implications (see Cloyne, Surico, and Ferreira 2020 for the United Kingdom and the United States and Inui, Sudo, and Yamada 2017 for Japan). In contrast, most recent research on the distributional effects of unconventional monetary policy shows that the relationship between monetary expansions and inequality is negative but small in magnitude (see, e.g., Casiraghi et al. 2018 for

Italy; see Guerello 2018 and Samarina and Nguyen 2019 for the euro zone). Most important, the existing evidence features survey-based estimates of income inequality and mostly focuses on a short time span.

The contribution of our paper departs from the existing literature in two important respects. First, we use tax-based estimates of top income shares from the World Inequality Database (WID) because, as shown by Atkinson, Piketty, and Saez (2011) and Burkhauser et al. (2012), such data (i) allow for better coverage of business and capital returns, which constitute the bulk of top incomes, and (ii) provide a more accurate picture of the trend of income inequality since the 1980s. In fact, as noted by Roine and Waldenström (2015), rich households are underrepresented in income and wealth surveys, which leaves out an essential piece of the income distribution for understanding the effects of monetary policy on inequality. We extend the empirical analysis by comparing the effect of monetary policy on the top 1 percent income share (P1) with other top income indicators, i.e., the share of national income held by the lower 9 percent of the top decile (P09) and the top 0.1 percent and 0.01 percent (P01 and P001, respectively) along with a standard income inequality measure, i.e., the Gini index (for market and disposable incomes). While P09 consists of highly salaried workers, the right-tail percentile shares (P01 and P001) could be considered the *ultra-rich*, for whom capital income matters most (see Roine, Vlachos, and Waldenström 2009 on the heterogeneity underlying incomes at the top). Second, our paper features a historical analysis covering a century of modern economic history. This approach has the advantage of dealing with several macroeconomic occurrences and covers important events experienced in the developed world, such as the Great Depression and the post-war boom, hence providing more variation in the data and, in particular, top income shares. For this purpose, long series of macroeconomic variables are extracted from the Jordà-Schularick-Taylor Macrohistory Database, developed by Jordà, Schularick, and Taylor (2017). Using such data is of great interest because they offer a rich set of control variables that could enter as potential determinants of top incomes.

Our main results are easily summarized. First, monetary policy has a significant and persistent effect on top income shares: monetary tightening decreases the share of national income held by the top 1 percent, while expansionary monetary policy has the opposite effect. A normalized +100 basis point (bp) exogenous increase in the short-term interest rate via the external instrument reduces P1 by 0.45 percentage point over a five-year horizon for the full sample, although the effects on top incomes are smaller during the post-WWII era (0.3 percentage point decline in P1 over a five-year horizon). Second, in line with Jordà, Schularick, and Taylor (2020), we find evidence of considerable attenuation bias in policy responses when we estimate the responses to monetary policy using traditional ordinary least squares (OLS) selection-on-observables versus IV identification. Third, it is shown that the effects of monetary policy on top incomes are (i) heterogeneous and (ii) not necessarily mirrored over the entire income distribution. On the one hand, a positive interest rate shock reduces the shares of national income held by the top 1, 0.1, and 0.01 percent, while its effect on the bottom 9 percent of the top decile is positive (although not statistically significant). On the other hand, monetary tightening increases the Gini index for market and disposable incomes. Fourth, with respect to the literature, we take several steps to explain that our difference with Furceri, Loungani, and Zdzienicka (2018) is not driven by our sample and is even less tied to the identification strategy; rather, it is very likely due to the different economies considered in our respective panels. Finally, we demonstrate that our baseline finding is arguably channeled via lower (real) asset returns, which is consistent with the income composition channel of Coibion et al. (2017). The results are valid regardless of the state of the economy and hold under a battery of robustness checks.

These findings contribute to Furceri, Loungani, and Zdzienicka (2018) and highlight that the effects of monetary policy on inequality crucially rely on the distributional indicator examined (tax-based estimates of income shares or synthetic inequality measures), the macroeconomic occurrences covered (historical data versus short period samples), and—most important—the countries considered along with the identification strategy adopted for monetary surprises.

The paper is structured as follows. Section 2 discusses the estimation methodology and the identification strategy. Section 3 thoroughly describes the data. The fourth section presents the LP results, while the fifth and final section concludes the paper.

2. Local Projections

We follow the general method proposed by Jordà (2005) and its very recent application to our context in Furceri, Loungani, and Zdzienicka (2018) by estimating impulse response functions (IRFs) from local projections (LPs). In its basic form, LP consists of a sequence of regressions of the endogenous variable shifted several steps ahead. As a result, the approach consists of estimating the following equation:

$$\Delta_h y_{i,t+h} = \alpha_i^h + \beta^h \Delta r_{i,t} + \theta^h X_{i,t} + \varepsilon_{i,t}^h, \tag{1}$$

where $\Delta_h y_{i,t+h} = y_{i,t+h} - y_{i,t}$ and corresponds to the change in the top income variable from the base year t_0 up to year $t + h$, with $h = 1, \ldots, H$; $\Delta r_{i,t}$ denotes the change in the short-term interest rate; and $X_{i,t}$ refers to a vector containing a set of control variables. The latter includes the lags of the first difference of $y_{i,t}$ and $r_{i,t}$, together with additional controls that could theoretically explain top income shares and, simultaneously, be correlated with monetary conditions.

It is important to note that each step of the local IRF is obtained from a different equation and directly corresponds to the estimates of β^h. Thus, unlike in a VAR approach, the estimated coefficients contained in θ^h are not used to build the IRF. Instead, they only serve as controls and cleanse the β^h of the effects of past top income and monetary policy changes, in addition to contemporaneous and past changes in other macroeconomic variables (output and CPI, for instance). Moreover, the LP approach is intentionally "model free" and therefore imposes fewer restrictions—with respect to VARs—when calculating IRFs. As shown by Jordà (2005), such an approach confers numerous advantages. This estimation technique (i) is actually more robust to model misspecification, (ii) does not suffer from the curse of dimensionality, (iii) can more easily accommodate non-linearities, and (iv) can also be estimated with simple regression techniques.[3] In what follows, we describe the benefits of LP with respect to our research question.

[3]However, it also has some drawbacks in terms of efficiency (see Ramey 2016 on the efficiency/flexibility tradeoff of LP).

First, LPs allow for the addition of several control variables—before encountering dimensionality problems—that may influence top income shares and, simultaneously, be correlated with monetary policy actions. The $X_{i,t}$ vector includes the first difference up to two lags of the log of the CPI, real GDP, real consumption, real investment, the government expenditure-to-GDP ratio, house prices, stock prices, total factor productivity, the total loans-to-GDP ratio, and a trade openness ratio. In addition to these country-time variables, we include world real GDP growth to parsimoniously remove global business cycle effects.[4]

The second benefit of LP is that it offers an original identification strategy to estimate dynamic causal effects. To build shock series, our strategy relies on external instruments, i.e., variables correlated with changes in short-term interest rates but not with the other macroeconomic shocks affecting the economy. Our aim is to obtain external sources of variation in short-term interest rates to provide quasi-random experiments and thereby more clearly identify causal effects. These types of strategies have recently attracted growing interest in applied macroeconomics (Jordà, Schularick, and Taylor 2015, 2020; Jordà and Taylor 2016; Ramey and Zubairy 2018; Stock and Watson 2018). Regarding our research question, monetary policy is unlikely to be driven by top incomes; therefore, the dynamic causal effect is clear (no simultaneity bias). However, even if the income distribution is not a target of central banks, both top incomes and monetary policy decisions depend on economic conditions, which may be improperly measured by the set of control variables in our regressions (omitted-variable bias) (Furceri, Loungani, and Zdzienicka 2018). Accordingly, this situation calls for the use of exogenous shocks to domestic monetary conditions rather than short-term interest rates. As is widely agreed upon in the literature, the challenge is to find external factors that would make the variations in monetary conditions a random treatment.

In this paper, we use the LP-IV method proposed by Jordà, Schularick, and Taylor (2015), Ramey (2016), and Stock and Watson (2018). We couple this method with the identification strategy for

[4]As noted by Jordà, Schularick, and Taylor (2020), adding time fixed effects would require almost 100 additional parameter estimates.

external variations in monetary conditions based on Jordà, Schularick, and Taylor (2015, 2020). The purpose here is to use the macroeconomic policy trilemma to find external variations in monetary conditions. The latter states that a country cannot simultaneously achieve free capital mobility, a fixed exchange rate, and independent monetary policy. When pursuing any two of these goals, it is necessary to abandon the third. Building on the trilemma (Obstfeld, Shambaugh, and Taylor 2004, 2005; Shambaugh 2004), we trace out episodes where monetary policy is not autonomous and external conditions from the base country can generate perturbations to the domestic short-term interest rate. Such perturbations are considered to be exogenous because the base country—for example, the United States during the Bretton Woods era—does not internalize the externalities of its own policy choices on partner countries. This makes the trilemma a source of natural experiments for domestic monetary policy.

The trilemma links the domestic interest rate to the base country's interest rate through the exchange rate regime and the intensity of financial openness. A suitable expression for such an instrumental approach is given by

$$\Delta r_{i,t} = a + b[PEG_{i,t} * KOPEN_{i,t} * \Delta r_{i,t}^{base}] + \Theta C_{i,t} + \mu_{i,t}, \quad (2)$$

where $PEG_{i,t}$ defines whether a country has a fixed ($PEG_{i,t} = 1$) or flexible ($PEG_{i,t} = 0$) exchange rate; $KOPEN_{i,t}$ indicates whether a country is open ($KOPEN_{i,t} = 1$) or closed ($KOPEN_{i,t} = 0$) to international capital markets; $\Delta r_{i,t}^{base}$ denotes the monetary policy change in the base country; and $C_{i,t}$ is a vector of macroeconomic controls in country i at time t.[5] Equation (2) corresponds to the first-stage IV approach adopted by Jordà, Schularick, and Taylor (2015) with the term $[PEG_{i,t} * KOPEN_{i,t} * \Delta r_{i,t}^{base}]$ referring to the external instrument ($z_{i,t}$).

The instrument has to fulfill two usual criteria. First, $z_{i,t}$ must have a significant influence on the endogenous variable. In practice,

[5]The controls include the contemporaneous and two lags of real per capita GDP growth; the CPI inflation growth rate; real consumption growth; government expenditure growth; real investment growth; stock price growth; house price growth; total factor productivity growth; the change in commercial openness; the change in the ratio of loans to the nonfinancial private sector to GDP; and world GDP growth.

when there is perfect capital mobility and a fixed exchange rate regime, the home country's monetary conditions ($\Delta r_{i,t}$) are perfectly related to those of the base country ($\Delta^{base} r_{i,t}$), which theoretically ensures the relevance of our instrument.[6] Second, $z_{i,t}$ should affect home monetary policy without influencing top incomes. This condition implies that only the international interest rate channel is at play. However, base monetary conditions may impact domestic outcomes other than interest rates. For instance, an increase of the base country's policy rate decreases its real GDP, which can have consequences for the peg countries and can ultimately affect top incomes. Such spillover effects lead to failure of the exclusion restriction. To control for such spillover confounding, we follow Jordà, Schularick, and Taylor (2020) and consider base-country policy surprises rather than the change in its interest rate. Therefore, the corresponding two-stage least squares (2SLS) model we estimate is given by

$$\Delta \hat{r}_{i,t} = a + b[PEG_{i,t} * KOPEN_{i,t} * \Delta M\hat{S}_{i,t}^{base}] + \Theta C_{i,t} + \mu_{i,t} \quad (3)$$

$$\Delta_h y_{i,t+h} = \alpha_i^h + \beta^h \Delta \hat{r}_{i,t} + \theta^h X_{i,t} + \varepsilon_{i,t}^h, \quad (4)$$

where $\Delta M\hat{S}_{i,t}^{base}$ corresponds to movements in base-country rates unexplained by observable controls. The latter include the current and lagged values of macroeconomic aggregates and the lagged values of the policy rates.[7]

The third motivation for using LP is that it easily accommodates nonlinearities.[8] This feature allows us to enrich our analysis by checking whether the IRFs of the top income share to a short-term rate shock are state dependent. This is of great interest because (i) we use historical data that cover different monetary policy regimes, and (ii) it also follows many studies that highlight that

[6] We discuss in subsection 3.3 the adopted base countries, which are allowed to vary over time.

[7] $\Delta M\hat{S}_{i,t}^{base} = \Delta i_{i,t}^{base} - \Delta \hat{i}_{i,t}^{base}$, where $\hat{i}_{i,t}^{base}$ is the fitted value of a simple linear model estimated by OLS.

[8] The VAR literature also offers some solutions to deal with nonlinearities. However, the richer structure of the VAR model entails several complications in computing IRFs, which often makes the estimation intractable in practice if we are outside the baseline framework.

the effects of monetary policy vary over the business cycle. In practice, we extend equation (4) and condition the effect of interest rates on the top income variable by a state variable:

$$\Delta_h y_{i,t+h} = \alpha_i^h + \beta_1^h \Delta \hat{r}_{i,t} * State_{i,t} + \beta_2^h \Delta \hat{r}_{i,t} * (1 - State_{i,t}) + \theta^h X_{i,t} + \varepsilon_{i,t}^h, \qquad (5)$$

where $State_{i,t}$ is a variable indicating a specific regime (i.e., business cycle, the inflation regime, credit cycles, stock return cycles, and monetary policy stance).

3. Data Description

3.1 Top Income Shares

Top income data are extracted from the World Inequality Database (2019).[9] Specifically, the main variable of interest is operationalized by the top 1 percent's pre-tax national income share (P1) in 12 OECD economies over the 1920–2016 period.[10] The countries considered include Australia, Canada, Germany, Denmark, France, the United Kingdom, Italy, Japan, the Netherlands, Norway, Sweden, and the United States. As noted by Leigh (2011), Roine, Vlachos, and Waldenström (2009), and Roine and Waldenström (2015), among others, top incomes present important heterogeneity: the lower parts of the top decile consist of the *upper middle class* (high-income wage earners) with stable income shares over time, while those at the top mainly receive capital shares and feature much larger fluctuations. That is why we separate P1 from the bottom nine percentiles of the top decile and test our model on P09, which is the income share of the top 10 percent less that of the top 1 percent. Figure A.2 in the appendix plots for each country P1 and P09 over the studied period. In addition, bearing in mind that the income share going to the 0.1 percent and 0.01 percent richest grew even

[9]The definition of income includes labor as well as business and capital incomes.

[10]We conduct our empirical analysis while excluding the years of WWII from the sample. Table A.1 in the appendix traces out the data sources and their availability for each country.

faster—notably in the United States and Anglo-Saxon countries—than that of P1 (see, e.g., Saez and Zucman 2016), we extend our analysis by checking how changes in monetary conditions affect the *ultra-rich.* To do so, we mobilize data on the share of national income held by the top 0.1 percent and 0.01 percent from Atkinson and Piketty (2014). Another important exercise consists of comparing the effect of monetary policy on top income shares with the entire income distribution using a synthetic measure of inequality, i.e., the Gini index, which is obtained from the Standardized World Income Inequality Database (SWIID) of Solt (2020).[11] A notable difference between WID and SWIID is that the latter offers data based on disposable income, thereby allowing us to account for redistributive transfers. Finally, we also check how monetary policy affects changes *within* the top of the distribution using the P1/P09 ratio.

3.2 Macroeconomic Variables

We exploit the Jordà-Schularick-Taylor (JST) Macrohistory Database, which provides us with a long series of macroeconomic data. In this database, information on several macroeconomic variables is available from 1870 to 2016 and covers 17 developed economies.[12] In addressing the question of monetary policy and top incomes, our paper also departs from the existing literature by building on several macroeconomic controls. The latter are important determinants of top incomes or more generally perceived by the literature as the main drivers of income inequality.

The set of specific control variables used for both LPs and the instrumental variable are summarized in table A.2 (see the appendix). They cover financial development, globalization, government spending, technological progress, and global shocks. The way in which financial development—considered in our paper by the ratio of total loans to GDP—shapes top incomes remains an open question. While it was widely believed that it would reduce inequality through better access to credit for low-income households, recent

[11]The time coverage of the Gini coefficients is fairly shorter than that of our baseline top income variable.

[12]Our sample is restricted only because of the limited availability of top income data.

findings (see De Haan and Sturm 2017 for a review) argue, on the contrary, that more finance mainly favors top income shares. In this respect, stock prices are also included because top incomes are highly exposed to the dynamics of financial markets (see, e.g., Kuhn, Schularick, and Steins 2019). Aside from financial development, real estate has become a strong factor in driving income inequality. As argued by Dustmann, Fitzenberger, and Zimmermann (2018), shifts in housing costs in Germany severely exacerbated the rise in income disparities net of housing expenditures. For this reason, we control for this factor by adding a housing price index. Regarding globalization, Jaumotte, Lall, and Papageorgiou (2013) demonstrate, for a panel of 51 countries, that its effect on the income distribution has two offsetting tendencies: while trade globalization is associated with a reduction in inequality, financial globalization is associated with its increase. We control for the first using the ratio of imports and exports to GDP. The ratio of government expenditure to GDP is also included in our control variables. In fact, based on a political economy model and an empirical analysis using data on OECD countries, Azzimonti, de Francisco, and Quadrini (2014) show that governments choose higher levels of public spending when inequality increases. Moreover, technological change has been repeatedly identified in the literature as playing a potent role in widening the gap between top and bottom income earners (see Acemoglu 1998 and Card and DiNardo 2002, among others). A standard way to control for this factor consists of mobilizing data on total factor productivity (TFP) per hour worked, which are obtained from Bergeaud, Cette, and Lecat (2016). Finally, we include world real GDP growth to account for global business cycle effects.

3.3 External Instruments

As discussed above, our IV strategy—based on the trilemma faced by policymakers—identifies exogenous changes in domestic monetary conditions resulting from estimated surprise movements in the base-country interest rate ($\Delta \hat{MS}_{i,t}^{base}$). Therefore, our sample implicitly includes three subpopulations: the first group concerns *base* countries whose monetary policy is relatively autonomous; the second group contains *pegs*, that is, economies that import monetary policy and for which the *base* country's currency serves a *focal anchor*; and the last group relates to *floats*, which are the economies allowing their currency to be determined freely in the market. This subsection briefly discusses the definition of base countries, the source for applicable exchange rate regimes, and the adopted capital mobility index.

In the interwar period, we follow Obstfeld, Shambaugh, and Taylor (2004) in using a hybrid "gold standard" short-term interest rate, which is a combination of U.S. and French rates. Similar to Jordà, Schularick, and Taylor (2020), we consider the United States as the base country for the entire panel in the Bretton Woods (BW) regime except for Australia, which is associated with the sterling bloc. The same selection is implemented during the post-BW period for the dollar bloc (Australia, Canada, Japan, Norway), while Germany is the base country after 1973 for the remaining European economies. The definitions of *pegs* prior to WWII are extracted from Obstfeld, Shambaugh, and Taylor (2004, 2005) and follow Ilzetzki, Reinhart, and Rogoff (2019) after WWII. Tables A.3 and A.4 in the appendix list for each period and country of our sample the base countries along with the applicable exchange rate regime. The indicator for capital mobility status builds on the index (which ranges from 0 to 100) initially introduced by Quinn, Schindler, and Toyoda (2011). As in Jordà, Schularick, and Taylor (2015, 2020), we use this index rescaled to the unit interval, with 0 meaning fully closed and 1 fully open. Figure A.3 in the appendix plots, for our panel, changes in home interest rate $\Delta r_{i,t}$ against the constructed LP-IV.

4. Local Projection Results

4.1 Baseline

Our empirical setup builds primarily on LP estimation, along with an identification strategy of monetary surprises that is consistent with the historical context of this study. The first step is to assess the strength of our instrument. To do so, we estimate, in the context of equation (3), a first-stage regression of changes in the short-term interest rate on the instrument $z_{i,t}$ and the aforementioned macroeconomic controls, including country fixed effects. The first-stage regression results are reported in table 1 and underline the importance of the pass-through from base to home interest rates over

Table 1. Local Projection-IV: First-Stage Results

Δ Short-Term Interest Rate	Year 0	Year 1	Year 2	Year 3	Year 4
Full Sample: IV	0.57***	0.58***	0.55***	0.55***	0.56***
	(0.12)	(0.12)	(0.12)	(0.13)	(0.13)
F-statistic	21.97	23.06	19.94	18.25	18.01
Observations	633	619	607	595	582
Post-WWII Sample: IV	0.53***	0.53***	0.52***	0.52***	0.52***
	(0.10)	(0.10)	(0.10)	(0.11)	(0.11)
F-statistics	27.06	27.03	24.90	23.42	21.38
Observations	565	552	540	528	515

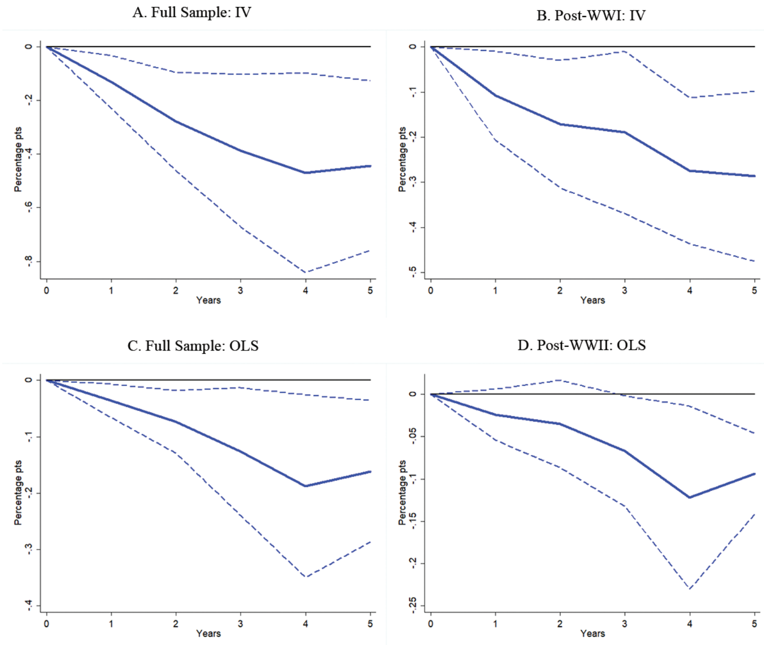
Notes: *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively. Country-based cluster-robust standard errors are in parentheses. The first difference of the short-term interest rate is regressed on the instrumental variable, using country fixed effects and macroeconomic controls (the change in the short-term interest rate; real per capita GDP growth; the CPI inflation growth rate; real consumption growth; government expenditure growth; real investment growth; stock price growth; house price growth; the level of commercial openness; the change in the loans to nonfinancial private sector to GDP ratio; total factor productivity growth; and world GDP growth). We include contemporaneous terms and two lags.

several periods. The coefficient estimates of the instrument $z_{i,t}$ are statistically significant at the 1 percent level and range between 0.52 and 0.58 from year 0 up to year 5, both across the full and post-WWII samples. Similarly, the F-statistics feature high values across samples. Note that Stock, Wright, and Yogo (2002) recommend a threshold of 10 for the first-stage F-statistic. Thus, we can now proceed to analyze the LP responses of the top 1 percent income share to exogenous fluctuations in the short-term interest rate.

The results obtained from the estimation of equation (4) by LPs are presented in figure 1. The four graphs illustrate IRFs (in percentage points) of P1—relative to their initial value in year 0—to a normalized +100 bp increase in the short-term interest rate, with the associated 90 percent confidence bands, which are constructed from cluster-robust standard errors. The impulse responses of P1 are reported using both the instrumental variable and OLS for the full and post-WWII samples.

An initial glance at the IRFs suggests that monetary tightening significantly and durably decreases the share of national income held

Figure 1. Top 1 Percent LPs to a Positive Short-Term Interest Rate Shock



Notes: The graphs show the responses (in percentage points) of the top 1 percent's income share—relative to its initial value in year 0—to a normalized +100 bp increase in the short-term interest rate via the instrument. We report IV and OLS estimates for the full sample along with the post-WWII period. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

by the top 1 percent.[13] Inasmuch as our empirical model is linear, the exact opposite effect holds with respect to monetary easing. Precisely, an exogenous increase of +100 bp in the short-term interest rate via the instrument (graph A on the left) reduces P1 by 0.4 percentage point three years after the shock. This effect is economically considerable, given that the average of P1 across the sample over

[13]The persistence of our results is particularly consistent with the recent evidence of Jordà, Singh, and Taylor (2020) indicating that monetary policy—based on a historical panel data for 17 advanced economies and using the macroeconomic policy trilemma to identify monetary surprises—affects TFP, capital accumulation, and output for a very long time.

the studied period amounts to 10 percent. The post-WWII sample follows a similar path, but the effect on P1 over a five-year horizon is smaller (graph B on the right).[14] The negative effect on P1 is, interestingly, more than halved across both samples when using an OLS estimation: a short-term interest rate shock in graph C reduces P1 by 0.19 and 0.16 percentage point four and five years following the shock, respectively.

These differences are clearer in table 2, which jointly reports coefficient estimates of OLS and LP-IV. We compare the results obtained by the two methods to assess the degree of attenuation bias in the OLS estimation. In doing so, we notice that the impulse responses under both methods exhibit relatively similar patterns. However, the coefficient estimates obtained via OLS are less statistically significant and substantially smaller than those produced by the IV. Note that Jordà, Schularick, and Taylor (2020) document the same observation and of a fairly similar magnitude. How should one account for such discrepancy between the OLS and LP-IV coefficient estimates? Some limitations of OLS regression may be at work and explain this contrast. As noted in section 2, given that monetary policy is not driven by top incomes, simultaneity bias is not a concern. However, both variables are affected by economic conditions, some of which may be omitted from the set of control variables.

Finding that monetary tightening decreases P1 over a long time span sets our paper apart from the literature. Particularly, our baseline result contradicts the cross-country evidence of Furceri, Loungani, and Zdzienicka (2018), who document that contractionary monetary policy has negative distributional effects for a panel of 32 advanced and emerging market countries over the period 1990–2013.[15] Hence, it is important to understand what explains such differences. First, we demonstrate that our result holds for a shorter

[14]This result also holds for the post–Korean War sample presented in figure A.6 of the appendix, which corresponds to the last episode of large spikes in government spending due to wars.

[15]The identification shock scheme adopted by Furceri, Loungani, and Zdzienicka (2018) is difficult to replicate in the context of our study because (i) our country sample is much smaller than theirs and (ii) macroeconomic forecasts offered by Consensus Economics are only available as of the 1990s.

Table 2. Local Projection: OLS and IV Estimation Results

	Year 1	Year 2	Year 3	Year 4	Year 5
IV Estimates: P1					
Full Sample					
$\Delta\hat{i}$	-0.13^{**}	-0.28^{**}	-0.39^{**}	-0.47^{**}	-0.44^{**}
	(0.06)	(0.11)	(0.17)	(0.23)	(0.19)
R^2	0.119	0.115	0.124	0.147	0.161
Kleibergen-Paap	4.89	4.89	4.66	4.54	4.47
Observations	633	619	607	595	582
Post-WWII Sample					
$\Delta\hat{i}$	-0.11^{*}	-0.17^{**}	-0.19^{*}	-0.27^{***}	-0.29^{**}
	(0.06)	(0.09)	(0.11)	(0.10)	(0.11)
R^2	0.118	0.139	0.168	0.174	0.186
Kleibergen-Paap	4.46	4.49	4.35	4.30	4.11
Observations	565	552	540	528	515
OLS Estimates: P1					
Full Sample					
Δi	-0.04^{**}	-0.07^{**}	-0.13^{*}	-0.19^{*}	-0.16^{**}
	(0.02)	(0.03)	(0.07)	(0.10)	(0.08)
R^2	0.119	0.125	0.136	0.173	0.211
Observations	656	641	629	617	604
Post-WWII Sample					
Δi	-0.02	-0.04	-0.07^{*}	-0.12^{*}	-0.09^{***}
	(0.02)	(0.03)	(0.04)	(0.07)	(0.03)
R^2	0.130	0.158	0.178	0.188	0.206
Observations	565	552	540	528	515

Notes: Country-based cluster-robust standard errors are reported in parentheses below the coefficient estimates. The controls include the twice-lagged terms of (i) the change in the short-term interest rate; (ii) the change in top income share; and the contemporaneous and twice-lagged terms of (iii) real per capita GDP growth; (iv) the CPI inflation rate; (v) stock price growth; (vi) real per capita consumption growth; (vii) the level of financial development; (viii) the level of commercial openness; (ix) house price growth; (x) government expenditure; (xi) real investment growth; (xii) total factor productivity growth; and (xiii) world GDP growth. We report the Kleibergen and Paap (2006) statistic for weak instruments. *, **, and *** indicate statistical significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

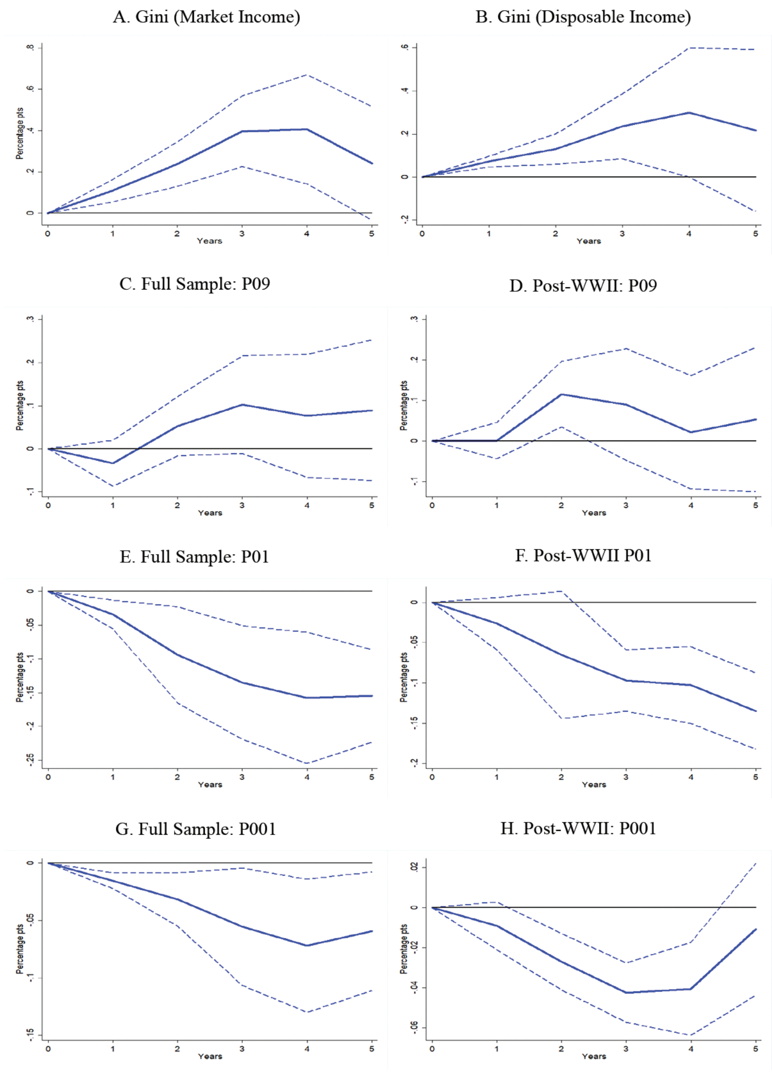
sample period (see figure A.4 in the appendix).[16] Second, we estimate equation (4) using the benchmark income inequality indicator considered by Furceri, Loungani, and Zdzienicka (2018), i.e., the Gini index. Graphs A and B in figure 2 indicate—as in Furceri, Loungani, and Zdzienicka (2018)—that contractionary monetary policy increases the Gini index for market and disposable incomes. This is a fairly standard result, but it has two important implications: (i) our difference with respect to Furceri, Loungani, and Zdzienicka (2018) does not depend on the sample period or the identification strategy, but it is most likely driven by the sample of economies considered; (ii) the impact of monetary policy on P1 is not necessarily mirrored on the entire income distribution. On the one hand, this is perhaps because the Gini index attaches greater importance to households in the middle of the distribution, who are likely to become unemployed following monetary tightening. On the other hand, unlike tax-based estimates from WID, SWIID relies on survey data and therefore features a lower representation of top income households.

Given the heterogeneity in the top decile, we decompose the effect of monetary policy on three distributional indicators presented in the data section: the national income shares held by the top 9 percent (P09), 0.1 percent (P01), and 0.01 percent (P001). The impulse responses displayed in graphs C and D are in sharp contrast to the baseline result, as they report a positive, albeit not statistically significant, effect on P09.[17] A plausible explanation for this finding is that provided by Roine, Vlachos, and Waldenström (2009), who find that changes in per capita GDP growth yield opposite effects for the top percentile (P1) and the bottom of the top decile (P09). In this respect, it can be assumed that output losses following monetary tightening strongly spill over onto capital income and performance-related payments (stock options, bonus programs, etc.), which constitute a significant share of P1's total income—this assertion is also confirmed for the *ultra-rich*, where capital income is bound to be larger (see the responses of P01 and P001 shown in graphs E–H).

[16]Such evidence should be cautiously interpreted, as Herbst and Johannsen (2020) recently find that impulse responses from LPs can be severely biased in the context of small sample sizes.

[17]This contrasts with the responses of the top 10 percent income share (P10), which are likely to be driven by that of P1 (see IRFs reported in figure A.8 of the appendix).

Figure 2. Alternative Distributional Indicator Responses to an Interest Rate Shock



Notes: The graphs show the responses (in percentage points) of various distributional indicators—relative to their initial values in year 0—to a normalized +100 bp increase in the short-term interest rate via the instrument. We report LP-IV results for the full sample along with the post-WWII period. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

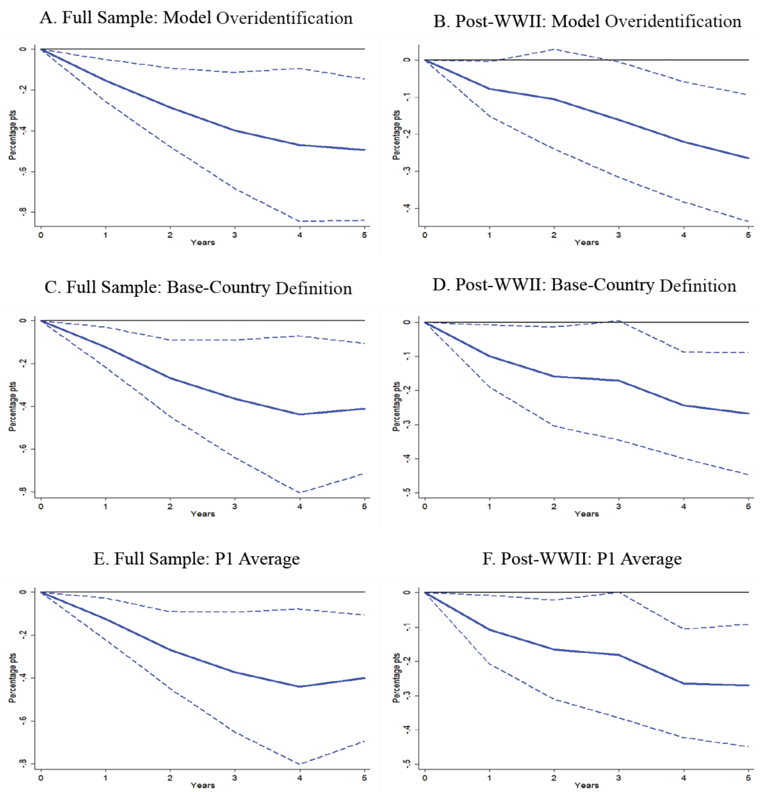
In contrast, P09 is much less linked to developments in the economy because highly salaried workers hold smaller capital shares and are arguably more protected by labor market settings, which makes such income groups less sensitive to unanticipated changes in the monetary policy stance. Hence, our empirical analysis reveals that the effect of monetary policy on top income shares would depend on the segment that is examined: income shares going from the top 1 to 0.01 percentiles or the residual part of the top decile (P09). Another useful exercise on distributional measures can check how monetary policy affects income changes *within* the top of the distribution. Figure A.5 in the appendix depicts the responses of the P1/P09 ratio for the full and post-WWII samples, suggesting that monetary tightening narrows the gap among top decile households.

4.2 Robustness Checks

The identification strategy adopted to estimate dynamic causal effects obviously requires checking the reliability of the instrument $z_{i,t}$. In the first step, we overidentify the estimated model by including the lag of $z_{i,t}$ as an additional instrument. The IRFs presented in graphs A and B of figure 3 are consistent and confirm that the maximum impact on P1 is smaller for the post-WWII sample. Furthermore, the related estimations fail to reject the null hypothesis of the Hansen-Sargan overidentification test, hence suggesting that the exclusion restriction holds. Second, the instrumental variable is constructed using the base-country definitions of Ilzetzki, Reinhart, and Rogoff (2019), which allows us to exploit different sources of changes in monetary conditions. In fact, Ilzetaki, Reinhart, and Rogoff (2019) do not consider, for instance, Norway as belonging to the dollar bloc during the post Bretton Woods era. Graphs C and D show that the negative effect of monetary tightening on P1 is still robust to a different base-country definition for both samples. Finally, we control for potential spatial correlations in the residuals by including the jackknifed average of P1 as a control variable. The estimated IRFs are depicted in graphs E and F of figure 3 and confirm the stability of our baseline estimate.

Having assessed the strength of our instrumental variable, we perform additional sensitivity analyses on the full and post-WWII samples. These are shown in figure 4 and include different model

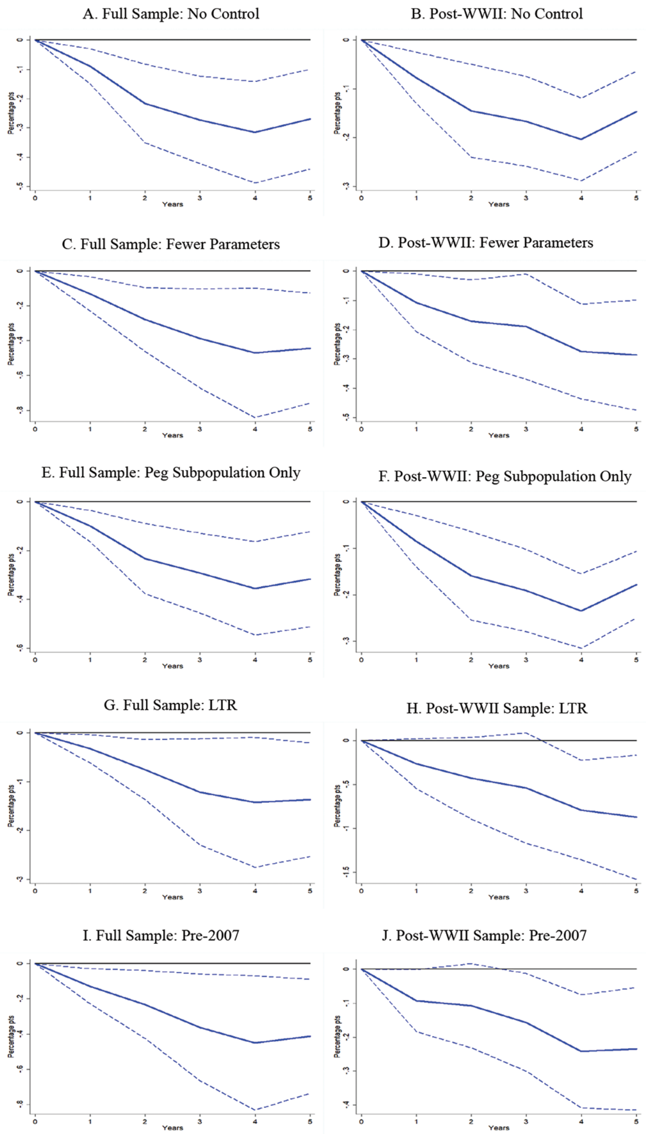
Figure 3. Top 1 Percent LP-IV Responses to Interest Rates: Instrument Robustness



Notes: The graphs depict the responses (in percentage points) of P1—relative to its initial value in year 0—to a normalized +100 bp increase in the short-term interest rate via the instrument. We report LP-IV results for the full sample along with the post-WWII period. In graphs A and B, the short-term interest rate is instrumented by the contemporaneous and lagged values of our IV. In graphs C and D, the instrumental variable is constructed using the base-country definitions adopted by Ilzetzki, Reinhart, and Rogoff (2019). Finally, graphs E and F report the jackknifed average of the top 1 percent's income share to control for potential spillover effects. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

specifications plus a pre-crisis analysis. The first test consists of estimating equation (4) with country fixed effects while omitting the rich set of control variables. This exercise is valuable because it

Figure 4. Sensitivity Tests



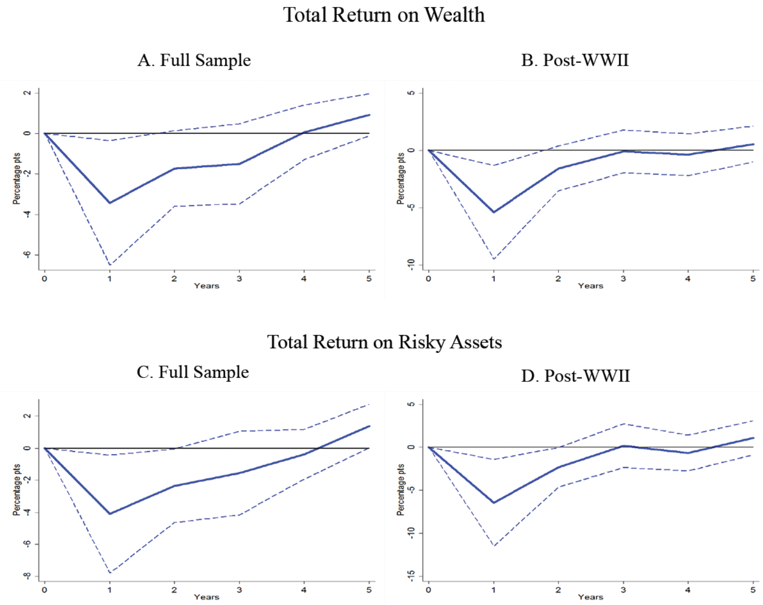
Notes: The graphs show the responses (in percentage points) of P1—relative to its initial value in year 0—to a +100 bp increase in the short-term interest rate. We report LP-IV results for the full sample along with the post-WWII period. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

is also a way to assess whether the IV exclusion restriction is violated. In fact, a correctly specified instrument would be sufficient to avoid potential endogeneity bias. The evidence depicted in graphs A and B does not contradict our main result. The second test presented in graphs C and D reduces the lag number of equation (4) and suggests that the LP framework remains robust to different lag numbers. The third test excludes the base countries from the sample and retains only observations from pegged regimes. The IRFs displayed in graphs E and F are in line with the main result. Another concern that may arise relates to the fact that our sample period covers episodes where the short-term interest rate reaches the lower bound and becomes inadequate to measure the monetary policy stance. To address this issue, we perform two robustness checks: first, we use long-term interest rates as the monetary policy instrument, and second, the Great Recession period is omitted from the sample. The results are reported from graphs G–J and show strong consistency with the LP-IV baseline finding. We note, however, that the impact on P1 is not statistically significant in the short run when considering the post-WWII sample.

4.3 Insights on the Income Composition Channel

Our baseline result suggested that monetary tightening lowers the share of national income held by the top 1 percent. That said, it is relevant to investigate one of the underlying transmission mechanisms of monetary policy towards top income shares. Specifically, we demonstrate here that our evidence can support the *income composition channel* introduced by Coibion et al. (2017). That is, considering the heterogeneity in income sources between households, monetary policy will probably affect the income distribution if it disadvantages some types of income. With respect to the top percentile, the idea we would like to support in this paper is straightforward: if the top 1 percent receive an important share of their total income from capital, then the effect of monetary policy is likely to be channeled through one or several assets' returns. For this purpose, we estimate the effect of monetary tightening on the (real) returns of different financial and real assets. The latter consists of returns on (i) total wealth (weighted average of housing, equity, bonds, and

Figure 5. Insights on the Income Composition Channel



Notes: The graphs show noncumulated IRFs of (real) returns on wealth and risky assets to an unexpected +100 bp increase in the short-term interest rate via the instrument. We report LP-IV results for the full sample during the post-WWII period. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

bills) and (ii) risky assets (weighted average of housing and equity).[18] We prefer capital returns over stock prices because the former include dividends and rents, while the latter are expected to have more impact—through asset valuations—on wealth than on income.

Figure 5 reports the noncumulated IRFs of asset returns to a normalized +100 bp exogenous increase in the short-term interest rate via the instrument for the full and post-WWII samples. The impulse responses depicted in graphs A and B show that the (real) total return on wealth is lowered by 3.7 percentage points in the

[18]These variables are obtained from the JST Macrohistory Database. Their construction and historical dynamics are lengthily discussed in Jordà et al. (2019).

full sample, while this reduction is slightly stronger during the post-WWII period. It is also worth noting that unexpected monetary tightening induces a more sizable reduction in risky asset returns (see graphs C and D in section 6). This means that monetary policy shocks will have a stronger effect on top income households if they hold a large share of risky assets in their portfolios.

Another way to investigate the *income composition channel* is to estimate the impact of monetary policy on the gap between returns on capital r and the real GDP growth rate of the economy g, i.e., $r - g$.[19] Such an approach makes it possible to appraise whether the negative effect of monetary tightening on (real) asset returns is more than proportional to that on growth. The results reported in figure 6 yield similar outcomes to the IRFs previously discussed: regardless of whether r is approached through total wealth or only risky assets, a positive interest rate shock narrows the gap $r - g$ for the full and post-WWII samples.[20]

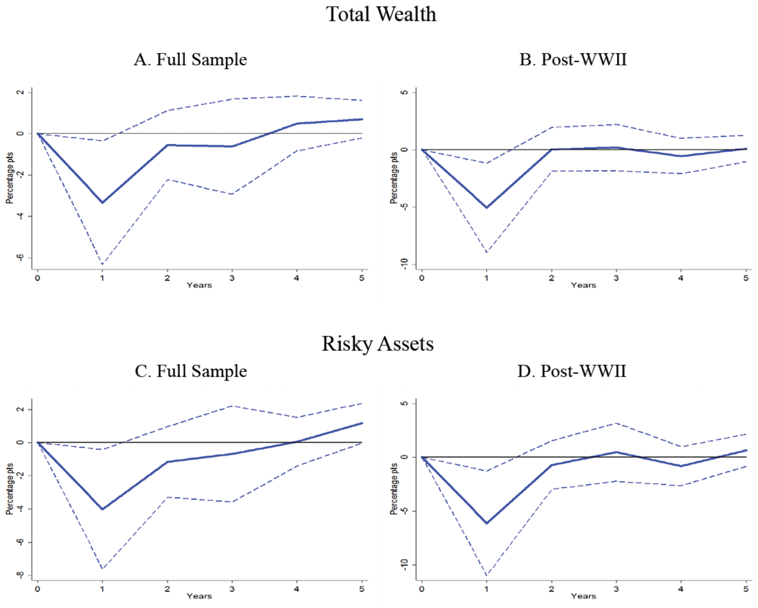
4.3.1 State-Dependent Effects

The results we have reported thus far support that monetary policy tightening decreases P1 and vice versa. There is, however, a potential pitfall because our sample encompasses very different economic regimes. Moreover, several studies indicate that some economic variables, such as the short-term interest rate, may, for instance, behave very differently during economic downturns. To overcome this limitation, we take advantage of the fact that the LP-IV framework easily accommodates nonlinearities. It is convenient to explore whether the effects of changes in monetary conditions on top income shares are state dependent. Thus, we allow the impact of monetary policy on the top income variable to depend upon the state of another variable (see equation (5)). In this way, we can compute conditional impulse

[19]The main idea of Piketty (2014) states that inequality and the capital share of national income systematically move up as $r - g$ grows. However, Piketty considers this gap to have a more potent effect on wealth inequality.

[20]It should be noted that a positive shock affecting the gap $r - g$ increases P1 in our sample. This contradicts Acemoglu and Robinson (2015), who find no correlation between $r - g$ and the top 1 percent share, which could be explained by the fact that they proxy returns on capital by the yields of long-term government bonds, while we adopt a measure that is more relevant to top incomes (returns on equity, housing, bills, and bonds).

Figure 6. $r - g$ **Evidence**



Notes: The graphs show noncumulated IRFs of $r - g$ (based on wealth and risky assets returns) to an unexpected +100 bp increase in the short-term interest rate via the instrument. We report LP-IV results for the full sample during the post-WWII period. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

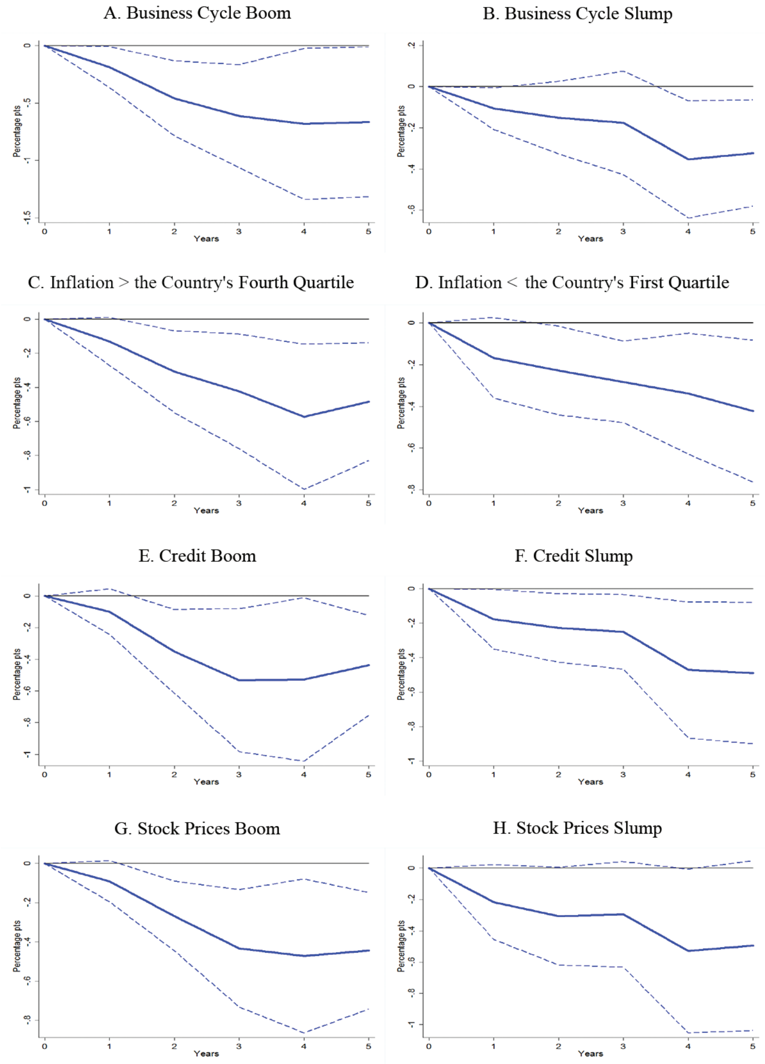
responses in a particular regime to a normalized +100 bp increase in the short-term rate.

We consider five factors that potentially lead to different IRFs of monetary policy: the state of the economy over the business cycle, the inflation regime, credit cycles, stock market cycles, and the monetary policy stance. The episodes of the business cycle are identified using the Hodrick-Prescott (HP) filter and take value 1 in the case of an economic expansion and value 0 during recessions. The same approach is adopted to identify credit and stock market surges/slowdowns. With respect to inflation, a high-inflation episode is defined as a period during which inflation is above its country-specific fourth quartile. Conversely, a country features a low-inflation regime when inflation is below its first quartile. With regard to the monetary policy stance, we define a binary variable taking value 1 when there is positive variation in the short-term interest rate (i.e., monetary tightening) and 0 in the case of negative variation (i.e., monetary easing). Finally, we check whether the responses in the aforementioned regimes are significantly different from each other by conducting a Wald chi-squared test.

Figure 7 reports the IRFs estimated with the state-dependent effect model and the instrumental variable (equation (5)) for the first four factors previously described. Overall, the displayed IRFs do not conflict with the previous results: the effect of monetary policy on P1 continues to hold, *irrespective of the state of the economy.* As shown in graphs A and B, monetary policy has more immediate effects on P1 during expansions than during recessions. This is an expected outcome, as Jordà, Schularick, and Taylor (2020) find that the effect of monetary policy on output is quite strong in booms but considerably weaker in slumps. Interestingly, it also appears from graphs C and D that monetary tightening has a strong effect in the medium run under a high-inflation regime. This makes sense considering that inflation itself is a redistributive tool, which, according to Paarlberg (1993) "steals from widows, orphans, bondholders, retirees, annuitants, beneficiaries of life insurance, and those on fixed salaries, decreases the value of their incomes."

In addition, the impulse responses presented in graphs E and F show that the impact of changes in short-term rates on P1 is not affected by credit cycles. In fact, during episodes of credit booms and slumps, restrictive monetary policy produces very similar impacts on P1. Another nonlinear experiment addresses the idea that during periods of high volatility in stock markets, investors are less willing to hold stocks, and the effects of monetary policy shocks could be limited. That is why we test the state-dependent effect on P1 in the context of stock market booms/slumps. Graphs G and H of figure 7 show that there is no difference in the response to monetary policy regardless of whether stock prices experience a boom or bust episode. However, the response of P1 during stock market slowdowns is not statistically significant, thereby lending some credence to this assumption. Finally, figure A.7 in the appendix supports our baseline result when considering potential asymmetries between expansionary and contractionary monetary policies. Table A.5 in the appendix, which reports the Wald test results for each regime along with their

Figure 7. Top 1 Percent LP Responses to a Positive Short-Term Interest Rate Shock: State-Dependent Effects



Notes: The graphs show, under several regimes, the responses (in percentage points) of P1—relative to its initial value in year 0—to an unexpected +100 bp increase in the short-term interest rate via the instrument. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

respective p-values, indicates that the responses in the respective regimes are not significantly different from each other. Overall, this confirms that monetary tightening reduces the national income share of P1 and vice versa for a monetary expansion, regardless of how the economy behaves.[21]

5. Conclusion

This paper sought to investigate the distributional consequences of monetary policy via top income shares between 1920 and 2016 in 12 OECD economies. The central idea that guided this paper's argument is that the existing empirical literature on the distributional effects of monetary policy mainly uses survey-based estimates of income inequality and covers a shorter period. This approach translates into lower inequality estimates—particularly due to the underestimation of business and capital incomes of rich households—and a lower coverage of exceptional macroeconomic occurrences (recessions, sovereign defaults, etc.). We address these shortcomings by studying how changes in the short-term interest rate over a century affected the share of national income held by the top 1 percent while controlling for the determinants of inequality and top incomes. To do so, we combined two large data sets: (i) the World Inequality Database to extract tax-based data on top income shares and (ii) the Jordà-Schularick-Taylor Macrohistory Database, which allows us to access a large series of macroeconomic and financial variables.

Our empirical strategy is based on local projections (LPs) to obtain the impulse responses of top income shares to a normalized +100 bp exogenous increase in the short-term interest rate via the instrument. The motivation for this empirical setup is threefold: (i) LP is a "model-free" approach, which allows us to control for several factors that may affect top income shares and, simultaneously, be correlated with monetary policy actions; (ii) it offers a quasi-natural experiment as an identification strategy, where exogenous

[21] We are unable to conduct such a test for the monetary policy stance because the effect of each regime (i.e., monetary tightening/easing) is estimated in a separate LP specification.

perturbations to the short-term rate are driven by factors unrelated to domestic economic conditions; and (iii) it easily accommodates nonlinearities, thereby allowing us to estimate potential state-dependent effects of monetary policy on the top 1 percent.

The results obtained from the LP estimates indicate that *tight monetary conditions strongly decrease the top 1 percent's income share and vice versa for an expansionary monetary policy.* In fact, following a positive perturbation to the domestic short-term rate via the external instrument, the share of national income held by the richest 1 percent decreases by 0.13 to 0.44 percentage point. This effect is economically sizable and statistically significant in the medium run. It is also shown that changes in monetary conditions produce a stronger effect on right-tail percentile shares (P1, P01, and P001) than the bottom 9 percent of the top decile. We also demonstrate that this negative effect on top incomes is not reflected in the whole income distribution, as the Gini index (for market and disposable incomes) responds positively to monetary policy shocks. Furthermore, regarding the transmission mechanism of this effect, the reduction in the top 1 percent's share is arguably the consequence of lower (real) asset returns (on equity, housing, and other safe assets), which is consistent with the income composition and indirect income channels.

The baseline results hold under a battery of robustness checks, which (i) introduce an empirical setting that is similar to that of Furceri, Loungani, and Zdzienicka (2018), (ii) overidentify the estimated model using the lagged term of the instrument, (iii) change the base-country definition, (iv) control for spatial correlations in the residuals, (v) remove the rich set of control variables, (vi) test different lag numbers, (vii) estimate the empirical model only on pegged regimes, (viii) use long-term interest rates as the monetary policy instrument, and (ix) omit the Great Recession from the sample. Finally, the state-dependent effects version of our model suggests that our conclusions are robust, regardless of the state of the economy.

In future research, we would like to test the effects of monetary policy on different income deciles to focus exclusively on poor and middle-class households (i.e., the bottom 5 percent or 1 percent with the lowest market incomes). From the same perspective, are the results obtained here also valid for wealth inequality? This aspect is important because wealth is more unevenly distributed than income. Moreover, while we use pre-tax data, policymakers may be interested in the effects of monetary policy on the income distribution net of the contribution of fiscal policy. Finally, in the spirit of the corresponding literature, the empirical approach adopted in this paper considers only the global effects of monetary policy on the income distribution. That is, we do not identify all the transmission channels through which monetary policy affects top incomes. Ultimately, what policy implications can we draw from these findings for the ongoing debate on monetary policy and the income distribution? Central bankers need to be attentive not only to the aggregate consequences of monetary policy but also to their side effects.

Appendix. Additional Tables and Figures

Table A.1. Data Sources and Periods of Top Income Shares

Country	Period	Details
Australia	1921–2015	WID (2019)
Canada	1920–2010	WID (2019)
Germany	1925–2013	WID (2019)
Denmark	1920–2016	WID (2019)
France	1920–2014	WID (2019)
United Kingdom	1951–2014	WID (2019)
Italy	1974–2009	WID (2019)
Japan	1920–2010	WID (2019)
Netherlands	1920–2012	WID (2019)
Norway	1948–2011	WID (2019)
Sweden	1943–2013	WID (2019)
United States	1920–2016	WID (2019), Atkinson et al. (2015)

Note: There are some years with missing values in each subperiod.

Table A.2. Control Variable Definitions

Variable	Variable Definition	Source
Hpnom	House Price Growth (Real Index, 1990=100)	Macrohistory Database JST
Stocks	Stock Price Index Growth (Real Index)	Macrohistory Database JST
CPI	Consumer Price Index Year-Over-Year Growth	Macrohistory Database JST
Tloans	Ratio of Total Loans to Nonfinancial Private Sector to GDP	Macrohistory Database JST, Own Calculations
Com_open	Ratio of Imports and Exports to GDP	Macrohistory Database JST, Own Calculations
gdp_pc	Country Real GDP per capita (Index, 2005=100)	Macrohistory Database JST
cons_pc	Country Real Consumption per capita (Index, 2006=100)	Macrohistory Database JST
Invest	Country Real Investment Growth	Macrohistory Database JST, Own Calculations
expenditure	Government Expenditure-to-GDP Ratio	Macrohistory Database JST
World_gdp	World Real GDP Growth	Macrohistory Database JST
TFP	Total Factor Productivity Growth	Long-Term Productivity Database
Gini_mkt	Gini Index, Market Income	SWIID (2020)
Gini_disp	Gini Index, Disposable Income	SWIID (2020)
risky	Tot. Rtn. on Risky Assets, Wtd. Avg. of Housing and Equity	Macrohistory Database JST
capital_tr	Tot. Rtn. on Wealth, Wtd. Avg. of Housing, Equity, Bonds, and Bills	Macrohistory Database JST
eq_tr	Equity Total Return	Macrohistory Database JST

Notes: This set of control variables has been used in the context of local projections. To ensure stationarity, real indexes are obtained by dividing the variables by CPI, and growth rates are computed in logs.

Table A.3. Base Countries for the 12 Economies

Country	Interwar	Bretton Woods	Post-BW
Australia*	Hybrid	UK	USA*
Canada	Hybrid	USA	USA
Germany	Hybrid	USA	Germany
Denmark	Hybrid	USA	Germany
France	Hybrid	USA	Germany
United Kingdom	Hybrid	USA	Germany
Italy	Hybrid	USA	Germany
Japan	Hybrid	USA	USA
Netherlands	Hybrid	USA	Germany
Norway	Hybrid	USA	USA
Sweden	Hybrid	USA	Germany
United States	USA	USA	USA

*Following Jordà, Schularick, and Taylor (2020), we treat Australia as moving to a U.S. dollar peg in 1967.

Notes: Hybrid refers to the gold standard base, which is a combination of U.S. and French rates. Interwar: 1920–1938; Bretton Woods: 1948–1973; Post-BW: 1974–2016.

Table A.4. Exchange Rate Regimes

Country	Fixed	Floating
Australia	1920–1938, 1946–1983	1939–1945, 1984–2015
Canada	1920–1938, 1946–2015	1939–1945
Germany	1920–1938, 1946–1972, 1999–2014	1939–1945, 1973–1998
Denmark	1920–1938, 1946–2016	1939–1945
France	1920–1938, 1949–2014	1939–1948
United Kingdom	1920–1938, 1946–2008	1939–1945, 2009–2015
Italy	1920–1938, 1949–2014	1939–1948
Japan	1920–1938, 1948–1977	1939–1947, 1978–2015
Netherlands	1920–1938, 1946–2014	1939–1945
Norway	1920–1938, 1946–2014	1939–1945
Sweden	1920–1938, 1946–2014	1939–1945
United States	1920–1938	1939–2016

Table A.5. Wald Chi-Squared Test of the Difference in the Cumulated Effect of the Interest Rate Shock Between the Two States

State:	Business Cycle	Inflation High/Low	Credit Boom/Slump	Stock Prices Boom/Slump
chi2 Year 5	0.67	0.24	0.09	0.03
Prob Year 5	0.41	0.62	0.76	0.86

Figure A.1. Sample Mean of Top Income Shares (P1 and P09)

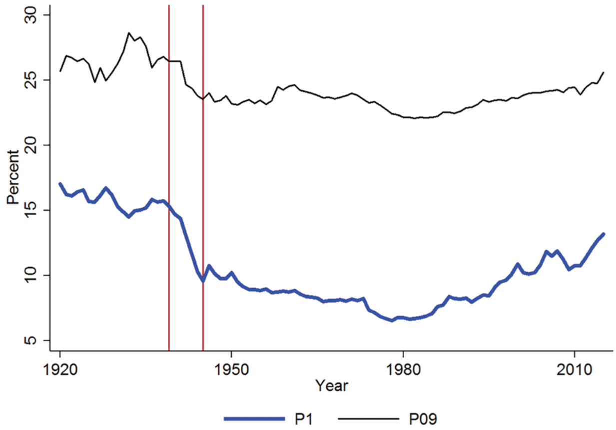


Figure A.2. Top Income Shares Over Time: 12 Countries

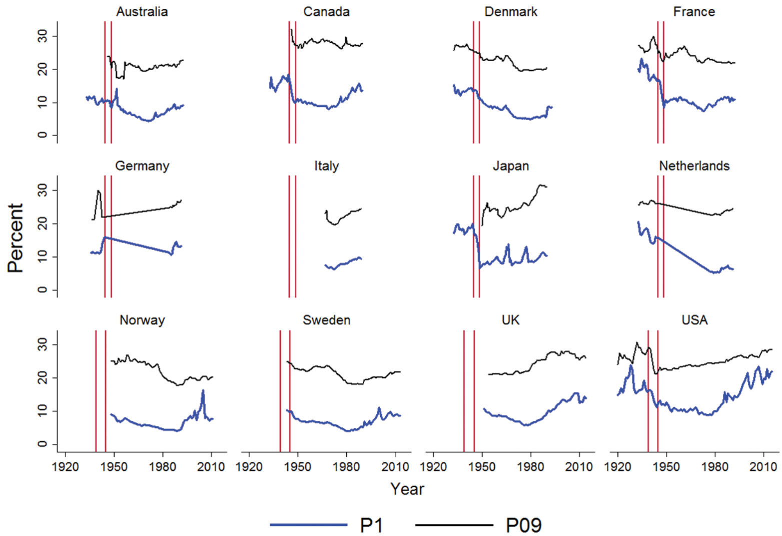


Figure A.3. Jordà, Schularick, and Taylor-Based IV: Change in Short-Term Interest Rate in Home and Base Countries

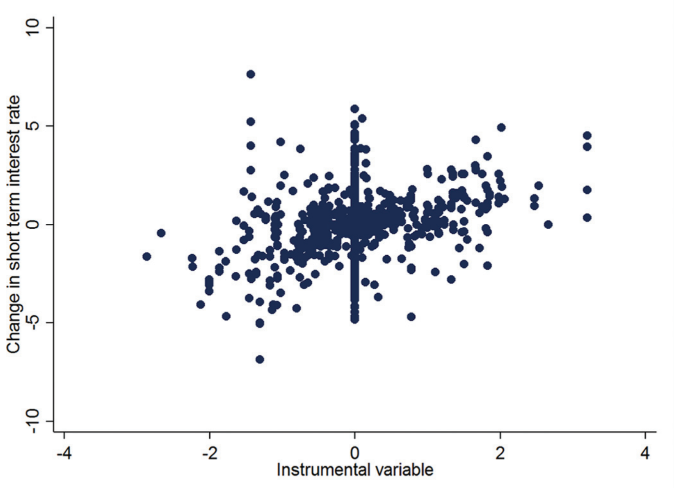
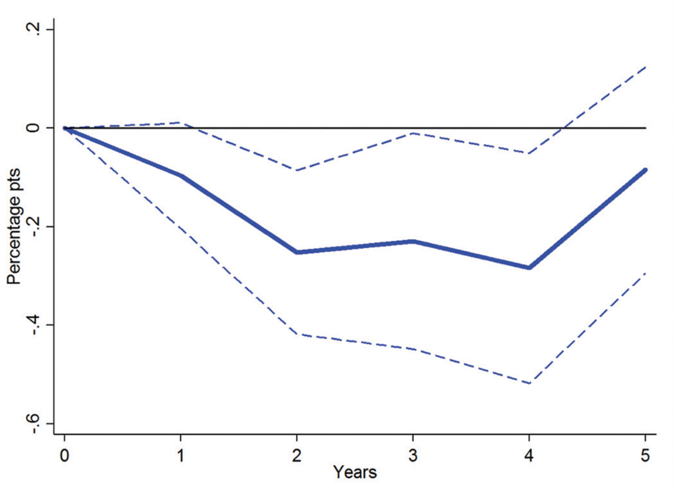
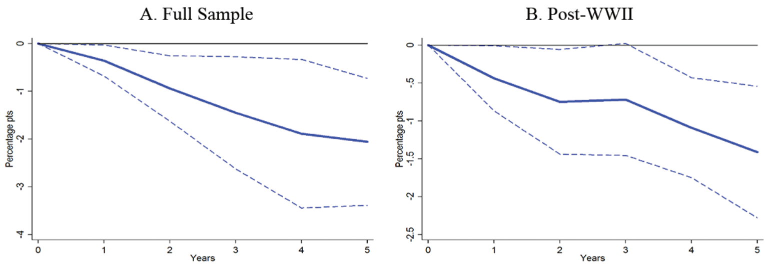


Figure A.4. LPs to a Positive Short-Term Interest Rate Shock: Post-1980



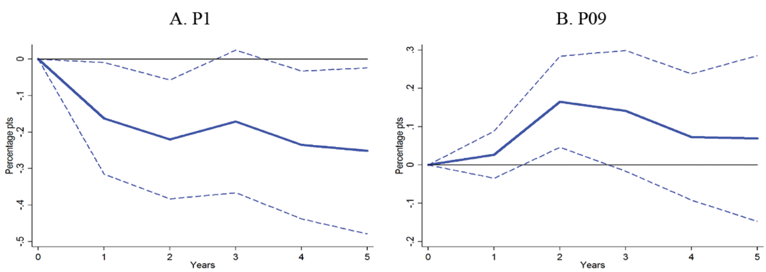
Notes: The graph shows the IRF (in percentage points) of P1—relative to its initial value in year 0—to a +100 bp increase in the short-term interest rate via the instrument. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

Figure A.5. LPs to a Positive Short-Term Interest Rate Shock: P1/P09 Ratio



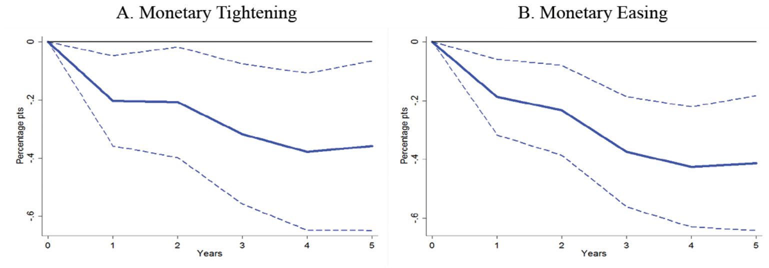
Notes: The graphs show the responses (in percentage points) of the P1/P09 ratio—relative to its initial value in year 0—to a +100 bp increase in the short-term interest rate via the instrument. We report LP-IV results for the full sample along with the post-WWII period. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

Figure A.6. LPs to a Positive Short-Term Interest Rate Shock: Post–Korean War Sample



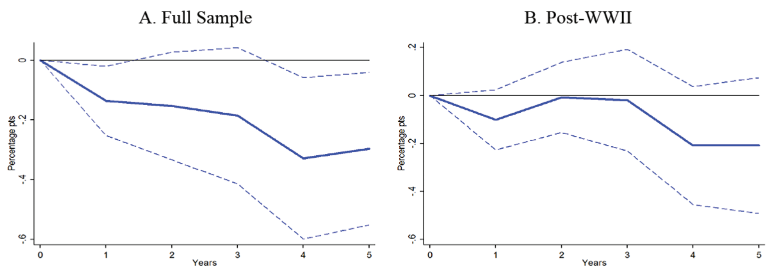
Notes: The graphs show the responses (in percentage points) of P1 and P09—relative to their initial values in year 0—to a +100 bp increase in the short-term interest rate via the instrument. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

Figure A.7. LP State-Dependent Effects: Monetary Policy Stance



Notes: The graphs show the responses (in percentage points) of P1—relative to its initial value in year 0—to a +100 bp increase in the short-term interest rate via the instrument. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

Figure A.8. LPs to a Positive Short-Term Interest Rate Shock: P10 Income Share Response



Notes: The graphs show the responses (in percentage points) of the top 10 percent income share—relative to their initial values in year 0—to a +100 bp increase in the short-term interest rate via the instrument. The dashed lines represent 90 percent country-based cluster-robust confidence bands.

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Monetary Normalizations and Consumer Credit: Evidence from Fed Liftoff and Online Lending*

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On December 16, 2015, the Federal Reserve initiated "liftoff," a critical step in the monetary normalization process. We use a unique panel data set of 640,000 loan-hour observations to measure the cross-sectional impact of liftoff on interest rates, demand, and supply in the peer-to-peer market for uncollateralized consumer credit. We find that the spread decreased by 17 percent, driven by an increase in supply. Our results are consistent with an investor-perceived reduction in default probabilities and suggest that liftoff provided a strong, positive signal about the future solvency of high credit risk borrowers.

JEL Codes: D14, E43, E52, G21.

1. Introduction

Between July 2007 and December 2008, the Federal Open Market Committee (FOMC) lowered its target rate from a pre-crisis high of

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5.25 percent to 0 percent. The federal funds rate then remained near 0 percent for seven years until the FOMC announced "liftoff"—a 25 basis points (bps) hike on December 16, 2015 that signaled an end to emergency measures (FOMC 2015a, 2015b). According to the FOMC's "Policy Normalization Principles and Plans" statement, which marked the return to conventional monetary policy, liftoff constituted the first step in a monetary normalization plan that will ultimately include additional rate hikes and balance sheet adjustments (FOMC 2014; Williamson 2015). Since the FOMC explicitly conditioned normalization on the state of the economy (FOMC 2014), this choice also provided a strong, positive signal about the Federal Reserve's (the Fed's) private assessment of the economy.[1]

We use a unique panel data set of 640,000 loan-hour observations to estimate the Fed liftoff's impact on the peer-to-peer (P2P) market for uncollateralized online consumer credit. The online consumer credit market has been growing rapidly and accounted for around one-third of the U.S. market for unsecured personal loans in 2018 (Balyuk and Davydenko 2019). Furthermore, it is at the forefront of the digitalization of credit, which makes it important for understanding how the online consumer credit market will be affected by future monetary policy. Our work complements the existing empirical literature that identifies the effects of monetary policy on credit availability, consumption, bond interest rates, stock prices, and risk premiums;[2] however, we focus exclusively on the first step of the monetary normalization process, use primary market data, and explore cross-sectional implications.

The existing literature finds that monetary contractions tend to decrease loan supply, increase interest rates, and increase spreads.

[1] James Bullard, President of the Federal Reserve Bank of St. Louis, emphasized the signaling channel in a December 7, pre-liftoff interview: "If we do move in December . . . [it] does signal confidence. It does signal that we can move away from emergency measures, finally" (Bullard 2015).

[2] See Bernanke and Blinder (1992), Bernanke and Gertler (1995), Kashyap and Stein (2000), and Jiménez et al. (2012) on credit availability and Di Maggio et al. (2017) on consumption. For the effect of surprise monetary contractions on bond interest rates, see Cook and Hahn (1989), Kuttner (2001), Cochrane and Piazzesi (2002), Wright (2012), and Hanson and Stein (2015). On stock prices, see Rigobon and Sack (2004) and Bernanke and Kuttner (2005). On risk premiums, see Gertler and Karadi (2015), and for the effects of quantitative easing, see Krishnamurthy and Vissing-Jorgensen (2011).

Our findings differ in sign; and our empirical evidence suggests that the contractionary component of liftoff—an interest rate hike that exceeded expectations—was dominated by the positive signal provided by the choice to proceed with normalization. The signaling effect is particularly strong for low-rated borrowers in the P2P market, who often exhibit subprime characteristics,[3] and, thus, may benefit from improvements in the future outlook of the economy—including the labor market—that lower perceived default probabilities. While we concentrate on the P2P market for uncollateralized consumer loans—which provides us with a laboratory to study the heterogeneous effects of monetary policy signaling—our findings are likely to bear relevance for other risky credit market segments that are also strongly influenced by broader economic developments.

The main results consist of estimates for two outcomes: (i) the change in the spread between high and low credit risk borrowers; and (ii) the change in the average interest rate on uncollateralized consumer loans. We find that the spread between high and low credit risk borrowers decreased by 17 percent. The spread reduction was primarily driven by a decrease in rates for the riskiest borrower segments, which experienced the largest increase in supply of funds. Moreover, we show that the average interest rate on loans in our data set fell by 16.9–22.9 bps. The decrease in the average interest rate is economically significant, and the magnitude of the observed 166 bps reduction in the spread between high and low credit risk borrowers after liftoff is equivalent to approximately one-third of the effect of moving up from Prosper rating category D to C or an improvement in the FICO score from 679 to 690.

These results are robust to the inclusion of all observable loan and borrower characteristics, as well as intraday fixed effects and intraweek fixed effects. We also show that our results are not driven by a change in borrower composition, a collapse in demand, a shift in investor risk appetite, a seasonal adjustment, or Fed undershooting;[4] and are robust to the choice of time window. Both narrow and

[3] Borrowers in the P2P market are typically above the subprime FICO cutoff; however, many exhibit other characteristics associated with subprime borrowing (e.g., missing documentation).

[4] We show that it is unlikely that the Fed undershot with respect to either the federal funds rate adjustment or the announced forward-guidance plan; however,

wide windows (including 3-day, 7-day, and 14-day windows around liftoff) yield statistically significant results. Visual inspection and placebo tests suggest that the change happened precisely at liftoff.

Additional evidence using separate hourly measures for demand and supply allows us to discriminate between different candidate explanations for our main results, and points clearly to a supply-side explanation. We show that demand does not decline after liftoff, which rules out most plausible alternative stories that rely on a demand decrease. To the contrary, investors' propensity to supply funds increases sharply—especially for the riskiest borrower groups. The probability of individual loans getting funded also increases. In sum, we can rule out explanations that are driven by the demand side, including those that rely on borrower composition shifts.

The primary data set we use was scraped at an hourly frequency from Prosper.com, the oldest and second-largest U.S.-based P2P lender. One distinctive feature of this panel data set is that it contains separate measures of demand and supply, unlike time-series market data or bank-based loan origination data. It also contains rejected loans, unlike most bank-based loan data sets. Moreover, it is uncommon that borrowers are discouraged from applying for loans in this platform, since the application cost is low. Demand is constructed by aggregating the amount requested on all loans posted on Prosper at a point in time. Supply measures are constructed using three different definitions: (i) the aggregate amount that has been funded across all loans at a point in time; (ii) the aggregate change in funding over a given time interval; and (iii) the realized probability that a loan will be funded. Exploiting this unique feature of our data set, we show that all measures of supply increased after liftoff, with the largest increase accruing to the high credit risk borrower segment. Demand also increased, but only slightly. Additionally, we also show that the funding gap—the aggregate amount that has been demanded, but not yet supplied—decreased after liftoff, suggesting that the increase in supply was larger than the increase in demand. Overall, these results point to a supply-side explanation for the reduction in the spread and in interest rates.

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our results do not depend on this assumption and would hold if the opposite were true.

We also collected a secondary data set from LendingClub.com by compiling Securities and Exchange Commission (SEC) records. This data set contains a higher number of individual loans but is available only at a daily frequency, since we were unable to track LendingClub originations in real time. This means that we cannot repeat the supply, demand, and funding gap exercises for this data, and we cannot observe interest rates at an intraday frequency. We can, however, replicate the average interest rate and spread results: both decline in the LendingClub data, and the magnitudes of the declines are nearly identical to our original findings. Taken together, both data sets cover more than 70 percent of the U.S. P2P market.

To further establish robustness, we demonstrate that the direction and magnitude of the liftoff results are not common to FOMC decisions by performing the same analysis on the January 27, 2016 decision not to raise rates. In contrast to liftoff, we find that this decision had no statistically significant impact on interest rates. This holds for both wide and narrow time windows, suggesting that there is no common announcement effect. We also perform a sequence of rolling regressions of the interest rate on loan-borrower characteristic controls using a narrow time window. We show that the results are only significant when liftoff is selected as the center of the window.[5] Additionally, the available data allow us to study the subsequent rate hikes on December 14, 2016 and March 15, 2017. We find no significant effect on the average P2P interest rates associated with these policy rate announcements, which confirms the unique role of liftoff in sending a strong positive signal.

The rest of the article proceeds as follows. Section 2 provides an overview of Fed liftoff and the P2P lending market, as well as the expected effects. Section 3 describes the data and how it was collected. Section 4 presents our findings. We discuss the related literature in section 5 and conclude in section 6.

2. Market Setting and Theoretical Framework

We proceed by describing Fed liftoff and market expectations in section 2.1. Thereafter, we describe the P2P lending market in the

[5]In addition to performing robustness tests, we have also discussed the paper with practitioners in the P2P market to ensure that the findings and proposed mechanism are credible.

United States and the Prosper P2P lending platform in section 2.2. Finally, we discuss the theoretical framework that guides our empirical investigation and the expected effects of liftoff in section 2.3.

2.1 Fed Liftoff

During the second half of 2015, the prospect of Fed liftoff was considered by many to be an important event with historic connotations. It marked the end of an unprecedented era of monetary easing and was regarded as an important step towards monetary normalization. On the day prior to liftoff, market participants largely anticipated that the FOMC would vote to raise rates. This is perhaps best reflected in futures contracts, which implied a .84 probability of the federal funds rate range increasing from 0–25 bps to 25–50 bps and a near-zero probability for a rate hike above the 25–50 bps range.[6] This suggests that the FOMC's rate decision overshot, rather than undershot, market expectations. Furthermore, yields on three- to five-year maturity corporate bonds also increased by 17 bps, suggesting that the announced path of forward guidance may have also overshot, pulling up longer term rates after liftoff.

Overall, we interpret the interest rate adjustment and forward-guidance path announcement as contractionary relative to expectations; however, our main results do not depend on this assumption. Even if the decisions were expansionary, the interpretation of all results in the paper would remain unchanged.[7]

Finally, while Fed liftoff was widely expected, there was uncertainty about the timing of the move, which drew substantial

[6]Source: The probability of a federal funds rate increase is based on futures, computed by Bloomberg one day prior to liftoff. The underlying contracts are written for the effective federal funds rate, rather than the Fed's target rate range, which means that the range probabilities are not assumption free. Importantly, however, Bloomberg's calculations were not anomalous and aligned closely with other estimates, including those produced by the Chicago Mercantile Exchange. Interest rates on short maturity debt, such as commercial paper, also increased after liftoff, which reinforces the claim that the Fed did not undershoot relative to expectations.

[7]If the FOMC statement undershot the expected forward-guidance path, this would be captured entirely by changes in rates for near-prime borrowers in our sample. In fact, we find that the reduction in rates is substantially larger for the riskiest borrowers.

attention in discussions among P2P market practitioners. Our identifying assumption is that Fed liftoff was the key event within the narrowest window around liftoff we use (±3 days). Furthermore, we argue that there were no other relevant events that could credibly explain the shift in the P2P lending market, such as substantial and unexpected news from economic data releases, and section 4.1 offers a robustness test.

2.2 The Prosper P2P Lending Platform

The P2P lending market is growing rapidly. In 2018 it reached around one-third of the U.S. market for unsecured personal loans (Balyuk and Davydenko 2019). Our primary data set comprises a panel of loan-hour observations from the P2P lending platform Prosper.com, which operates the oldest and second-largest lending-based crowdfunding platform for uncollateralized consumer credit in the United States, and has been operating since February 2006. As of January 2016, Prosper has more than 2 million members (investors and borrowers) and has originated loans in excess of $6 billion. Borrowers ask for personal uncollateralized loans ranging from $2,000 to $35,000 with a maturity of three or five years. The highest-rated borrowers may have access to traditional sources of credit from banks and credit cards, but the lowest-rated borrowers are unlikely to have such outside options.

After the loan application is submitted, the platform collects self-reported and publicly available information, including the borrower's credit history. Prosper uses a credit model to decide on the borrower's qualification for the loan, to assign a credit score, and to set a fixed interest rate and repayment schedule. The process is fast, and qualified borrowers can expect to receive an offer within 24 hours. The funding phase takes place during a 14-day listing period. Investors review loan listings that meet their criteria and invest (e.g., in $25 increments). A loan can be originated as soon as 100 percent of the funding goal is reached or if a minimum of 70 percent is reached by the end of the listing period. Provided borrowers accept the loan, the total funding volume (net of an origination fee) is disbursed. Prosper services the loan throughout the duration and transfers the borrower's monthly installments to lenders.

According to its website, Prosper assigns rates to loans based on a proprietary measure of expected loss (Prosper rating), the loan term, the economic environment, and the competitive environment. Similarly, LendingClub's website explains that rates are adjusted in response to "macroeconomic conditions, supply and demand on the LendingClub platform, and evolving default and chargeoff rates." Prosper and LendingClub provide lists of average rates and rate ranges associated with their respective proprietary rating groups. For the sample period we study, the minimum value of the best-rated group, the base rate, is lower than 5 percent on both platforms. The maximum value in the worst-rated group is 30.25 percent. Importantly, shifts in these averages and ranges reflect all of the aforementioned pricing factors, as well as changes in how individuals are assigned to different rating groups. For this reason, interest rate change announcements cannot be meaningfully interpreted without first controlling for loan and borrower characteristics.[8]

P2P lending platforms generate fee income that relates to the transaction volume. Specifically, Prosper's fee structure consists of (i) an origination fee of 0.5–5 percent paid by borrowers at loan disbursement; (ii) an annual loan servicing fee of 1 percent paid by lenders; (iii) a failed-payment fee of $15; (iv) a late-payment fee of 5 percent of the unpaid installment or a minimum of $15; and (v) a collection agency recovery fee in the case of a defaulting borrower. The first three fees generate income for Prosper, while the late-payment fee and the collection agency recovery fee are passed on to the lenders. The net profit from late-payment fees is likely to be negligible after accounting for administrative costs. Hence, origination and servicing fees are the key contributors to platform profits.

Given the fee structure, we argue that maximizing of the origination volume is a close approximation to Prosper's interest rate setting problem, conditional on Prosper maintaining appropriate underwriting standards that shield it from potential reputational losses.

[8]Prosper is privately owned and is not obligated to announce rate changes. LendingClub announced an interest rate shift after Fed liftoff. After controlling for loan and borrower characteristics, this shift had a negative impact on the average rate of a constant-quality borrower.

2.3 Expected Effects

The interest rate set for individual Prosper loans can be understood as a function of the risk-free reference rate, economic risk premiums, and market conditions. The risk-free reference rate is influenced by monetary policy. The Federal Reserve targets the overnight federal funds rate and, thereby, affects the nominal risk-free reference rate. Moreover, monetary policy also influences the term structure via expectations of future federal funds rates. The risk premium on Prosper P2P loans comprises credit risk and term risk.[9] Given the uncollateralized nature of the P2P consumer credit segment, the credit risk of individual borrowers is arguably the dominant determinant of the risk premium and of key interest in our study. Moreover, our evidence from section 2.1 suggests that term risk does not appear to be a substantial driver.[10] The dominant role of credit risk also resonates with our cross-sectional analysis. Important factors of influence are unemployment risk, health risk, divorce, or expenditure needs.

When setting the interest rates on individual loans, the Prosper P2P lending platform faces changing market conditions in the form of stochastic supply and demand. One way to understand the interest rate setting problem is to compare it to a joint pricing and inventory control problem with perishable inventory. Such problems have been discussed in the operations research literature.[11] In the context of the P2P lending platform, the inventory corresponds to the funding gap, which is the difference between the cumulative inflows of funds and the target for the outstanding total loan amount for all listings at a given point in time. It is in the interest of the lending platform to safeguard against a scenario where the supply of funds cannot be met by means of an inventory of unfunded loans at a given point in time. The inventory, however, is perishable, since loans are not originated and are permanently delisted if not funded by at least

[9]Recall that the interest rate on Prosper loans is fixed at origination and the average maturity is between three and five years. As a result, investors are exposed to term risk since the short-term risk-free reference rate may not evolve as expected.

[10]This also excludes forward-guidance channels (e.g., Del Negro, Giannoni, and Patterson 2012).

[11]See, e.g., McGill and van Ryzin (1999); Petruzzi and Dada (1999); Elmaghraby and Keskinocak (2003).

70 percent within a 14-day period. Hence, it is undesirable to maintain a large funding gap. At the same time, a positive funding gap or "excess demand" serves an important purpose, as it allows investors to have access to a sufficiently deep pool of loan listings at a given point in time.

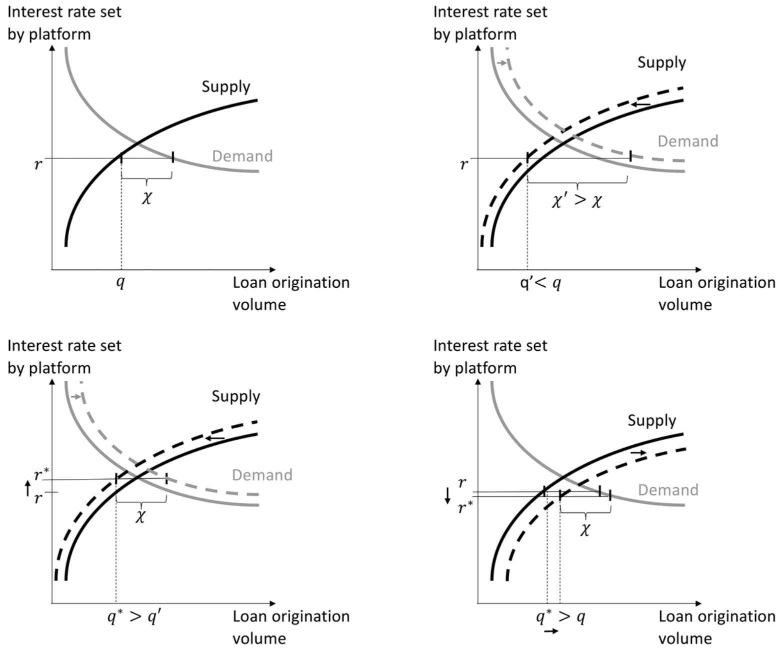
In contrast to other markets, the inventory is not produced, but the interest rate set by the lending platform affects both supply and demand. Moreover, the interest rate is set before an individual loan is listed on the platform and cannot subsequently be adjusted. This differs, for instance, from the case of event admission tickets, which can be discounted when demand is revealed to be weak.[12] In addition, Prosper's interest rate setting is complicated by the fact that newly listed loans compete with previously listed loans, resulting in potential crowding-out effects when rates differ. This latter feature is likely to prevent Prosper from significantly changing the pricing as long as it does not face lasting changes in market conditions. We continue discussing a decomposition of expected effects of such changes in market conditions based on a stylized description of online lending market segment specific supply and demand.

Risk-Free Reference Rate Channel. Based on the existing literature on event studies, which identifies the effect of monetary policy on bond prices, we expect to observe at least partial interest pass-through (e.g., Cook and Hahn 1989 or Kuttner 2001). Namely, an unexpected increase in the reference rate is, in isolation, associated with an increase in the funding costs of P2P borrowers. More specifically, we would expect the propensity of investors to supply funds to decrease for all market segments, because investors earn a lower premium over the risk-free rate. We use graphs to offer a stylized illustration.

The upper left panel of figure 1 depicts market clearing in a given segment of the online lending market, assuming that the platform targets an inventory of > 0 to give investors a sufficiently deep pool of potential investments and to allow for diversification across loans. We depict the inventory, χ, as excess demand and recall that in our sample 25.3 percent of loans are identified as unfunded after the 14-day period. The upper right panel of figure 1 shows the inward

[12] See Sweeting (2012).

Figure 1. P2P Consumer Credit Market Supply and Demand



shift in supply associated with an unexpected increase in the reference rate. Arguably, unsophisticated loan applicants are likely to be less responsive to interest rate changes. Nevertheless, the unexpected increase in the reference rate may increase their costs for alternative funding. Consequently, we may expect to see an increase borrowers' propensity to list a loan on the platform, which corresponds to an outward shift in demand as depicted in the lower left panel of figure 1. In case the interest rate, r, set by the platform is unchanged, the excess demand will be higher, $\chi' > \chi$, and the loan origination volume lower, $q' < q$. A platform expecting the change in market conditions to persist will increase the rate to $r > r$ to balance the market at its excess demand target level, as depicted in the lower left panel. This also increases the loan origination volume to $q^* > q'$.

Credit Risk Channel. In isolation, a reduction in perceived credit risk increases the attractiveness of the online lending market for investors. Consequently, we would expect an increase in the propensity of investors to supply funds to online lending. This is depicted as an outward shift in supply in the lower right panel of figure 1. Everything else equal, the excess demand is reduced below its target. Arguably, this is even more so in a case in which the reduction in perceived credit risk improves outside options of loan applicants, causing an inward shift in the demand schedule. A platform expecting the change in market conditions to persist will decrease the interest rate to $r^* < r$ in order to balance the market at its excess demand target level, thereby increasing the origination volume to $q^* > q$.

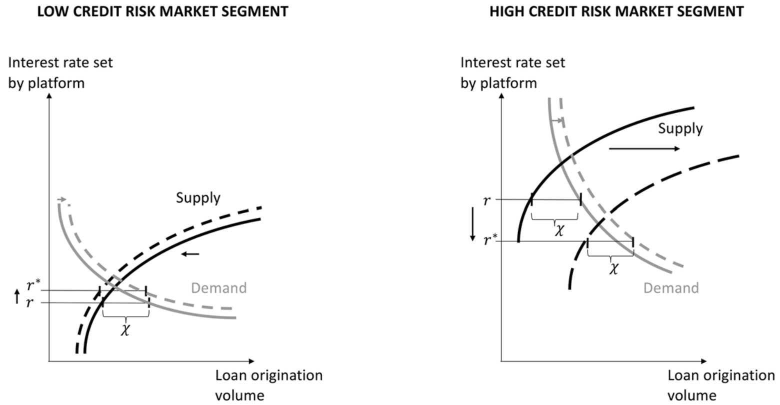
Liftoff Signaling Channel. We next discuss the combined effect of the risk-free rate channel and the credit risk channel. This is because monetary contractions can also affect credit risk, the key determinant of the risk premium in the P2P segment for consumer credit. Regarding the credit risk channel, there can be two opposing effects. First, the empirical literature finds that surprise monetary contractions are associated with an increase in credit spreads (e.g., Gertler and Karadi 2015). Second, credit spreads are known to be countercyclical and are regarded as a leading indicator for economic activity (e.g., Gilchrist and Zakrajsek 2012).[13] As a result, a monetary contraction that ushers in monetary normalization may be associated with a reduction in credit spreads if the decision sends a strong positive signal about the state of the economy. This is true even more so if the normalization is conditioned on an improvement in the economic outlook.

More specifically, taking a significant step towards monetary normalization, such as the Fed liftoff decision to move away from near-zero rates, constitutes a strong positive signal about the Fed's private assessment of future employment and growth prospects.[14] This interpretation is supported by empirical studies that demonstrate the Fed's good nowcasting performance (Faust and Wright 2009) and suggest that the disclosure of information by central banks plays an important role in coordinating market expectations and

[13]This countercyclical nature of credit spreads has been rationalized most prominently in the financial accelerator proposed by Bernanke and Gertler (1989).

[14]Following the end of quantitative easing in October 2014, liftoff can be regarded as the first step towards monetary normalization, with the reduction of the Fed's balance sheet being the second step (FOMC 2014).

Figure 2. P2P Consumer Credit Market Specific Supply and Demand



Note: Market specific supply and demand for the low credit risk segment (left panel) and for the high credit risk segment (right panel).

provides relevant macroeconomic information to markets (Swanson 2006; Ehrmann and Fratzscher 2007; Campbell et al. 2012; Boyarchenko, Haddad, and Plosser 2016; Ehrmann, Eijffinger, and Fratzscher 2016).

For uncollateralized consumer credit, the assessment of future employment prospects is an important determinant of perceived credit risk. Moreover, the default risk of high credit risk borrowers is arguably most sensitive to changes in the economic outlook. Hence, we would expect a strong credit risk channel associated with the positive signal of a monetary normalization, which outweighs the risk-free rate channel, to crystallize in a reduction of the spread between high and low credit risk borrowers. We provide a formalization in online appendix B and the outcome is illustrated in figure 2 (see http://www.ijcb.org for online appendix).

The left panel of figure 2 shows in a stylized way the low credit risk market segment where the credit risk channel is weak. Due to the small increase of the risk-free reference rate during liftoff, we expect a rather small inward shift in supply. At the same time, there may be a small outward shift in demand due to the deteriorating outside options of loan applicants. Taken together, the two effects both tend to increase the excess demand and, thereby, warrant a small interest rate increase by the platform for the lowest credit risk segment that appears to be approximately the same size as the risk-free rate increase. Conversely, the credit risk channel is considerably stronger in the high credit risk segment. Here, the supply shift outward is much larger, as depicted in the right panel of figure 2. This warrants a substantial interest rate reduction for the borrowers with the low credit ratings to balance the market and achieve the platform's objective. In sum, we expect a strong credit risk channel associated with the positive signal of a monetary normalization to show as a reduction of the spread between high and low credit risk borrowers. Prediction 1 summarizes the liftoff channel, which is consistent with our empirical work.[15]

PREDICTION 1. *If we observe that liftoff is associated with a reduction in the average funding costs of P2P borrowers, then the spread between high and low credit risk borrowers should decline.*

Given the importance of investor propensity to supply of funds, the availability of high-frequency flow-of-funds information allows us to further discriminate between supply and demand effects. An observed reduction in interest rates on Prosper loans may be driven by supply or demand factors. First, we would expect a reduction in perceived default probabilities on P2P loans to be associated with higher loan attractiveness, leading to an increase in the supply of funds, as measured by a decrease in the funding gap (the aggregate amount that has been demanded, but not yet supplied), and an increase in the funding speed and the funding success. As Prosper learns about such a lasting change in market conditions, it reduces the interest rates on individual loans to attract more borrowers and, therefore, match the supply increase. Second, an observed reduction in interest rates on Prosper loans is also consistent with a lasting reduction in demand, where Prosper responds to a demand reduction

[15]The conditional statement in prediction 1 describes a necessary and sufficient condition under the plausible assumption that the risk-free rate channel dominates the credit risk channel for borrowers in the lowest credit risk categories. To see this, recall that a perceived reduction of credit risk has a stronger effect for the high credit risk market segment (recall figure 2 and online appendix B). As a result, the average funding cost of P2P borrowers can only decline if there is a sufficiently high reduction of credit risk for high credit risk borrowers that outweighs the risk-free rate channel, which crystallizes in the reduction of the spread.

by reducing rates. Prediction 2 follows and our empirical analysis validates the liftoff signaling channel described previously.

PREDICTION 2. *(a) If we observe that liftoff is associated with a reduction in the funding costs of P2P borrowers, but not with a reduction in demand, then we should see a decrease in the funding gap, and an increase of the funding speed and success probability. (b) If we see a reduction in the spread between high and low credit risk borrowers, then the change in supply should be largest for high credit risk borrowers.*

3. Data and Descriptive Statistics

Our primary data set comprises loan-hour observations from the Prosper P2P lending platform.[16] We collected hourly observations of loan funding progress and loan-borrower characteristics from Prosper's website between November 20, 2015 and January 20, 2016 using web scraping.[17] In total, our sample covers 326,044 loan-hour observations.[18] Among the 4,257 loan listings in the data set, 3,015 loans can be identified as having successfully originated using the 70 percent funding rule.[19] Loan listings occur continuously around

[16] To provide external validity, we use data from LendingClub.com, another P2P lending platform. This secondary data set comprises loan-level origination data from the U.S. P2P lending platform LendingClub.com starting from December 2014, which we obtained from the public SEC records. The LendingClub.com and Prosper.com platforms both specialize in uncollateralized consumer credit and target a very similar slice of the market. As a result, the descriptive statistics for our secondary data set are similar, with an average loan size of $15,775.86, an average interest rate of 12.92 percent, and an average debt-to-income (DTI) ratio of 19.85 percent.

[17] We use scraping to obtain hourly microdata about loans posted on Prosper.com. Specifically, we collected all information posted publicly about Prosper loans—including their funding and verification statuses—using custom Bash and Python scripts.

[18] Our sample starts from November 20, 2015 and is updated hourly until the current date. Initially, we used a sample of 640,000 loan-hour observations, which overlaps with two FOMC meetings: December 15–16, 2015 and January 27–28, 2016. We decided to drop the data after January 20, 2016—about one week before the January meeting—to avoid picking up interest rate changes related to the January FOMC meeting. The complete sample of 640,000 loan-hour observations is, however, used for a placebo test.

[19] Recall that, according to the Prosper documentation, a loan is originated when reaching a funding status of at least 70 percent. However, the funding

the clock. The loan terms are fixed by Prosper and posted online once the funding phase starts. The verification status of a loan does occasionally improve as more documents are verified by Prosper.

The data set contains loan information, such as size, purpose, interest rate, maturity, and monthly payment; and borrower information, including employment status, income bracket, debt-to-income ratio, and a credit score issued by Prosper. Panel A of table 1 gives summary statistics for the full sample of borrowers with loans posted. The loan size varies from \$2,000 to \$35,000, but has an (unweighted) sample average of \$13,100. The majority of loans have a three-year maturity. Loan purpose categories include business, consumption (e.g., auto, boat, vacation, etc.), debt consolidation, special loans (e.g., baby and adoption, medical, etc.), and others. More than 75 percent of the listings are in the debt consolidation category. The average interest rate, without taking into account the loan-borrower characteristics, is 14.22 percent. Figure 3 shows two histogram plots of the interest rates, divided into pre- and post-liftoff subsamples. After liftoff, the interest rate distribution appears more skewed to the left. This is consistent with the direct observation from descriptive statistics that the average interest rate drops from 14.29 percent to 14.15 percent after liftoff.

Prosper provides rich information about borrowers on its website, including a credit rating that is mostly based on the borrower's Fair Isaac Corporation (FICO) score and credit history. Prosper assigns one of seven credit ratings to each borrower: AA, A, B, C, D, E, and HR, which are monotonically increasing in the perceived credit risk.[20] For our analysis, we later group credit ratings into three bins: high ratings (AA and A), middle ratings (B and C), and low ratings (lower than C). This classification helps us to divide the borrowers into three groups of similar sizes. The employment status is another important variable in assessing the borrower's default

phase continues if the funding status reaches the 70 percent level before the end of the listing period.

[20]While it was possible to translate Prosper's credit ratings from the FICO scores (Butler, Cornaggia, and Gurun 2017), we expect that Prosper now uses additional information to assign credit ratings, such as behavioral user data, the user's history on the platform, and social media data.

Table 1. Descriptive Statistics

Panel A: Full Sample

	Mean	**SD**	**Min.**	**Max.**	**Obs.**		**Obs.**	**Pct.**		**Obs.**	**Pct.**
Size	13.10	7.13	2.00	35.00	4,257	Business	93	2.18	\$1–24,999	175	4.11
Int. Rate	14.22	6.46	4.32	30.25	4,257	Cons.	415	9.75	\$25,000–49,999	1,682	39.51
DTI	27.32	12.33	1	68	4,257	Debt	3,222	75.69	\$50,000–74,999	1,213	28.49
Maturity	3.77	0.97	3	5	4,257	Other	344	8.08	\$75,000–99,999	601	14.12
Verif.	2.30	0.76	1	3	4,257	Special	183	4.30	\$100,000+	586	13.77
Δfunding	0.95	3.91	0	99	322,600	Total	4,257	100	Total	4,257	100

Panel B1: Sample before the Liftoff

	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Size	13.05	7.25	2.00	35.00	2,029
Int. Rate	14.29	6.46	4.32	30.25	2,029
DTI	27.10	12.24	1	63	2,029
Maturity	3.85	0.99	3	5	2,029
Verif.	2.30	0.76	1	3	2,029

Panel B2: Sample after the Liftoff

	Mean	**SD**	**Min.**	**Max.**	**Obs.**
Size	13.14	7.01	2.00	35.00	2,228
Int. Rate	14.15	6.46	4.32	30.25	2,228
DTI	27.52	12.41	1	68	2,228
Maturity	3.69	0.95	3	5	2,228
Verif.	2.30	0.76	1	3	2,228

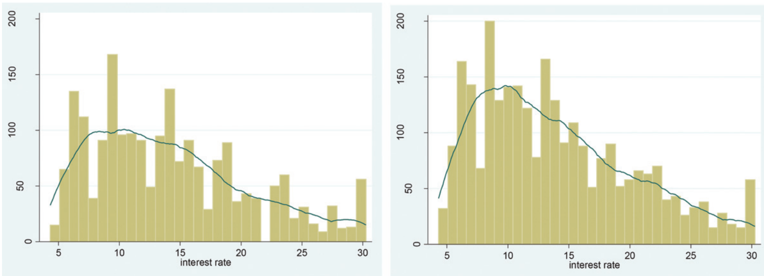
(*continued*)

Table 1. (Continued)

Panel C1: ES = Employed						**Panel D1: CR = High**					
	Mean	**SD**	**Min.**	**Max.**	**Obs.**		**Mean**	**SD**	**Min.**	**Max.**	**Obs.**
Size	13.80	7.43	2.00	35.00	3,166	Size	13.28	6.44	2.00	35.00	1,198
Int. Rate	13.66	6.35	4.32	30.25	3,166	Int. Rate	7.28	1.37	4.32	9.43	1,198
DTI	27.35	12.05	1	68	3,166	DTI	24.84	10.21	1	62	1,198
Maturity	3.77	0.97	3	5	3,166	Maturity	3.80	0.98	3	5	1,198
CreditBin	0.95	0.76	0	2	3,166						
Panel C2: ES = Self-Employed						**Panel D2: CR = Middle**					
	Mean	**SD**	**Min.**	**Max.**	**Obs.**		**Mean**	**SD**	**Min.**	**Max.**	**Obs.**
Size	10.59	3.66	2.00	15.00	520	Size	14.38	7.84	2.00	35.00	1,825
Int. Rate	17.42	6.40	5.76	30.25	520	Int. Rate	13.06	2.21	9.49	16.97	1,825
DTI	23.60	12.12	1	63	520	DTI	27.87	12.52	1	66	1,825
Maturity	3.74	0.97	3	5	520	Maturity	3.79	0.98	3	5	1,825
CreditBin	1.34	0.66	0	2	520						
Panel C3: ES = Unemployed						**Panel D3: CR = Low**					
	Mean	**SD**	**Min.**	**Max.**	**Obs.**		**Mean**	**SD**	**Min.**	**Max.**	**Obs.**
Size	11.49	7.07	2.00	35.00	571	Size	11.02	6.11	2.00	30.00	1,234
Int. Rate	14.37	6.27	4.32	30.25	571	Int. Rate	22.65	3.90	17.61	30.25	1,234
DTI	30.54	13.12	1	63	571	DTI	28.90	13.53	2	68	1,234
Maturity	3.75	0.97	3	5	571	Maturity	3.69	0.95	3	5	1,234
CreditBin	1.04	0.73	0	2	571						

Notes: The sample includes all loan listings on Prosper.com over the period between November 20, 2015 and January 20, 2016. The loan size is measured in thousands of dollars. The interest rates are quoted in percentage points. DTI is the monthly debt-service-to-income cost. ES is the employment status. CR is short for the borrower credit rating. CreditBin takes on the value 0 if CR = Low, 1 if CR = Middle, and 2 if CR = High. Verif. denotes the verification stage. It takes on a discrete value from 1 to 3, where 3 indicates that most of the documents have been verified by Prosper. Δfunding is the hourly percentage change in the funding status. Cons. Denotes the purpose consumption.

Figure 3. Histogram of Loan Interest Rates



Note: Histogram of interest rates for loans in our observed period, before (left panel) and after (right panel) Fed liftoff on December 16, 2015.

risk, which contains three categories: employed, self-employed, and unemployed.[21]

We track all observed loans with an hourly frequency by scraping Prosper's website to update the sample. The major advantage of an hourly data set is that we see funding status changes over time. This provides an up-to-date snapshot of the P2P lending market, which is potentially reacting to the monetary policy announcement. Furthermore, this data set enables us to construct an hourly measure of fund inflows to different loans and determine the size of aggregate demand at any hour in our sample. The loan-hour observations are used to calculate the funding gap, defined as the gap between cumulative inflow of funds and the loan amount target, for each listing, borrower group, and the whole market. The funding gap is an essential variable for understanding Prosper's interest rate setting problem and interest rate dynamics as discussed in section 2.3.

4. Results

Section 4.1 presents our main findings on interest rates and spreads for the P2P lending market after Fed liftoff. These results speak to prediction 1. Section 4.2 suggests a mechanism for the interest rate

[21] A few employed borrowers indicate their employment status as "full-time." The last category is reported as "other" in Prosper, but we interpret it as unemployed.

and spread results by exploring measures of supply, demand, and the funding gap in the P2P market. The analysis of supply and demand speaks to prediction 2. Finally, section 4.3 provides external validity and corroborates the employment outlook as a channel driving the investor-perceived reduction in default probabilities after liftoff.

4.1 Interest Rates and the Credit Spread

We analyze interest rates of loans listed within ±3-day, ±7-day, and ±14-day windows around December 16, 2015, the date of Fed liftoff. Our longest window—hereafter, "LONG" —spans the entirety of our main sample for Prosper, which runs from November 20, 2015 to January 20, 2016. Note that this window starts with the first day of data collection and ends one week prior to the first 2016 FOMC meeting.

The baseline model regresses the interest rate of loans posted around the Fed's liftoff decision and a large number of observed loan-borrower characteristics. Table 2 summarizes the results for our sample with various window sizes. We use the following specification:

$$\begin{aligned} \text{InterestRate}_{i,t} &= \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t + \gamma_1 \text{LoanCharacteristics}_i \\ &\quad + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}, \end{aligned} \tag{1}$$

where α captures the constant term, while α_h and α_d control for hour-of-day and day-of week effects, respectively.[22] The inclusion of loan-borrower controls and fixed effects ensures we compare interest rates of loans with similar characteristics before and after liftoff. Liftoff_t is an indicator that takes on a value of 1 if the loan i is posted at a time t, which is after the Fed liftoff announcement. The estimated value of β_1 is between -0.169 and -0.229 and is highly significant at multiple time windows. Hence, the average interest rate for loans drops by 16.9–22.9 bps post-liftoff, after controlling for all loan and borrower characteristics. When narrowing the event

[22]Platforms tend to post loans in groups throughout the day. Additionally, investor visits to the platforms are likely to be clustered around certain hours of the day and certain days of the week. Controlling for hour-of-day and day-of-week effects captures recurring variation in borrower and lender density on the platform. Since such changes are predictable, it is possible that the platforms could adjust interest rates accordingly. We do not, however, find large effects from the inclusion of such fixed effects.

Table 2. Baseline Regressions

	Dependent Variable: Interest Rate			
	(1)	**(2)**	**(3)**	**(4)**
Explanatory Variables				
Liftoff	-0.195^{*}	-0.229^{***}	-0.173^{***}	-0.169^{***}
	(−1.74)	(−3.10)	(−3.17)	(−4.36)
Additional Controls	√	√	√	√
Controls				
Loan Characteristics	√	√	√	√
Borrower Characteristics	√	√	√	√
Main Effects				
Weekday FE		√	√	√
Hour FE	√	√	√	√
Window Size	±3d	±7d	±14d	LONG
Adj. R^2	0.971	0.972	0.972	0.970
Observations	445	987	1,818	4,257

Notes: The dependent variable is the interest rate, in percentage points, posted on Prosper. The variable Lifoff_t is a dummy that equals 1 after the liftoff announcement on December 16, 2015. The borrower characteristics controls include debt-to-income ratio, income group, prosper credit rating, and employment status. The loan characteristics include the loan size, maturity, purpose, and verification stage. We also include weekday fixed effects, hour-of-the-day fixed effects, and additional covariates, such as cross-products of loan-borrower characteristics and the liftoff dummy, to validate the robustness of our findings. We run the regression for different window sizes (±3-day, ±7-day, ±14-day, LONG), including in the main sample over the period November 20, 2015 to January 20, 2016. We drop the weekday dummies in the ±3-day regression because of multicollinearity. t statistics are shown in parentheses. The results are robust to standard error clustering at time or borrower location. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

window to ±3 days around liftoff, we still observe a drop in average interest rates of a similar magnitude, as shown in column 1.[23]

Selection effects are an important concern. Unlike Jiménez et al. (2012), we cannot use lender-borrower fixed effects, since we cannot observe and track the identity of individual investors on the platform. For the same reason, we cannot employ time-lender fixed effects. Moreover, we are also unable to employ time-borrower fixed effects, since individual borrowers are not applying for multiple

[23] We have to drop weekday fixed effects in the ±3 days regression, due to the multicollinearity between the weekday dummies and the liftoff variable.

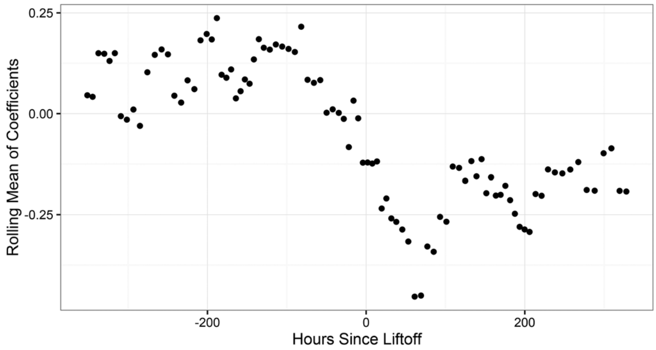
loans. To rule out the possibility that the regression results are mainly driven by the econometric model's (mis-)specification, we run two additional estimations to check the validity of the interest rate reduction result. The first robustness check expands the baseline regression by including the cross products of various loan-borrower characteristics (DTI, maturity, verification, etc.) and the liftoff dummy as regressors. The interest rate reduction survives this test, as documented in table A.11 of the online appendix. In the second robustness check, we regress the interest rate on all combinations of loan-borrower characteristics and the liftoff dummy. After obtaining the coefficients on liftoff, we run a sample mean test of the coefficient differences for the groups sharing similar loan-borrower characteristics before and after liftoff. The t-statistics suggest that the interest rate is lower after liftoff and the difference is significantly negative. The estimation results are available in table A.3 of the online appendix. We conclude that changes in borrower composition or substitution into shorter maturity loans are not driving our main results.

Both visual inspection and placebo tests suggest that the change in P2P lending rates happened precisely at liftoff.[24] In figure 4, we first recover the residuals from a regression of the interest rate on all loan-borrower information. We then compute the mean of the residuals for all loans posted in the same hour and plot the three-cohort rolling mean over time. We observe a clear drop in the average level of interest rates after the liftoff, controlling for all observable loan-borrower characteristics.[25]

[24]Notably, there is both a small increase in the rate prior to liftoff and a small decrease after that, but prior to liftoff. It is possible that these small movements could have been generated by other announcements or movements in the expected probability of liftoff, which we address in a simulation exercise.

[25]While Prosper and LendingClub occasionally announce rate changes, this communication is primarily directed at investors and is voluntary for Prosper. Additionally, these announcements may be accompanied by reallocations of borrowers across internal credit rating bins. For this reason, the meaning of interest rate change announcements is unclear. LendingClub, for instance, announced a rate increase in late December, while Prosper made no such announcement. In the data, however, the net effect of all changes appears to be a decline in average rates and spreads for borrowers with similar characteristics on both platforms. We also observe unannounced shifts in rates associated with credit bins in the data, which reinforces this point.

Figure 4. Time Trend in the Interest Rate After Controlling for Loan and Borrower Composition

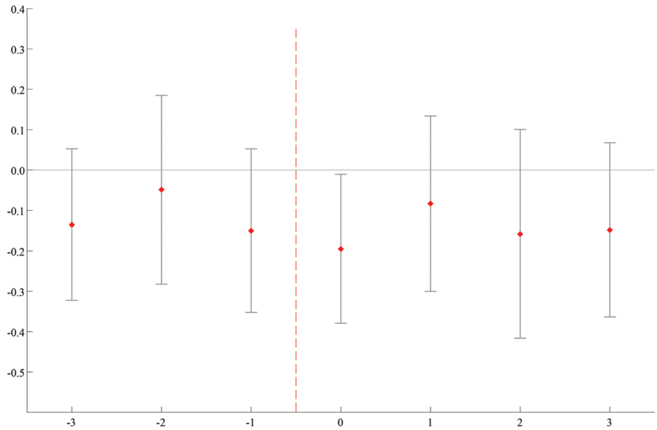


Notes: We recover the trend by performing a regression of the interest rate on all loan-borrower controls and computing the means of the residuals for all loans posted in the same hour. Finally, we plot the three-cohort rolling mean of the cohort-specific means over a ± 14-day window around liftoff.

In a separate exercise, we run a placebo test that conducts a rolling regression of the interest rate with loan-borrower characteristic controls and the narrowest window of ± 3 days. Within the window, we define a pseudo-liftoff variable $D(\tau)_t$ to replace Liftoff_t from equation (1). The variable $D(\tau)_t$ is a dummy whenever t is in the second half of the time window, where $\tau = -3, \cdots, 3$ refers to the number of days since the liftoff date. Figure 5 illustrates that only the time dummy coinciding with the liftoff dummy is significantly different from zero. This suggests that our results are unlikely to be driven by pre-existing trends or other news events unrelated to liftoff.

The estimated coefficients in regression (1) also confirm the presence of the usual channels for default risk in Prosper data. The coefficients on credit risk and unemployment, reflected in Prosper credit scores, are positive, indicating that the interest rate is higher for borrowers with higher perceived credit risk. Detailed estimation results are provided in table A.4 of the online appendix. Since our panel data contain loan listings with various characteristics, we estimate the model on data in different categories that are defined using the borrower's employment status and credit score. The equation we estimate is still the baseline regression, but we divide the data into

Figure 5. Pseudo-Liftoff Rolling Regression



Note: Point estimates and 90 percent confidence interval of the pseudo-liftoff coefficient estimates from a rolling regression of the interest rate with loan characteristics controls over a ±3-day window.

subsample categories. We find a statistically significant interest rate reduction of approximately 40 bps for borrowers with lower Prosper credit ratings (lower than A). The interest rate reduction is significant for both employed and unemployed borrowers, but the drop is 6 bps larger for unemployed borrowers.

To further establish robustness, we also expand the sample to include observations until February 26, 2016, a few days before the March FOMC meeting. We run a regression to measure the impact of the January 27, 2016 FOMC decision to keep the federal funds rate range at 0–25 bps on Prosper loan interest rates. The results are reported in table A.5 of the online appendix. We find that the January announcement did not have a statistically significant impact on the P2P lending rate. This suggests that the reduction in interest rates at liftoff cannot plausibly be attributed to a placebo effect, since no such effect is present at the January 27 meeting, where there was neither strong Fed signaling nor an unexpected adjustment in interest rates. In a further expansion of the sample to the end of March 2017, we extend the baseline interest rate regression to include two more FOMC decisions to increase the policy rate.[26] After

[26]These decisions are announced on December 14, 2016 and March 15, 2017.

identifying the press conference time in the scraped data, we reestimate the regression to evaluate the average interest rate changes in the platform around these rate hikes. Table A.6 of the online appendix shows that these two policy rate hikes did not lead to significant interest rate changes on the Prosper platform in short time windows. In the longest time window we consider, the later policy rate increase event generates a rate increase on the Prosper platform. This confirms that the strong reduction in perceived credit risk in the uncollateralized consumer credit market was unique to liftoff, which supports the important role played by the signaling channel at liftoff.

Although Fed liftoff was partially anticipated by the market (see section 2.1), the difference in the pre-announcement trend for different segments of the P2P lending market was negligible, especially close to the FOMC's policy meeting. We next narrow in on a window of ± 7 days around the announcement date to pin down the effect on the credit spread between less risky and risky borrowers. We divide the loan listing observations into three groups: employed borrowers with high credit ratings (AA and A), unemployed borrowers with middle or low credit ratings (not AA or A), and others. We focus on the first two groups in the regression, using the unemployed and lower credit rating borrower groups as the benchmark to control for any shared trend before the liftoff decision. The sample size is reduced to 355 loan listings, of which one-third are from unemployed borrowers with a low credit rating.

$$\begin{aligned}\text{InterestRate}_{i,t} = {} & \alpha + \alpha_h + \alpha_d + \beta_0 1\{EMP, High\}_i \\ & + \beta_1 \text{Liftoff}_t + \beta_2 1\{EMP, High\}_i \times \text{Liftoff}_t \\ & + \gamma_1 \text{LoanCharacteristics}_i \\ & + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}. \end{aligned} \tag{2}$$

Table 3 reports the estimation results with different controls. Columns 1–4 show results with all possible controls at the loan level, three dummies corresponding to before-after group differences, and the cross-product of group and liftoff time periods. It appears that the interest rate spread before liftoff between the two borrower groups is around 960 bps, and the gap is reduced by 166 bps after liftoff. This indicates that the spread between the high credit risk

Table 3. Before/After Regressions on the Interest Rates for Different Groups

	Dependent Variable: Interest Rate			
	(1)	**(2)**	**(3)**	**(4)**
Explanatory Variables				
Liftoff	−1.810***	−1.884***	−1.891***	−1.934***
	(−2.81)	(−2.92)	(−2.87)	(−2.94)
$1\{EMP, High\}$	−10.360***	−10.376***	−9.605***	−9.629***
	(−21.52)	(−21.37)	(−17.61)	(−17.55)
$1\{EMP, High\} \times$ Liftoff	1.536**	1.654**	1.601**	1.658**
	(2.01)	(2.16)	(2.08)	(2.15)
Controls				
Loan Characteristics			√	√
Borrower Characteristics			√	√
Main Effects				
Weekday FE		√		√
Hour FE		√		√
Window Size	±7d	±7d	±7d	±7d
Pre-liftoff, Int. Rate Mean $1\{EMP, High\} = 0$	17.805	16.085	19.974	19.315
F-test (Liftoff, $1\{EMP, High\} \times$ Liftoff)	4.165	4.402	4.312	4.484
Adj. R^2	0.663	0.668	0.671	0.675
Observations	355	355	355	355

Notes: We focus on ±7-day windows centered around the liftoff date. The interest rate is regressed on the liftoff dummy, borrower riskiness (Employment and Credit Rating), and their interaction terms. Additional controls include loan characteristics, borrower characteristics, and time dummies. The empirical specification treats the borrower with high credit ratings and employment as the focus, and benchmarks their interest rate variation with unemployed borrowers who receive a low credit rating from Prosper. t statistics are shown in parentheses. We report the F-test statistics for the joint significance of "Liftoff" and "$1\{EMP, High\} \times$ Liftoff." Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

borrowers with the lower credit rating and the good borrowers drops by around 17 percent on average, after controlling for all observable loan-borrower characteristics and possible time trends. Our findings on the spread are also robust to the window size, but have lower significance when a window shorter than ± 7 days is used. Our findings are also robust to the choice of econometric specification and standard error clustering. Moreover, as we demonstrate in table A.7 of the online appendix, they also survive the inclusion of the variance risk premium (Bollerslev, Tauchen, and Zhou 2009) as a control for shifts in risk appetite over time.[27]

In a final robustness exercise, we perform a simulation to determine whether other macro news events surrounding liftoff could have plausibly explained the reduction in rates at liftoff. Since the inclusion of time dummies does not allow us to control for macroeconomic and financial events in the window around liftoff, we construct a non-overlapping sample that spans the period between January 2016 and December 2017. We use the loans in this sample to compute the average daily interest rate and then take the first difference. We then regress the first difference in the average rate on the forecast errors for all of the indicators that (i) had announcements in the liftoff window; and (ii) had a sufficient number of observations in the extended sample. This includes the surprise series for jobless claims, retail sales, core inflation, housing starts, the Federal Reserve Bank of Chicago national activity index, personal income, and the Federal Reserve Bank of Philadelphia manufacturing index. Cumulating the surprises over a seven-day window around liftoff, we find a change of –0.9 bps, which is considerably smaller in magnitude than the –22.9 bps we measure at liftoff. We conclude from this that it is unlikely that news announcements surrounding liftoff could credibly explain the observed shift in online lending rates.

To conclude, we find robust evidence that the Fed liftoff announcement was associated with a sharp drop in the average interest rate of around 16.9–22.9 bps. Moreover, the spread between high and low credit risk groups experienced a relatively large drop of around 17 percent after liftoff. The decrease in the average interest rate is economically significant, and the magnitude of the observed

[27]See the online appendix for more details about the variance risk premium's construction.

166 bps reduction in the spread between high and low credit risk borrows after liftoff compares to approximately one-third of the effect of moving up from Prosper rating category D to C or an improvement in FICO score from 679 to 690. Our empirical findings confirm prediction 1, which suggests that the spread between high- and low-risk borrowers should decrease if the risk-free rate channel is outweighed by the credit risk channel, as suggested by the reduction in P2P lending rates after liftoff. While it is perhaps counterintuitive at first glance that the increase of the risk-free reference rate is associated with a reduction in interest rates, especially for borrowers with low credit ratings and no stable labor income, we will argue in the remainder of the paper that a reduction in perceived default probabilities, induced by positive Fed signaling, is the most plausible explanation for these findings. That is, the positive liftoff signaling dominates the credit risk channel, especially for riskier market segments.

We proceed by linking our main results to supply-side factors in section 4.2. Thereafter, section 4.3 provides evidence for external validity and discusses the employment outlook as a key driver of perceived default risk.

4.2 Supply and Demand Analysis

In addition to our main data set, we also obtained hourly updates of loan funding progress for each listing. The granular data allows us to construct measures of supply that can be used to gain a better understanding of the channels described in section 2.3 by testing predictions 2a and 2b. The loan funding progress is of key interest in this section and we use a loan-level indicator variable for loans being funded. Moreover, the additional measures of funding increase and funding speed are at the funding increment level, which is even more granular. To isolate the liftoff channel, we examine how liftoff affects the funding gap and find that it drops significantly. We also show that the funding gap reduction appears to be driven by an increase in supply, rather than a demand reduction. Our supply measures—funding speed and funding success—both increase, especially for high credit risk borrowers, validating predictions 2a and 2b. Taken together, the results support the mechanism for the post-liftoff reduction in average interest rates, discussed in section 4.1.

The funding gap, defined as the size of the unfunded portion of the loan at each time t for loan listing i, provides a natural metric for the P2P platform when choosing individual interest rates to maximize the origination volume. We can aggregate the funding gap for the whole sample and also for different categories (e.g., according to credit ratings and/or employment status). This allows us to distinguish between different market segments.

Demand and supply in the lending market are endogenous to the interest rate decision in equilibrium, making it difficult to identify the driving forces behind observed interest rate changes after liftoff. However, the funding gap, which is defined as

$$\begin{aligned}\text{FundingGap} = {} & \text{RequestedLoanAmount} \\ & - \text{FundedLoanAmount},\end{aligned} \tag{3}$$

is a key variable in the P2P platform's profit maximization problem. Specifically, the platform maximizes the origination volume by assuring that the funding gap remains narrow, especially after lasting changes in supply and demand conditions.

The first two columns in table 4 show the corresponding regressions for the effect of liftoff on the funding gap measure. We first study the impact of liftoff on the aggregate funding gap over time with the following regression:

$$\begin{aligned}\text{FundingGap}_t = {} & \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t \\ & + \gamma \text{LoanBorrowerCharacteristics}_t + \epsilon_t.\end{aligned} \tag{4}$$

Columns 1 and 2 in table 4 present results for the aggregate funding gap over time. Consistent with prediction 2a, we find that it is reduced after liftoff, dropping significantly by around \$400,000. This result is robust to inclusion of intraday and intraweek fixed effects, as well as average loan and borrower characteristics, including the size of the loan itself. Speaking to prediction 2b, we explore the funding gap in different market segments classified by credit riskiness, we run the regression of the funding gap in market segment j:

$$\begin{aligned}\text{FundingGap}_{j,t} = {} & \alpha + \alpha_h + \alpha_d + \beta_0 1\{EMP, High\}_j + \beta_1 \text{Liftoff}_t \\ & + \beta_2 1\{EMP, High\}_j \times \text{Liftoff}_t + \epsilon_{j,t}.\end{aligned} \tag{5}$$

Table 4. Before/After Regressions for the Aggregate Funding Gaps and Demand

Dependent Variable	(1) Funding Gap	(2) Funding Gap	(3) Demand	(4) Demand
Explanatory Variables				
Liftoff	−0.474***	−0.383***	0.031***	0.017**
	(−23.12)	(−10.84)	(5.81)	(2.23)
Controls				
Loan Characteristics		√		√
Borrower Characteristics		√		√
Main Effects				
Weekday FE		√		√
Hour FE		√		√
Window Size	LONG	LONG	LONG	LONG
Adj. R^2	0.113	0.555	0.023	0.397
Observations	1,403	1,403	1,403	1,403

Notes: We focus on the LONG window size, using the main sample over the period November 20, 2015 to January 20, 2016. We regress funding gaps and demand (in millions of USD) on liftoff, and intraday and intraweek dummies. We include all borrower types in the aggregation. Additional controls include sample average loan characteristics and average borrower characteristics. t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5 shows the results. In columns 1 and 2 we use a ±7-day window, centered around the liftoff announcement, to study the dynamics of the funding gap in two distinct groups: employed borrowers with high credit ratings and unemployed borrowers with low credit ratings. We find that the funding gap is higher for employed borrowers with high credit ratings. Furthermore, it increases after the liftoff decision by $57,000 (summing up β_1 and β_2 in column 2). Taken together, this differential impact of the liftoff on the funding gap for different borrower groups also reinforces our second main finding in section 4.1 on the spread reduction between low and high credit rating borrowers. This is because a lasting reduction in the funding gap for low credit rating borrowers is associated with downward pressure on the interest rates of these borrowers.

We next test whether the funding gap reduction was driven by an increase in supply or a decrease in demand. We investigate aggregate new demand in different market segments of the P2P lending

Table 5. Before/After Regressions for the Funding Gaps and Demand of Different Groups

	(1)	(2)	(3)	(4)
Dependent Variable	**Funding Gap**	**Funding Gap**	**Demand**	**Demand**
Explanatory Variables				
Liftoff	-0.047^{***}	-0.044^{***}	0.005^{*}	0.006^{**}
	(−7.99)	(−9.81)	(1.70)	(2.01)
$1\{EMP, High\}$	0.181^{***}	0.181^{***}	0.031^{***}	0.031^{***}
	(31.09)	(41.40)	(10.36)	(11.77)
$1\{EMP, High\} \times$ Liftoff	0.101^{***}	0.101^{***}	0.030^{***}	0.030^{***}
	(12.03)	(16.03)	(6.87)	(7.77)
Controls				
Main Effects				
Weekday FE		$\checkmark$		$\checkmark$
Hour FE		$\checkmark$		$\checkmark$
Window Size	±7d	±7d	±7d	±7d
Pre-liftoff, $\{UnEMP, Low\}$	0.232	0.184	0.028	0.007
F-test	72.683	130.616	14.312	18.484
Adj. R^2	0.828	0.903	0.463	0.583
Observations	650	650	650	650

Notes: We focus on the ±7-day windows centered around the liftoff date to study the aggregate funding gap and demand in different market segments. This table shows regressions of funding gaps and demand (in millions of USD) on liftoff, borrower-loan characteristics (Employment and Credit Rating), and intraday and intraweek dummies. The two borrower categories are defined as borrowers with high credit ratings and employment, versus unemployed borrowers with low credit ratings from Prosper. We report the F-test statistics for the joint significance of "Liftoff" and "$1\{EMP, High\}$ × Liftoff." t statistics are shown in parentheses. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

platform. A decrease in demand would suggest that the mechanism behind the reduction in the funding gap and reduction in interest rates is not identified. To the contrary, we find that demand increases slightly after liftoff, reinforcing our supply-driven hypothesis. The following regression uses aggregate new demand as the dependent variable:

$$\begin{aligned}\text{Demand}_t = \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t \\ + \gamma \text{LoanBorrowerCharacteristics}_t + \epsilon_t. \qquad (6)\end{aligned}$$

Columns 3 and 4 in table 4 show that new demand increases after liftoff for all groups by \$17,000. This provides strong evidence that the interest rate reduction results are not driven by a collapse of demand in the market.

To capture the demand shift in market segment j, we also employ the following regression:

$$\begin{aligned} \text{Demand}_{j,t} = \alpha + \alpha_h + \alpha_d + \beta_0 1\{EMP, High\}_j + \beta_1 \text{Liftoff}_t \\ + \beta_2 1\{EMP, High\}_j \times \text{Liftoff}_t + \epsilon_{j,t}. \end{aligned} \tag{7}$$

Hour-of-day and day-of-week fixed effects are included as α_h and α_d. In columns 3 and 4 in table 5, we separate the market into high and low credit risk segments using a ±7-day window around liftoff. We find that the increase is stronger for borrowers with high creditworthiness, which is consistent with the interest rate changes and funding gap dynamics in these segments.

Finally, we construct three separate measures of loan funding supply. A post-liftoff increase in these variables supports the hypothesis that the average interest rate reduction was driven by an increase in supply. Furthermore, taken together with the reduction in the interest rate spread, it also supports the hypothesis that perceived default probabilities fell, leading to a stronger inflow of funds.

We first test the supply increase hypothesis using the realized probability that a loan listing is funded $Pr(1\{LoanFunded\} = 1)$ as a measure of supply. The logit regression for a loan posted at time t is

$$\begin{aligned} 1\{LoanFunded\}_i = \alpha + \alpha_h + \alpha_d + \beta_1 \text{Liftoff}_t \\ + \gamma_1 \text{LoanCharacteristics}_i \\ + \gamma_2 \text{BorrowerCharacteristics}_i + \epsilon_{i,t}. \end{aligned} \tag{8}$$

We also use other measures of supply to study whether the funding gap changed, such as

$$\text{Funding Increase}_{i,t} = \Delta(\text{Funding Percentage})_{i,t} \tag{9}$$

for each loan posting at time t. A loan is more likely to be funded after liftoff (reaching at least 70 percent of the total funding target) if the increase is large. With this approach, we can exploit variation

Table 6. Before/After Regressions for the Funding Success Measures

Dependent Variable	(1) $\mathbf{1}\{LoanFunded\}$	(2) Funding Increase	(3) Funding Speed
Explanatory Variables			
Liftoff	0.238**	0.137***	0.028**
	(2.39)	(11.23)	(1.98)
Controls			
Loan Characteristics	√	√	√
Borrower Characteristics	√	√	√
Main Effects			
Weekday FE	√	√	√
Hour FE	√	√	√
Window Size	LONG	LONG	LONG
R^2	0.094	0.098	0.015
Observations	2,858	237,296	237,296

Notes: We focus on the LONG window size, using the main sample over the period November 20, 2015 to January 20, 2016 and the loan listings where we observe the whole funding process. Funding success is regressed on a liftoff dummy, loan-borrower characteristics (as in previous regressions), and intraday and intraweek dummies. The funding success variable is measured as the probability of getting funded, the funding increase, and the funding speed. t statistics are shown in parentheses. Results are from OLS regressions, except for a logit regression with the funding probability $1\{LoanFunded\}$. The variables Funding Increase and Funding Speed are in percentage (%). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in the loan-time observations. Similarly, we replace the dependent variable in equation (5) with the funding speed increase:

$$\text{Funding Speed}_{i,t} = \Delta(\text{Funding Increase})_{i,t}, \tag{10}$$

to calculate the speed of reaching the funding target. We select loans posted on the Prosper website from November 20, 2015 to January 5, 2016, such that we observe the whole funding process of the loan listings.

The estimation results are reported in table 6. In column 1, the logistic regression for funding probability yields a coefficient estimate of 0.24, which translates into an odds ratio of 1.27 or a 5.37 percent increase in the funding probability after liftoff. Moreover, this result is statistically significant. The second column shows that the funding increase is larger after liftoff by 0.14 percentage point.

The last regression, which uses funding speed as the dependent variable, indicates that liftoff increased the rate of funding progress by 0.03 percentage point over time.

Taken together, the results are in line with predictions 2a and 2b. Moreover, the supply results, coupled with the average interest rate and spread reductions, suggest that liftoff may have been associated with a reduction in the perceived probability of default. Section 4.3 demonstrates this further by showing that improvements in the expected future state of the economy, as measured by changes in the real yield curve, are associated with a reduction in interest rates in the P2P market. Finally, we discuss how unemployment at the state level affects the rates that borrowers receive, even when we control for employment status at the individual level, and link it to the credit risk channel.

4.3 External Validity

This paper emphasizes the role that Fed liftoff played as a strong, positive signal about future macroeconomic conditions. In the P2P segment of the online credit market, it translated into a lower perceived default probability and, thus, a lower interest rate. In this section, we provide evidence for the external validity of these findings over time and across markets. Moreover, we discuss the employment outlook as an explanation for the investor-perceived reduction in default probabilities after the signaling effect of liftoff.

First, we generalize the link between improvements in the expected economic outlook and our key findings on the interest rate and credit spread. If the improvement of future economic conditions affects the P2P lending rate, then changes in the slope of the real yield curve, a proxy for measuring future economic development used in the literature (Harvey 1988, Estrella and Hardouvelis 1991), should induce interest rate adjustments in the market we study. In table A.8 of the online appendix, we regress the interest rates observed in the Prosper market on the slope, defined as the difference between the five-year TIPS yield and the one-month real interest rate.[28] An increase in the real slope is usually associated

[28]The construction of the real interest rate and the data sources are explained in the online appendix.

with an improvement in fundamental economic conditions. We find that interest rates for high credit risk borrowers decrease by 2.03 percent for every percentage-point increase in the real slope variable $\text{Slope}_t^{(5)}$. We also see that the credit spread between borrowers with low credit rating and borrowers with high credit rating is reduced by 21.5 percent for every percentage-point increase in the real slope.

The effect of the real yield-curve slope on P2P lending rates is large and statistically significant. Replacing the 5-year real slope with the 10-year real slope yields does not change the direction and does not substantially change the magnitude. Furthermore, if we include the real slope as an explanatory variable, the impact of liftoff becomes less significant. This suggests that the information revealed by liftoff is similar to the information embodied by real yield-curve slope adjustments, which provides further support for the claim that liftoff was interpreted as a positive signal about future economic conditions.

Second, we validate our key findings by studying LendingClub, another major P2P lending platform in the United States. We obtain daily loan origination reports of LendingClub to the U.S. Securities and Exchange Commission for the same sample period from November 20, 2015 to January 20, 2016. The reports provide interest rates and loan-borrower information variables for all loan postings that have been successfully originated on the LendingClub platform. Unfortunately, the reports do not contain information about loans that have not been funded and cannot be used to construct intraday measures of demand and supply in the market. We explore the interest rate data for originated loans and report the regression results for the liftoff dummy and different interest dynamics for high- versus low-risk borrowers in table A.9 of the online appendix. We find that the average interest rate drops and the credit spread narrows after liftoff. This result confirms our findings from the Prosper data set and suggests that the monetary policy signaling associated with the Fed liftoff decision also affected other lending markets where many borrowers exhibit risky characteristics.

Finally, an additional result strengthens the hypothesis that liftoff reduced the perceived default probabilities of P2P borrowers. Borrowers in states with higher unemployment rates received higher interest rates, even after controlling for borrower and loan characteristics, including their own employment status. The additional finding, which is reported in online appendix section A.3, suggests that a channel exists in the P2P market for macroeconomic factors to affect perceived default probabilities and, therefore, individual loan interest rates. More specifically, we argue that liftoff cannot be reduced to an increase in the risk-free rate, since it was paired with a signal about the economic outlook, which had implications for perceived default probabilities. This resonates with the view that monetary policy is reacting to changes in macroeconomic conditions (e.g., Rigobon and Sack 2003) and with the extensive literature on the signaling role of central bank communication (e.g., Blinder et al. 2008).

5. Related Literature

Our paper relates to several different strands of literature. First, our work complements the existing empirical literatures on the bank lending channel and on event studies. We use primary market data and attempt to capture the impact of a rare monetary normalization event, which means that we cannot achieve identification using repeated observations of the same event category. In this sense, we are closer methodologically to the literature on the bank lending channel of monetary policy (Kashyap and Stein 2000),[29] but with the advantage that we observe loan outcomes at an hourly frequency instead of a monthly or quarterly frequency.

We employ panel data to study how a monetary normalization affects uncollateralized consumer credit with a focus on the cross-sectional dimension.[30] One way to establish identification, which has been employed in the literature on the bank lending channel, is to use a difference-in-differences (DID) specification (see, e.g., Heider, Saidi, and Schepens 2019). In our setting, we observe an exogenous shock that affects one group more than another, and where one of the main objects of interest is the difference in outcomes across group.

[29] See also Jiménez et al. (2012, 2014) and Di Maggio et al. (2017). For negative rates and unconventional monetary policy, see Heider, Saidi, and Schepens (2019) on bank lending and Mamatzakis and Bermpei (2016) on bank profitability.

[30] There exist only a few works on monetary policy interest rate pass-through to consumer credit. See Ludvigson (1998) for monetary policy transmission and automobile credit and Agarwal et al. (2018) for a recent study on credit cards.

While we use fixed effects to estimate the impact of liftoff on different groups, this can be interpreted as a double difference: one over time and one across groups. Our cross-sectional regressions reveal the different impact of liftoff on borrowers with heterogenous characteristics. Taking differences across borrower groups cancels out the effect of the liftoff event on risk-free rates and term premiums. What remains is the differential effect on perceived default probabilities. Since high-rated borrowers have very low default probabilities, a positive signal about solvency cannot reduce their interest rates substantially. Thus, while our estimate captures the lower bound of the magnitude of the effect, it is likely to be close to the actual treatment effect on the high credit risk segment.

This paper also relates to the extensive literature on monetary policy signaling with an interest in both the disclosure of monetary policy actions and revelation of information about macroeconomic variables (Andersson, Dillén, and Sellin 2006; Blinder et al. 2008). While the desired degree of transparency about the central bank's information on economic fundamentals has been intensely debated,[31] the literature suggests that the central bank information disclosure plays an important role in coordinating market expectations and provides relevant macroeconomic information to market participants (Swanson 2006; Ehrmann and Fratzscher 2007; Campbell et al. 2012; Boyarchenko, Haddad, and Plosser 2016; Ehrmann, Eijffinger, and Fratzscher 2016; Schmitt-Grohé and Uribe 2017).[32] Relatedly, Faust and Wright (2009) document the Fed's good nowcasting performance. Moreover, in line with our findings on the P2P lending market, perceived probabilities of default play an important role (e.g., in the context of bank lending policies (Rodano, Serrano-Velarde, and Tarantino 2018), and employment risk appears to be a key contributing factor (e.g., as a predictor of mortgage defaults (Gerardi et al. 2015).

Our work focuses on the distributional impact of the monetary normalization process within online credit markets. Specifically, we examine heterogeneity in the response to liftoff across

[31] See, e.g., Morris and Shin (2002), Angeletos and Pavan (2004), Hellwig (2005), Svensson (2006), and Cornand and Heinemann (2008).

[32] Furthermore, monetary policy action might also provide a signal about inflationary shocks to unaware market participants (Melosi 2016).

credit risk types. This is closely related to the growing literature on distributional effects of monetary policy.[33] In particular, the effects we measure capture something similar to the interest rate exposure channel described in Auclert (2019), but instead pick up the differential impact of monetary policy signaling, rather than policy rate shocks.

We also contribute to the growing literature on P2P lending and on consumer credit, more broadly.[34] P2P lending targets a slice of the consumer credit market—namely, high-risk and small-sized loans—that is neglected by traditional banks (De Roure, Pelizzon, and Tasca 2016). A number of papers employ the P2P market as a laboratory to study different aspects of lending, such as the role of informational frictions, using U.S. data from Prosper.com[35] and LendingClub.com, as well as from other platforms.[36] To our knowledge, the only other paper prior to ours that has attempted to link online lending markets to macroeconomic developments is Crowe and Ramcharan (2013), which studies the effect of home prices on borrowing conditions. More recent work by Chu and Deng (2019) and Huang, Li, and Wang (2019) find for the United States and for China that more accommodative monetary policy is associated with

[33]See Doepke and Schneider (2006) and Albanesi (2007) for the distributional impact of inflation on wealth, and Erosa and Ventura (2002) for the regressivity of inflation as a consumption tax. Gornemann, Kuester, and Nakajima (2012) evaluate the impact of monetary policy in an environment with heterogeneous agents.

[34]For a recent review of the literature on crowdfunding, see Belleflamme, Omrani, and Peitz (2015).

[35]Papers using Prosper.com data study the role of soft information, such as the appearance of borrowers (Pope and Sydnor 2011; Duarte, Siegel, and Young 2012; Ravina 2012; Gonzales and Loureiro 2014), screening of hard information in lending decisions (Iyer et al. 2015; Hildebrand, Puri, and Rocholl 2016; Faia and Paiella 2017; Balyuk 2018), herding of lenders (Zhang and Liu 2012), geography-based information frictions (Lin and Viswanathan 2016; Senney 2016), the auction pricing mechanism that existed prior to 2011 (Chen, Ghosh, and Lambert 2014; Wei and Lin 2016), and the ability of marginal borrowers to substitute between financing sources (Butler, Cornaggia, and Gurun 2017).

[36]Papers using data from LendingClub.com study adverse selection (Hertzberg, Liberman, and Paravisini 2018), retail investor risk aversion (Paravisini, Rappoport, and Ravina 2016), P2P as a substitute for bank lending (Tang 2019), and bank misconduct (Bertsch et al. 2020). Franks, Serrano-Velarde, and Sussman (2016) use auction data from FundingCircle.com to study information aggregatoin and liquidity.

an expansion of credit especially to riskier borrower segments, which the authors link to the risk-taking channel of monetary policy. Our paper complements this work by highlighting the signaling role in the context of a monetary policy normalization. In line with the key role of employment risk for our mechanism, Lam (2019) highlights the important role played by the loan applicants' employment length for lenders' funding decisions on LendingClub.com.

Finally, there is a large literature on household credit that spans a broad range of topics from mortgage debt to the different types of consumer credit (e.g., Bertola, Disney, and Grant 2006; Agarwal and Ambrose 2007). Nourished by increasing household indebtedness in many advanced economies over the last decade, the field has enjoyed increased attention (Guiso and Sodini 2013). Early papers studying the impact of FinTech on mortgage and consumer credit include Buchak et al. (2018), Fuster et al. (2018), and Berg et al. (2020). We differ from this work in that we study P2P markets; however, there are credit markets that have similar characteristics and are, therefore, closely related. For instance, credit cards are close substitutes for P2P personal loans. We expect access to new alternative sources of finance to be relevant for the spending behavior of consumers.

6. Conclusion

This paper contributes to the emerging literature on monetary normalizations by measuring the effect of Fed liftoff on the P2P segment of the uncollateralized online consumer credit market. We compile a unique panel data set of loan-hour observations from the online primary market for uncollateralized consumer credit. This allows us to monitor the funding process in real time, and to separately measure supply and demand. We find that liftoff reduced the spread between high and low credit risk borrowers by 17 percent and lowered the average interest rate by 16.9–22.9 bps. This change was not caused by Fed undershooting, a reduction in demand, a change in borrower composition, or a shift in risk appetite, but appears to be driven by a drop in investor-perceived default probabilities. We also use a separate data set to demonstrate that this effect generalizes to over 70 percent of the P2P market; and also show that these findings are not common to all FOMC announcements.

In addition to our interest rate results, we exploit a unique feature of our data set to demonstrate that (i) supply increased after liftoff; and (ii) demand did not fall. This is consistent with the narrative that liftoff revealed the Fed's strong, positive assessment of the future state of the economy. Borrowers in the P2P market are particularly sensitive to such assessments, since many of them have risky characteristics, including partial documentation and uncertain unemployment statuses. Indeed, we find that the net effect of the interest rate hike and FOMC signaling (i.e., proceeding with normalization) was small for highly rated borrowers, but was large and negative for borrowers with poor credit histories. This suggests that the effect we identify may be difficult to measure in other markets, such as the market for corporate or government debt, where default probabilities are less sensitive to signaling about future employment probabilities. Our findings are most easily generalizable to the uncollateralized consumer credit market.

Overall, our work complements the empirical event studies literature on monetary contractions, but is closer methodologically to work on the bank lending channel of monetary policy. We contribute to the literature by providing one of the first assessments of a critical stage in the monetary normalization process; and use a unique panel data set that allows us to monitor funding in real time and to disentangle supply and demand. Our results suggest that monetary normalizations may actually decrease interest rates for borrowers with poor credit histories by lowering their perceived default probabilities. This may, of course, depend on the content of the signals a central bank sends about its monetary normalization plan. In this case, the FOMC explicitly announced that liftoff would be contingent on the state of the economy, which framed the event as a positive revelation about the Fed's private assessment.

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Real-Time Forecasting and Scenario Analysis Using a Large Mixed-Frequency Bayesian VAR*

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We use a mixed-frequency vector autoregression to obtain intraquarter point and density forecasts as new, high-frequency information becomes available. This model, delineated in Ghysels (2016), is specified at the lowest sampling frequency; high-frequency observations are treated as different economic series occurring at the low frequency. As this type of data stacking results in a high-dimensional system, we rely on Bayesian shrinkage to mitigate parameter proliferation. We obtain high-frequency updates to forecasts by treating new data releases as conditioning information. The same framework is used for scenario analysis to obtain forecasts conditional on a hypothetical future path of the variables in the system. We show that the

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methodology results in competitive point and density forecasts and illustrate the usefulness of the methodology by providing forecasts of real GDP growth given hypothetical paths of a central bank policy rate.

JEL Codes: C22, C52, C53.

1. Introduction

Economic forecasting typically requires managing mixed-frequency data. Across any particular quarter, policymakers and professional forecasters analyze monthly, weekly, and sometimes even daily indicators of economic activity. For instance, the Federal Reserve Bank of Atlanta maintains the GDPNow series on its website, while the Federal Reserve Bank of New York regularly publishes a Nowcasting Report. Both of these forecast series use high-frequency data releases to provide an updated view on the performance of the economy—often viewed through the lens of real GDP growth, which is released at a lower, quarterly frequency.

A variety of statistical methods enable the integration of high-frequency variables into forecasting models that predict lower-frequency variables such as real GDP growth. Corrado and Green (1988) and Parigi and Schlitzer (1995) use linear bridge equations to map monthly data into quarterly frequency when modeling GDP for the United States and Italy, respectively. Giannone, Reichlin, and Small (2008) and Blasques et al. (2016) use dynamic factor models to generate forecasts of U.S. GDP using monthly, weekly, and daily data releases. Zadrozny (1990) and Mittnik and Zadrozny (2005) employ a Kalman-filtering-based maximum-likelihood estimation method to modeling mixed-frequency data in a single vector autoregression (VAR) by treating the low-frequency release as a missing-value problem: GDP exists at a monthly frequency, but we only observe it once every three months. Eraker et al. (2015), Schorfheide and Song (2015), and Brave, Butters, and Justiniano (2019) also treat the low-frequency release as a missing-value problem but use Bayesian methods. Foroni and Marcellino (2013) offer a review of these and other mixed-frequency models.

In this paper, we investigate an alternative approach to forecasting delineated in Ghysels (2016), who addresses the forecaster's mixed-frequency problem using a mixed-frequency vector autoregression estimated at the lowest common data frequency. As an example, suppose we want to forecast real GDP growth using the three monthly nonfarm payroll employment data releases that occur during the quarter. In this case, the VAR would be based on a four-dimensional vector formed by the three monthly and one quarterly series. Bacchiocchi et al. (2016) and Ghysels, Hill, and Motegi (2016) have recently used such a model to investigate the role mixed frequencies play in topics ranging from tests of Granger causality to the construction of impulse response functions, respectively. In other fields—particularly engineering—theoretical aspects of this modeling approach (sometimes referred to as "blocking") have been explored (see Bittanti, Colaneri, and De Nicolao 1988 and, more recently, Chen et al. 2012). As noted in Ghysels (2016), the model can also be interpreted as a multivariate version of the univariate, unrestricted mixed-frequency data-sampling (MIDAS) model discussed in Foroni, Marcellino, and Schumacher (2015).

By stacking the series this way, one can use a conventional, conditional forecasting framework (e.g., Waggoner and Zha 1999) to obtain nowcasts and forecasts consistent with the high-frequency information flow throughout the quarter without computationally intensive filtering (see Ghysels 2016 and Brave, Butters, and Justiniano 2019 for related discussions). Nowcasting, forecasting, and scenario analysis can be treated in the same framework using well-established Bayesian methods in a way that should be particularly appealing for both policymakers and other practitioners.

In this paper, we provide empirical evidence on the ability of this mixed-frequency VAR to forecast in real time as we move within a quarter and additional higher-frequency data become available. Our analysis focuses on the nowcasting problem (i.e., forecasting the current quarter), although we also provide results for a longer, four-quarter-ahead horizon. In our application, we use real-time vintage data on 12 monthly frequency predictors and quarterly GDP, yielding a heavily parameterized, 37-dimensional VAR.[1] To handle the high dimensionality, we estimate the model using Bayesian

[1] Prior to 1992, we forecast real GNP growth. Throughout the remainder we simply reference our target variable as GDP without also referencing GNP.

techniques, where we allow data-driven shrinkage to resolve the bias-variance tradeoff in the forecasting problem. Specifically, we use estimation procedures for reduced-form VARs developed by Giannone, Lenza, and Primiceri (2015; henceforth GLP), to obtain the posterior distribution of the parameters and the predictive densities.

To understand the nature of the model, it is instructive to compare it with the one posited by Carriero, Clark, and Marcellino (2015; henceforth CCM). In their model, CCM construct nowcasts of real GDP growth based on monthly indicators using the unrestricted MIDAS approach delineated in Foroni, Marcellino, and Schumacher (2015). Among other experiments, they use four separate linear scalar models to nowcast current-quarter real GDP growth from information available as of the first week in each month—i.e., after the release of the Employment Situation Report. Their direct multistep (DMS) approach to GDP forecasting has the advantage of not having to form a complete model for all variables in the system as one would with a VAR. Bhansali (1997) and Schorfheide (2005) provide theoretical results showing that DMS approaches to forecasting can be more robust to model misspecification than iterated multistep (IMS) forecasts generated by a fully specified VAR. On the other hand, Marcellino, Stock, and Watson (2006) show that IMS-based models often lead to more accurate predictions relative to DMS-based models. The model we use can be viewed as the VAR-based IMS analogue to the DMS system of equations that CCM use to forecast. While working with a fully specified VAR marginally complicates the empirics, the benefit is a more general framework that can be used for multivariate forecasting and scenario-based conditional forecasting of the type often used by central banks.[2]

Given similarities between our model and CCM's, we compare our nowcasting approach to theirs, noting some advantages to our approach. We use the same monthly predictors and data release schedule; consider the same intraquarter forecast origins (as well

[2]In related work, Kuzin, Marcellino, and Schumacher (2011) compare a MIDAS technique to a mixed-frequency VAR for euro-area data, where the latter is estimated using a frequentist state-space model. Our innovation is that we use a stacked VAR and estimate with Bayesian methods, which arguably provides a more flexible setup. Most notably, we use the conditional forecasting framework jointly for both nowcasting/forecasting and scenario analysis.

as others) and set of models (small and large) that are comparable with their specification. We then directly compare our IMS approach to current-quarter point and density nowcasts of real GDP growth to CCM's DMS approach. We also compare these nowcasting results to forecasts from the Survey of Professional Forecasters (SPF), forecasts from the Blue Chip Economic Indicators (BCEI) survey, and predictions from a quarterly frequency AR(2). In addition, we use the mixed-frequency Bayesian VAR (MF-BVAR) to produce point and density forecasts of GDP growth and several of our high-frequency variables at a longer, four-quarter-ahead horizon and compare the efficacy of these forecasts to those from the SPF and the BCEI.

We find that the MF-BVAR model provides competitive nowcasts and four-quarter-ahead forecasts. The nowcasts, in general, are comparable to the ones obtained using our version of the model proposed in CCM and can be as accurate as those from the SPF and BCEI at certain forecast origins. The four-quarter-ahead forecasts, on the other hand, are as good as or better than those in the SPF for variables such as industrial production, housing starts, and Treasury yields. A small-scale version of the MF-BVAR is also competitive for four-quarter-ahead real GDP growth forecasts relative to the SPF. In general, it is often the case that a lower-dimensional MF-BVAR, consisting of fewer stacked monthly series, provides more accurate point forecasts than those from a larger MF-BVAR with many stacked monthly series. Regardless of which MF-BVAR is being used, the intraquarterly arrival of additional information improves the accuracy of both point and density forecasts.[3]

We also provide two examples of conditional, scenario-based forecasting—both of which are designed to highlight the mixed-frequency nature of the model. In each experiment, we emulate a situation in which a central bank is forming forecasts of a low-frequency variable (i.e., real GDP growth), based on a hypothetical path for a high-frequency variable (i.e., a policy rate). In our first experiment, for a fixed hypothetical path of the policy rate, we show

[3]Bańbura, Giannone, and Reichlin (2010), among others, show that the medium-scale VAR performs similar to the large-scale one in terms of point forecasts accuracy, thus our finding is not surprising in the context of the literature.

how the arrival of other high-frequency observables can lead to significant revisions to the forecast as we move across forecast origins within a quarter. In the second experiment, we instead highlight the intraquarterly timing of the hypothetical path for the policy rate given a fixed forecast origin. For this experiment, we find that conditional forecasts of real GDP growth are monotonically higher the later the policy changes are made within a calendar quarter. This experiment could be potentially informative for a central bank considering the timing of policy actions. In each experiment, we compare our results to those from a model that relies solely on low-frequency aggregates, with the goal of emphasizing that such a model lacks the agility to adapt to intraquarterly movements in high-frequency observables.

The remainder of the paper is organized as follows. Section 2 lays out the specification of the model, discusses the data, and delineates the estimation methodology. Section 3 describes the construction of point and density forecasts; section 4 discusses the forecasting results and compares them to various alternatives. We conclude with section 5.

2. The Setup

The model we use is a quarterly reduced-form VAR, where a monthly variable is represented by three quarterly variables, each corresponding to an intraquarter month.[4] We estimate the model using a procedure suggested in GLP using Minnesota priors reconfigured for stationary data. In GLP, the amount of shrinkage is chosen to maximize the marginal data density. In what follows, we describe the data and the real-time properties of the various series included in our VAR specification. We then provide more details on the stacked VAR and outline the GLP estimation procedure.

2.1 Data

Our choice of predictors aims to facilitate a close comparison of our forecasting results with other mixed-frequency models in the

[4] While our application uses monthly/quarterly data, extension to any mixed frequency is straightforward.

literature, particularly the ones in CCM. CCM includes variables that have proven useful for forecasting U.S. real GDP growth (or GNP for earlier portions of our sample) and are followed by markets and policymakers. The complete set of our monthly predictors, their transformations, and mnemonics are as follows: the S&P 500 composite index (log-change, "stprice"), the 3-month Treasury bill rate ("tbill"), the 10-year Treasury bond yield ("tbond"), the Institute for Supply Management manufacturing index ("ISM"), the ISM supplier deliveries index ("supdel"), the ISM new orders index ("orders"), total nonfarm payroll employment (log-change, "emp"), average weekly hours of production and supervisory workers (log-change, "hours"), real retail sales (the nominal series is deflated using the consumer price index; log-change, "RS"), industrial production (log-change, "IP"), housing starts (change, "starts"), and finally initial unemployment claims ("claims").[5] The transformations are chosen to induce stationarity in the series. If no transformation is listed, the variable is used in levels. In addition, growth rates have been annualized.

Because the model treats higher-frequency series as multiple quarterly frequency series, the number of estimated parameters grows faster than in a standard VAR of equal lag order. In order to mitigate parameter proliferation, we consider data only in monthly and quarterly frequencies. Financial variables are summarized at a monthly frequency, constructed as averages of daily observations. For similar reasons, we do not use weekly releases of initial claims; instead, we choose the four-week moving average. The 12 monthly series, along with the quarterly GDP series (log-change), imply that our large mixed-frequency VAR has $12 \times 3 + 1 = 37$ dimensions. To allow more direct comparison to CCM, we also investigate the performance of a small mixed-frequency VAR that only uses five of the monthly variables yielding 16 dimensions.

[5]In 2001, the Census changed details in the construction of retail sales (RETAIL) and started releasing the new version (RSAFS). Therefore, we use RETAIL for all vintages up to 2001:06 and RSAFS for the vintages after. Morover, when RSAFS was released, the historical sample was extended back only to 1992. Therefore, when we use the RSAFS vintages, we splice the pre-1992:01 values from the last vintage of RETAIL in order for RSAFS to have data dating back to 1970.

While not necessary for estimating the model, we choose to organize our data based on the approximate release calendar. Because the longest publication lag in our data set is one month, we have realizations for all the information associated with the previous month by the end of the next month. Within each month, the data are ordered as follows: (i) the monthly averages of the S&P 500 composite index, 3-month Treasury bill rate, and 10-year Treasury bond yield computed on the first day of the following month; (ii) the ISM manufacturing, supplier deliveries, and new orders indexes; (iii) total nonfarm payroll employment and average weekly hours; (iv) real retail sales; (v) industrial production; (vi) housing starts; and (vii) the four-week moving average of initial unemployment claims. GDP growth is observed following initial unemployment claims.

In all of our forecasting exercises, we use real-time monthly vintage data starting in January 1985 and ending in April 2017. The monthly sequence of 388 real-time vintages of our predictors and GDP are gathered from Haver Analytics, the ALFRED database hosted by the Federal Reserve Bank of St. Louis, and the Real-Time Data Set for Macroeconomists hosted by the Federal Reserve Bank of Philadelphia. Each vintage consists of observables dating back to the first quarter of 1970. Accordingly, the target quarters for nowcasting and forecasting span from 1985:Q1 to 2017:Q1.

2.2 Model

The forecasting model is based on a standard reduced-form VAR, estimated at the lowest sampling frequency. We treat multiple releases at the highest frequency as separate observations modeled in a blocked linear form. For illustrative purposes, consider the case of one quarterly variable (e.g., real GDP) and one monthly variable (e.g., payroll employment) released in each of the three intraquarter months. Let $x_{t-\tau}$ represent the high-frequency (monthly) variable and y_t denote the low-frequency (quarterly) variable, for quarters $t = 1, \ldots T$ and months within the quarter $\tau = \{0, 1/3, 2/3\}$. In this setup, each τ represents an intraquarter month, hence $x_{t-2/3}$, $x_{t-1/3}$, and x_t index data that are observed during the second and third calendar months of quarter $t-1$ and first calendar month of quarter t, respectively.

Define the vector of data releases as $Y_t = [x_{t-2/3}, x_{t-1/3}, x_t, y_t]'$. The reduced-form VAR is

$$Y_t = C + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \Sigma^{1/2}\varepsilon_t, \tag{1}$$

where B_l are $n \times n$ parameter matrices, p is the lag order of the VAR, C is an $n \times 1$ vector of intercepts, $\varepsilon_t \sim N(\mathbf{0}, I)$, and Σ is the variance of the reduced-form shocks $\Sigma^{1/2}\varepsilon_t$. Let $X_t = [Y'_{t-1}, \ldots, Y'_{t-p}, 1]'$. We can then write (1) as

$$Y_t = DX_t + \Sigma^{1/2}\varepsilon_t, \tag{2}$$

where $D = [B\ C]$ and $B = [B_1 \ldots B_p]$. It will further be useful to define $\beta = vec(D)$. In our empirical section, we use a lag order of $p = 1$ as selected recursively by BIC as well as a desire to align the lag structure with that in CCM.

In general, the model is flexible enough to be generalized to include Q quarterly variables and M monthly variables. In such an environment one would treat y_t as a $(Q \times 1)$ vector and $x_{t-\tau}$ as a $(M \times 1)$ vector, producing a VAR of dimension $n = Q + 3M$.

One notable feature of the model is that monthly series have a nonstandard lag structure. For instance, an observation for July will depend explicitly on the lagged data pertaining to February, March, and April monthly series and, in addition, depend on the May and June values through the contemporaneous correlation across these monthly series. In general, this makes determining whether or not the system is stationary more complicated than is typical. See Chen et al. (2012) and Ghysels (2016) for more detail. As a practical matter, because all of our data have been transformed to remove unit roots, we maintain throughout that the VAR is stationary and has a finite-order lag polynomial.

2.3 Priors and Estimation

The dimension of the VAR increases quickly: An additional monthly predictor adds three variables to the VAR. To handle the parameter proliferation problem, we estimate the model using Bayesian methods and utilize a hierarchical shrinkage prior. Bańbura, Giannone, and Reichlin (2010) show that Bayesian VARs can forecast well, even with 100+ variables, when the shrinkage is chosen appropriately such that the prior tightness increases with the model size. Thus, given the size of the model, a careful choice of prior hyperparameters is important. We use the procedure outlined in GLP to choose hyperparameters that maximize the marginal data density for each estimation sample.

We employ a normal-inverse-Wishart prior distribution for the VAR parameters. More formally, let the priors be defined as

$$\Sigma \sim IW(\Psi, d),$$
$$\beta|\Sigma \sim N(0, \Sigma \otimes \Omega),$$

where the degrees-of-freedom parameter of the inverse-Wishart distribution $d = n + 2$, the minimum value that guarantees the existence of the prior mean for Σ. Ψ is a diagonal matrix where each element of the diagonal is set to the residual variance of an AR(1) process for the respective variable in the VAR.[6] Ω is a $k \times k$ matrix, $k = np + 1$, parameterized such that the prior covariance of the regression coefficients takes the following form:

$$cov\left((B_s)_{ij}, (B_r)_{hm} | \Sigma\right) = \begin{cases} \lambda^2 \frac{1}{s^2} \frac{\Sigma_{ih}}{\psi_j/(d-n-1)} & if \quad m = j \text{ and } r = s \\ 0 & otherwise \end{cases}.$$

Thus, while the coefficients $B_1, \ldots, B_p$ are assumed to be independent of each other, coefficients associated with the same variable are allowed to be contemporaneously correlated across different equations. In general, the prior imposes a tighter variance on the distant lags; however, given that in our specification $p = 1$, this feature of the prior is not relevant. The hyperparameter λ governs the overall tightness of the prior by controlling the scale of the variances and covariances of the VAR coefficients. The prior variance on the constant term C is diffuse.

This prior is standard, taken directly from GLP, but reconfigured for a stationary process. We rely on their procedure and accompanying codes to estimate the VAR such that the hyperparameters (in

[6]Limited robustness analysis shows that treating diagonal elements of the scale matrix Ψ as hyperparameters does not generate meaningful gains; thus, we resort to GLP's default implementation of the Minnesota prior.

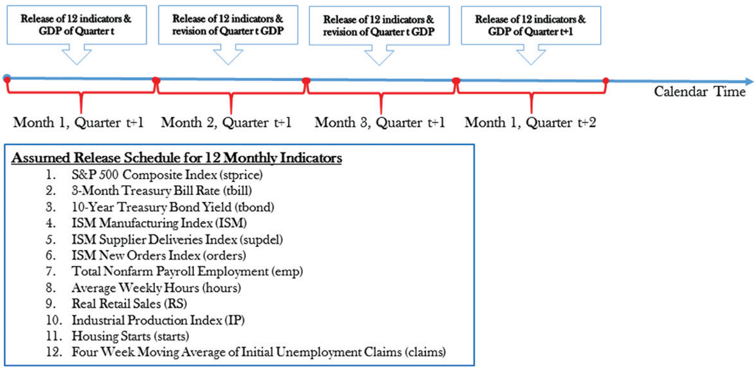
our case λ) impose an optimal amount of shrinkage consistent with the marginal data density criterion. GLP simulate the posterior distribution of λ based on a standard Metropolis algorithm, under the assumption that the prior for λ follows a gamma distribution with a mode of 0.2 and standard deviation of 0.4, values consistent with those in Sims and Zha (1998). Given the posterior of the hyperparameter λ, we obtain the posterior distribution of the VAR parameters (β and Σ) by drawing from normal-inverse-Wishart posterior distributions implied by the conjugate prior. Our reported results are based on 5,000 draws.

The prior used here is conjugate and has a Kronecker covariance structure that imposes symmetric treatment of variables across equations. The prior covariance matrices for the lag coefficients pertaining to the k-th variable in different equations are proportional. This yields a computational advantage, which is essential when evaluating models' out-of-sample forecasting ability. On the other hand, one might want to treat the lags of different frequency variables differently. Our method could be adapted for more general priors (e.g., Carriero, Clark, and Marcellino 2019 and Chan 2019). We leave this for future research.

The model is estimated every month using a new vintage of real-time data. When constructing the forecasts, we use the posterior distribution of the parameters obtained from the past vintage of monthly data. We hold the posterior constant within a month. For example, analysis over the first calendar quarter would unfold as follows. On January 1, we estimate the model using the vintage of data ending on December 31. The last row of this vintage will have a ragged edge because fourth-quarter data continue to be released during January. We drop the ragged edge and estimate the model. Draws from this posterior are used throughout January. To ensure the real-time nature of the exercise, as we move across data releases within January, new vintages of monthly data supplant those available in the December 31 vintage and are used as predictors when forming the forecasts. A similar pattern of updating the posterior and constructing forecasts consistent with the real-time nature of the data continues as we move across February and March.[7]

[7]We estimate the model once per month rather than once per quarter. In those months for which we have a ragged edge, the ragged edge is dropped. An

Figure 1. Data Releases and Forecast Timing



Note: The figure outlines the timing of the data releases and forecasts over the course of the quarter.

3. Forecasting

We formulate the intraquarter forecasting problem in a conditional forecasting framework. We treat the quarter-t information set as complete when the first (advance) release of GDP is released. This happens at the end of the first calendar month in quarter $t + 1$. At this point, we construct unconditional h-step-ahead point and density forecasts. As we move across the quarter, high-frequency data become available. We update the h-step-ahead unconditional forecasts using existing results on conditional forecasting as presented in Waggoner and Zha (1999). The approximate release schedule of the high-frequency data, which determines the sequence by which we update the forecasts, is delineated in section 2.1 and depicted in figure 1.

As figure 1 shows, our results are based on forecast updates across four months. In the context of forecasting current, first-quarter GDP,

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alternative approach would be to introduce a Tanner and Wong (1987) step as in Waggoner and Zha (1999) (see their algorithm 1). We have performed a limited set of robustness experiments related to this step and, other than adding runtime, found that it had limited effect on our results. Since we want to keep our modeling framework simple to ease its use in the context of policymaking, we do not incorporate this feature into the benchmark setup.

we begin with a two-quarter-ahead forecast formed conditional on all previous-quarter information up to and including the first data release of January. We then update that forecast until obtaining end-of-January claims. When we observe the previous-quarter GDP, we now form the one-quarter-ahead forecast using a complete set of previous-quarter data. As we move into February, we then update this one-quarter-ahead forecast sequentially across each data release. This continues into March and finally ends with end-of-April claims. All together we obtain a sequence of 49 intraquarter forecasts for first-quarter GDP based on the 12 monthly releases in each month and the advance release of previous-quarter GDP.

3.1 Point Forecasts and Predictive Densities

Our forecasting model is estimated using Bayesian techniques, providing a natural characterization of uncertainty. The time-t predictive density of Y at horizon h, $p(Y_{t+h}|\mathbf{Y_t})$, is

$$p(Y_{t+h}|\mathbf{Y_t}) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} p(Y_{t+h}|\mathbf{Y_t}, D, \Sigma)p(D|\Sigma, \mathbf{Y_t})p(\Sigma|\mathbf{Y_t})dDd\Sigma, \tag{3}$$

where $\mathbf{Y_t} = [Y_1, \ldots, Y_t]'$ represents the history of observables up to time t and $p(D|\Sigma, \mathbf{Y_t})$ and $p(\Sigma|\mathbf{Y_t})$ are the time-t posterior distributions of the parameters in D and Σ, respectively.

For each saved draw, $D^{(i)}$ and $\Sigma^{(i)}$, from their respective posteriors, we obtain a forecast draw $\hat{Y}^{(i)}_{t+h|t}$ from the conditional predictive density $p(Y_{t+h}|\mathbf{Y_t}, D^{(i)}, \Sigma^{(i)})$. Collecting these draws across Markov chain Monte Carlo (MCMC) iterations yields the predictive density that accounts for the uncertainty in the estimated parameters (including the uncertainty associated with the setup of the prior tightness) and the uncertainty from the unobservable future shocks. Then, based on arguments made in Gneiting (2011), we obtain the point forecast as the mean of the predictive density.

The posterior distributions $p(D|\Sigma, \mathbf{Y_t})$ and $p(\Sigma|\mathbf{Y_t})$ are readily available as a result of the reduced-form VAR estimation in GLP framework. Next, we consider the simulation from the conditional predictive density $p(Y_{t+h}|\mathbf{Y_t}, D^{(i)}, \Sigma^{(i)})$, keeping in mind that this distribution changes with each new high-frequency release.

3.2 Conditional Predictive Density Simulation

In this section, we describe how we obtain a forecast draw, $\hat{Y}^{(i)}_{t+h|t} \sim p(Y_{t+h}|\mathbf{Y_t}, D^{(i)}, \Sigma^{(i)})$, conditional on the i-th draw of the VAR parameters obtained from the MCMC. In what follows, we suppress the superscript i denoting the MCMC iteration for notational simplicity. As we intimated above, our forecasting procedure has two components, each of which is based on the composition of the information set at the time the forecast is constructed. Specifically, at the time the last-quarter GDP value is released and the information set is deemed complete, the forecast is constructed as an *unconditional* forecast. As the quarter progresses, the forecast is constructed as a *conditional* forecast, where the already-released intraquarter data are treated as restrictions in the forecasting model. In what follows, we delineate our unified approach for producing both h-period-ahead conditional and unconditional forecasts based on well-established results in Waggoner and Zha (1999), implemented with computational simplifications proposed in Jarociński (2010).

Because our forecasting approach is an iterative (rather than direct) one, we demonstrate how to draw $\hat{Y}_{t+h|t}$ for a general h-steps-ahead horizon, assuming we have already obtained draws for the forecasts $\hat{Y}_{t+h-1|t}, \ldots, \hat{Y}_{t+1|t}$. Let $\mu = (I - \Sigma^{p}_{l=1} B_l)^{-1} C$ represent the mean of Y_t implied by the VAR; then, $Z_t = Y_t - \mu$ is the demeaned vector of period-t observables and $\hat{Z}_{t+h|t} = \hat{Y}_{t+h|t} - \mu$ are the demeaned forecast draws. Let $\hat{\mathbf{Z}}_{t+h-1|t} = [\hat{Z}'_{t+h-1|t}, \hat{Z}'_{t+h-2|t}, \ldots, \hat{Z}'_{t+h-p|t}]'$. When $h - j \leq 0$, $\hat{Z}_{t+h-j|t} = Z_{t+h-j}$, i.e., it represents observed data.

We are interested in the joint distribution of the one- to h-step-ahead forecasts of Y obtained at time t. Let $\mathbf{Y} = [Y'_{t+1}, \ldots Y'_{t+h}]'$, $\hat{\mathbf{Y}}^u = [\hat{Y}^{u'}_{t+1|t}, \ldots \hat{Y}^{u'}_{t+h|t}]'$, and $\hat{\mathbf{Z}}^u = [Z_t, \hat{Z}^{u'}_{t+1|t} \ldots \hat{Z}^{u'}_{t+h-1|t}]'$, where superscript u denotes unconditional forecasts. Define $\Phi_j \Sigma^{1/2}$ as the matrix of orthogonalized impulse responses after $j = 1, \ldots, h$ periods and let

$$R_{nh \times nh} = \begin{pmatrix} \Sigma^{1/2} & 0 & & 0 & 0 \\ \Phi_1 \Sigma^{1/2} & \Sigma^{1/2} & & 0 & 0 \\ & & \cdots & \Sigma^{1/2} & 0 \\ \Phi_{h-1} \Sigma^{1/2} & \Phi_{h-2} \Sigma^{1/2} & & \Phi_1 \Sigma^{1/2} & \Sigma^{1/2} \end{pmatrix},$$

where $\Sigma^{1/2}$ can be obtained as a Cholesky factor of Σ.

Suppose we know a subset m of the future values of $\mathbf{Y}$. Let ω be a $(m \times nh)$ selection matrix, such that $\omega\mathbf{Y}$ results in an $m \times 1$ vector, consisting of the known future elements of $\mathbf{Y}$. Let $r = \omega(\mathbf{Y} - \hat{\mathbf{Y}}^u)$. Then, the known future values can be thought of as linear restrictions on future values of the error term $\varepsilon = [\varepsilon'_{t+1}, \ldots, \varepsilon'_{t+h}]'$. These restrictions take the form $\tilde{R}\varepsilon = r$, where $\tilde{R} = \omega R$. For example, suppose we have one monthly and one quarterly variable and hence, for our model, $n = 4$. Now suppose we are forming a two-quarter-ahead forecast ($h = 2$) of GDP growth and we have observed the first two monthly releases in the current quarter. $\tilde{R}$ is the (2×8) matrix formed by stacking the first and second rows of R.

We can then draw the h-period-ahead conditional forecast $\hat{\mathbf{Y}}^c = [\hat{Y}^{c'}_{t+1|t}, \ldots, \hat{Y}^{c'}_{t+h|t}]'$ from the following conditional predictive distribution:

$$\hat{\mathbf{Y}}^c \sim N\left(\psi_{t+h|t}, \Psi_{t+h|t}\right), \tag{4}$$

where $\psi_{t+h|t}$ captures the conditional mean, while $\Psi_{t+h|t}$ is the conditional variance of the predictive density determined as

$$\psi_{t+h|t} = \iota_h \otimes \mu + (I_h \otimes B)\hat{\mathbf{Z}}^u + \tilde{R}'(\tilde{R}\tilde{R}')^{-1}r, \tag{5}$$

$$\Psi_{t+h|t} = R\left(I - \tilde{R}'(\tilde{R}\tilde{R}')^{-1}\tilde{R}\right)R', \tag{6}$$

and ι_h is an h-dimensioned vector of ones. Equations (5) and (6) follow from equations (6) and (9) of Jarociński (2010).

The first two terms of (5) are invariant to whether we have observed any of the intraquarter data—i.e., whether the forecast is conditional or unconditional. The third term captures the adjustment to the mean as more information, either arising from intraquarter data releases or hypothetical scenarios about future path of the variables, becomes available. In the absence of any conditioning information, model residuals are unrestricted, $\tilde{R} \equiv 0$, and this third term does not affect the mean of the predictive density. In contrast, when conditioning information exists, this third term provides the adjustment needed to revise the unconditional forecast to a conditional one. As equation (6) indicates, conditioning information affects the variance of the predictive distribution as well, thus changing the characterization of forecast uncertainty arising due to unobservable future shocks in the model's reduced-form errors. Conditioning information restricts the model residuals ($\tilde{R} \not\equiv 0$) and, in general, reduces the uncertainty of the predictive density.

We assume that the conditioning variables do not change the posterior distribution of the parameters and simulate the predictive density by relying on the computational simplifications provided in Jarociński (2010). Let USV' denote the singular value decomposition of $\tilde{R}$. Define E as the $m \times m$ diagonal matrix of m singular values of $\tilde{R}$, and let V_1 and V_2 denote matrices formed from the first m and remaining $nh - m$ columns of V, respectively. Under our assumptions, Jarociński (2010) shows that $V_1 E^{-1} U' r + V_2 \eta$, for $\eta \sim N(0, I_{(nh-m \times nh-m)})$, has the same normal distribution as that in (4) and is computationally more efficient in many cases.

3.3 Competing Models

When forecasting real GDP growth, we consider a few alternatives to our mixed-frequency Bayesian VAR. A simple and competitive alternative that has also been considered by CCM is an AR(2), which we reestimate each month with each new vintage of GDP. We use the same prior and estimation procedure proposed by GLP and used for our MF-BVAR.

We also report results associated with the DMS approach to forecasting developed in CCM. As noted previously, CCM models GDP growth directly and reports results on monthly nowcasts of GDP growth using the information available at the time of the Employment Situation Report in each month. Thus, the model size changes over the quarter: in month 1 of the quarter, the model is larger in size, while in month 2 it is the smallest. Table 1 in CCM describes the models explicitly. We extend the analysis in CCM to forecast origins other than the employment release. In particular, we consider origins associated with each data release using the schedule detailed in section 2.1. This provides us with the ability to compare our IMS-based and their DMS-based approaches to forecasting at each data release. The CCM-type models are again estimated using the GLP code described earlier, adjusted to work with autoregressive distributed lag type models. It is worth emphasizing that there will be differences between our results and those obtained by CCM. For example, our prior on quarterly and monthly series is symmetric, while CCM impose a distinct prior on series that are at the quarterly versus monthly frequencies. In addition, our prior is optimized for each estimation sample consistent with the GLP procedure, while the CCM prior is fixed. Finally, CCM also permit stochastic volatility in their model, while we abstract from such in our version.

In addition, we consider both small and large versions of our model and that of CCM. These models are defined relative to those described in CCM. Our large model uses all 12 monthly predictors and 1 quarterly predictor to form a 37-dimensional VAR. These variables are described in section 2.1 and figure 1. Our small model only considers one quarterly and five monthly predictors including the ISM manufacturing index, payroll employment, industrial production, retail sales, and housing starts, and thus forms a 16-dimensional VAR.

Finally, we compare the accuracy of our small and large models with the mean of the responses from the SPF and BCEI. We do this for GDP growth forecasts and for forecasts of some of the monthly variables in our system. For the GDP growth forecasts, we are able to compare forecasts directly because annualized quarterly GDP growth is a component of our model and is also part of both surveys.

For the monthly variables, we only compare the forecasting performance of the models to the SPF. The BCEI contains forecasts for the monthly variables. However, given our focus on GDP growth forecasting as well as the proprietary nature of the BCEI survey, we have decided not to report that comparison here. Comparing the model forecasts of monthly variables to those from the SPF is complicated by the fact that the survey provides forecasts of quarterly aggregates. For example, the SPF forecasts of the 3-month and 10-year Treasury yields are quarterly averages of the daily series, while SPF forecasts of retail sales, industrial production, and housing starts are quarterly averages of the monthly series. Our forecast of the 3-month and 10-year quarterly yield is formed by taking the average of the three monthly averages within the target quarter. Our forecast of the quarterly level of housing starts is formed by cumulating the forecasts of changes from the current level of the series and then averaging the three relevant months in the target quarter. Finally, our forecasts of the quarterly level of industrial production and retail sales are formed by extrapolating from the current level of the series based on the forecasted monthly growth rates at the one- through four-quarter-ahead horizons—and then averaging the three relevant months of the target quarter.[8] The remaining monthly series are either not in the SPF or, in the case of employment, have only been part of the survey for a brief time and hence are not included in the evaluation exercise.

3.4 Evaluation

We evaluate point forecasts using root mean square error (RMSE). We calculate RMSEs after each intraquarter data release, obtaining a term structure of RMSEs as we move across the quarter. We consider two out-of-sample evaluation periods. The first evaluation period is the same as that in CCM, where we use real-time data to obtain nowcasts for the advance release of GDP growth between 1985:Q1 and 2011:Q3. We also consider a comparably sized out-of-sample period ranging from 1992:Q2 to 2017:Q1, which has the advantage that it allows us to focus exclusively on forecasting real GDP growth rather than a mixture of GNP and GDP growth depending on the vintage.

We then evaluate the accuracy of our density forecasts based on the continuous ranked probability score (CRPS). Relative to other scoring functions, such as the log-scores, the CRPS is less sensitive to outliers and puts higher weight on draws from the predictive distribution that are close to but not equal to the outcome (see Gneiting and Raftery 2007 and Gneiting and Ranjan 2011 for further discussion). Similar to the RMSE, the CRPS is defined such that the lower the value, the better the score, and is given by

$$\begin{aligned} CRPS_t(y_{t+h}) &= \int_{-\infty}^{\infty} \left(P(z) - 1\{y_{t+h} \leq z\}\right)^2 dz \\ &= E_p \left|\hat{y}_{t+h|t} - y_{t+h}\right| - \frac{1}{2} E_p \left|\hat{y}_{t+h|t} - \hat{y}'_{t+h|t}\right|, \end{aligned} \tag{7}$$

[8]Industrial production rebases itself seven times across all of our vintages. In order to ensure that the levels at the forecast origin align with those in the target quarter, we unwind the new base year back to the base year at the forecast origin.

where $P(.)$ denotes the cumulative distribution function (CDF) associated with the predictive density $p(y_{t+h}|\mathbf{Y}_t)$, $1\{y_{t+h} \leq z\}$ denotes the indicator function, taking value 1 if the outcome $y_{t+h} \leq z$ and 0 otherwise, and $\hat{y}_{t+h|t}$ and $\hat{y}'_{t+h|t}$ are independent random draws from the conditional predictive density $p(y_{t+h}|\mathbf{Y}_t)$. We compute the CRPS using the empirical CDF-based approximation given in equation (9) of Krueger et al. (2017). As for the case of RMSEs, we obtain average CRPS values for each intraquarter data release and report the term structure of CRPS values for each out-of-sample period.

Pairwise differences in RMSEs and CRPS values across models are evaluated using a standard normal approximation to t-type tests of predictive ability akin to that developed in Diebold and Mariano (1995). Newey and West (1987) standard error estimates are used with lag orders equal to the forecast horizon plus one. All point and density forecasts of real GDP growth are evaluated using the advance release. Point and density forecasts of the monthly series are evaluated using the same vintage of data used to evaluate the real GDP growth forecasts.

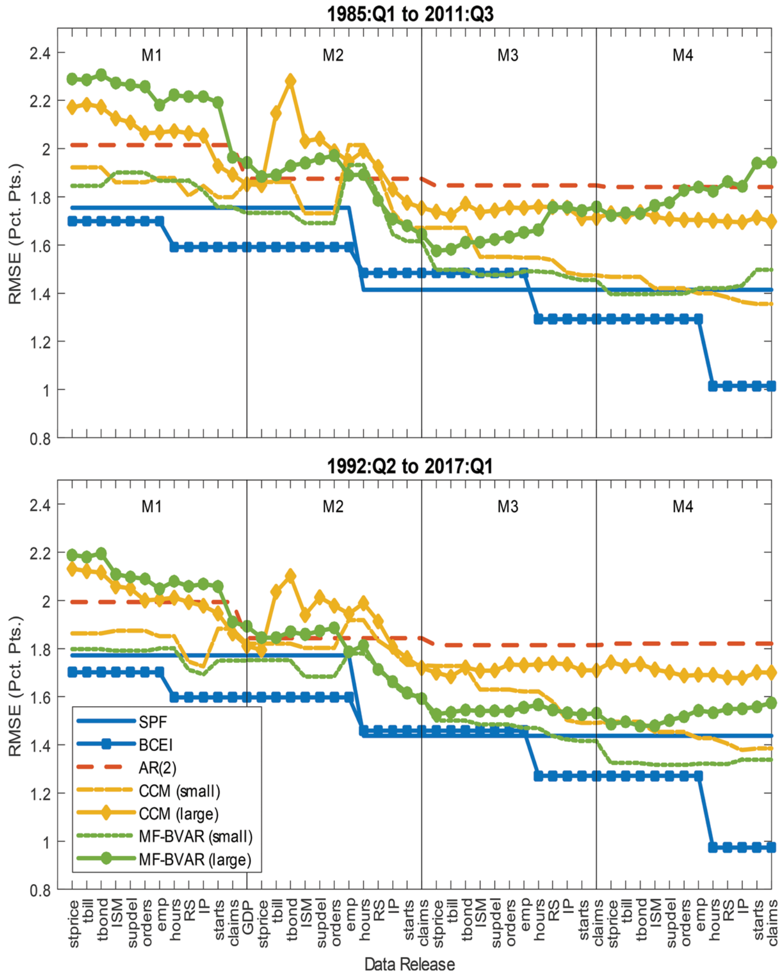
4. Forecasting Results

In this section, we delineate some of the advantages of the blocked, mixed-frequency VAR in the context of forecasting. We begin by evaluating the real-time accuracy of our point and density forecasts relative to a handful of competitors outlined in section 3.3. We use figures to present measures of accuracy across all intraquarter horizons. For each figure, we also have a table that presents the value of the measure of accuracy, the ratio of these measures across models, and pairwise tests of equal accuracy—but only for those forecast origins associated with the Employment Situation Report. In our sequencing of data releases, this lines up with "hours." We then illustrate the usefulness of the model for producing scenario-based forecasts of low-frequency variables when the conditioning variable is observed at a higher frequency.

4.1 Current-Quarter Forecasts

In figure 2, we plot the term structure of RMSEs for real GDP growth nowcasts from each of the models as we move across the

Figure 2. RMSE Paths for GDP Growth Nowcasts



Notes: The figure depicts the RMSE paths for nowcasts of the advance release of the real GDP growth. The upper panel considers the evaluation period in CCM, while the lower panel shows the results associated with real GDP (as opposed to GNP) growth forecasting. Each tick represents a data release in the respective month.

intraquarter forecast origins. The upper panel shows the results for the subsample used by CCM in which nowcasts are generated for 1985:Q1 through 2011:Q3, while the lower panel shows the results for the pure GDP subsample—i.e., nowcasts for 1992:Q2 through 2017:Q1. For comparison with the results in CCM, we begin forecasting on the first day of the first calendar month of quarter $t+1$ (e.g., January 1 when forecasting Q1 GDP). We then proceed across all data releases until the last high-frequency release prior to the release of advance GDP (e.g., late April when forecasting Q1 GDP).

Each panel in figure 2 contains paths associated with seven forecasts: the SPF, the BCEI, an AR(2), both small and large versions of the CCM models, and both small and large versions of our MF-BVARs. For both large models, we have 49 intraquarter updates associated with three monthly releases of the 12 monthly indicators and the quarter-t GDP advance release at the end of the first calendar month. The small models, on the other hand, are updated only at a subset of these forecast origins. More specifically, we obtain 16 updates to the forecasts, associated with three monthly releases of five monthly indicators and the quarter-t GDP advance release at the end of the first calendar month. Between updates we simply flatline the RMSE path. The AR(2) model updates its forecasts at the end of each month—i.e., after a new release or a revision to previously released GDP numbers.

The current-quarter SPF is timed to arrive after the Employment Situation Report but prior to the release of retail sales. In the first calendar month of the quarter $t+1$, we report RMSEs for the one-quarter-ahead SPF forecasts released in the second calendar month of the previous quarter. In the case of the BCEI, we have more frequent updates since it is a monthly survey. Typically, the survey is published on the 10th of the month, while the forecasts are collected earlier in the month. Accordingly, each month we time the BCEI forecasts to arrive after the Employment Situation Report but prior to the release of retail sales. For the first three calendar months in the quarter $t+1$ we use the BCEI nowcasts. In the first calendar month of quarter $t+2$, prior to the GDP advance release, we use the BCEI backcast. In the first calendar month of the quarter $t+1$, but prior to the release of the Employment Situation Report, we use the one-quarter-ahead forecast from the survey conducted a month earlier.

Looking at figure 2, perhaps the clearest observation across both evaluation samples is that the SPF and BCEI point forecasts of advance GDP growth are extremely difficult to beat. Further, in the first subsample, the best model-based forecasts tend to be those from the small-models—both CCM and the MF-BVAR—but even these are comparable to the SPF only early in the second month and at the end of the fourth month. The large models generally improve in performance across the first two calendar months of the quarter, but then either stagnate or even deteriorate as we get closer to the GDP release date. For reasons that are not obvious to us, the RMSEs of the direct multistep models both deteriorate sharply in month 2 before improving across the remaining intraquarter releases. The AR(2) performs worse than both survey forecasts, but is often competitive with the other model-based forecasts. The larger models tend to have better performance relative to the AR(2) after the second month of the calendar quarter. Across most forecast origins, the BCEI nowcasts tend to be the most accurate, with the exception that the SPF forecasts tend to be best for the first month of its release.

The models seem to perform much better relative to the SPF when we move forward into the pure GDP subsample (i.e., 1992:Q2–2017:Q1). As before, both small models are competitive with the SPF early in the second month and at the end of the fourth month but are now also competitive over a broader stretch of the quarter. While the large MF-BVAR is generally dominated by its smaller version, the large MF-BVAR has improved substantially and is competitive with the SPF in all periods except early in the first month. Relative to the first evaluation sample, the MF-BVAR models generally outperform the DMS models in terms of their point forecasts. BCEI nowcasts continue their superiority over the other forecasts though, once again, the SPF is very competitive for the first month of its release.

We assess the statistical significance of these results in table 1. The diagonals in the table have two numbers that are obtained as of the release of the Employment Situation Report: (i) the RMSE (below the slash) and (ii) the CRPS value (above the slash). For example, the third diagonal entry in the top panel, 2.01\3.41, indicates that for this sample the AR(2) has an RMSE of 2.01, while the average CRPS is 3.41. The lower off-diagonal portion of each panel in the table reports the ratio of RMSEs in the row-model to the column-model, where numbers greater than 1 indicate that

Table 1. RMSEs and Mean CRPSs of GDP Growth Nowcasts

		SPF	**BCEI**	**AR(2)**	**CCM (Small)**	**CCM (Large)**	**MF-BVAR (Small)**	**MF-BVAR (Large)**
1985:Q1 to 2011:Q3								
M1	SPF	1.75\NA						
	BCEI	0.91	1.59\NA					
	AR(2)	1.15	1.26	2.01\3.41	**1.13**	**1.21**	**1.19**	**1.26**
	CCM (Small)	1.07	**1.18**	0.93	1.88\3.03	**1.08**	**1.06**	**1.12**
	CCM (Large)	1.18	**1.30**	1.03	1.10	2.07\2.82	0.98	1.04
	MF-BVAR (Small)	1.06	**1.17**	0.93	0.99	0.90	1.87\2.86	**1.06**
	MF-BVAR (Large)	**1.27**	**1.40**	1.10	**1.18**	1.07	**1.19**	2.22\2.71
M2	SPF	1.41\NA						
	BCEI	**1.05**	1.48\NA					
	AR(2)	1.33	1.26	1.87\3.23	**1.22**	**1.21**	**1.32**	**1.44**
	CCM (Small)	**1.43**	**1.36**	1.07	2.01\2.64	0.99	**1.08**	**1.18**
	CCM (Large)	**1.41**	**1.34**	1.06	0.99	1.99\2.67	**1.09**	**1.19**
	MF-BVAR (Small)	**1.37**	**1.30**	1.03	0.96	0.97	1.93\2.45	**1.09**
	MF-BVAR (Large)	**1.34**	**1.28**	1.01	0.94	0.95	0.98	1.89\2.24
M3	SPF	1.41\NA						
	BCEI	**0.91**	1.29\NA					
	AR(2)	**1.31**	**1.43**	1.85\3.22	**1.47**	**1.28**	**1.63**	**1.64**
	CCM (Small)	1.09	**1.20**	0.84	1.55\2.19	**0.87**	**1.11**	**1.12**
	CCM (Large)	**1.24**	**1.36**	0.95	1.14	1.76\2.51	**1.27**	**1.28**
	MF-BVAR (Small)	1.05	1.15	0.81	0.96	0.85	1.49\1.97	1.01
	MF-BVAR (Large)	**1.18**	**1.29**	0.90	1.07	0.95	1.12	1.66\1.96
M4	SPF	1.41\NA						
	BCEI	**0.72**	1.01\NA					
	AR(2)	**1.30**	**1.81**	1.84\3.23	**1.52**	**1.29**	**1.73**	**1.64**
	CCM (Small)	0.99	**1.38**	**0.76**	1.40\2.12	**0.84**	**1.14**	1.07
	CCM (Large)	**1.20**	**1.68**	0.92	**1.22**	1.70\2.51	**1.35**	**1.27**
	MF-BVAR (Small)	1.01	**1.40**	0.77	1.02	0.84	1.42\1.86	0.94
	MF-BVAR (Large)	**1.29**	**1.80**	0.99	**1.30**	1.07	**1.28**	1.82\1.07

(*continued*)

Table 1. (Continued)

		SPF	**BCEI**	**AR(2)**	**CCM (Small)**	**CCM (Large)**	**MF-BVAR (Small)**	**MF-BVAR (Large)**
1992:Q2 to 2017:Q1								
M1	SPF	1.77\NA						
	BCEI	0.90	1.60\NA					
	AR(2)	1.12	1.25	1.99\3.21	**1.15**	**1.18**	**1.20**	**1.25**
	CCM (Small)	1.04	**1.16**	0.93	1.85\2.79	1.02	**1.04**	**1.08**
	CCM (Large)	1.13	**1.26**	1.01	1.09	2.01\2.73	1.02	**1.06**
	MF-BVAR (Small)	1.02	**1.13**	0.90	0.97	0.90	1.80\2.67	1.04
	MF-BVAR (Large)	1.17	**1.30**	1.04	1.12	1.3	1.15	2.08\2.57
M2	SPF	1.44\NA						
	BCEI	1.02	1.46\NA					
	AR(2)	1.28	1.26	1.84\3.04	**1.22**	**1.19**	**1.33**	**1.41**
	CCM (Small)	**1.34**	**1.32**	1.04	1.92\2.50	0.98	**1.10**	**1.16**
	CCM (Large)	**1.38**	**1.36**	1.08	1.04	1.99\2.55	**1.12**	**1.18**
	MF-BVAR (Small)	**1.24**	**1.22**	0.97	0.93	0.90	1.78\2.29	**1.06**
	MF-BVAR (Large)	**1.26**	**1.24**	0.98	0.94	0.91	1.02	1.81\2.16
M3	SPF	1.44\NA						
	BCEI	**0.88**	1.27\NA					
	AR(2)	1.26	**1.43**	1.82\3.03	**1.41**	**1.27**	**1.59**	**1.63**
	CCM (Small)	1.13	**1.28**	0.89	1.62\2.15	**0.90**	**1.13**	**1.15**
	CCM (Large)	**1.21**	**1.36**	0.96	1.07	1.73\2.39	**1.26**	**1.28**
	MF-BVAR (Small)	1.02	1.16	0.81	**0.91**	0.85	1.47\1.90	1.02
	MF-BVAR (Large)	1.09	**1.23**	0.86	0.97	0.90	1.07	1.57\1.86
M4	SPF	1.44\NA						
	BCEI	**0.68**	0.97\NA					
	AR(2)	1.27	**1.87**	1.82\3.04	**1.50**	**1.27**	**1.72**	**1.69**
	CCM (Small)	0.99	**1.46**	**0.78**	1.43\2.03	**0.85**	**1.15**	**1.13**
	CCM (Large)	1.18	**1.74**	0.93	1.19	1.69\2.40	**1.36**	**1.34**
	MF-BVAR (Small)	0.92	**1.36**	**0.73**	0.93	**0.78**	1.32\1.76	0.98
	MF-BVAR (Large)	1.07	**1.57**	0.84	1.07	0.91	**1.16**	1.53\1.79

Notes: The table shows the RMSEs (below the slash) and mean CRPSs (above the slash) of each model on the diagonal. The lower off-diagonal portion of each panel in the table reports the ratio of RMSEs in the row-model to the column-model. The upper off-diagonal portion of each panel reports the ratio of average CRPS in the row-model to the column-model. The results are as of the "hours" release in each month. Off-diagonal numbers greater than 1 indicate that the column-model is nominally more accurate. Ratios in bold are statistically different from 1 at the 5 percent significance level.

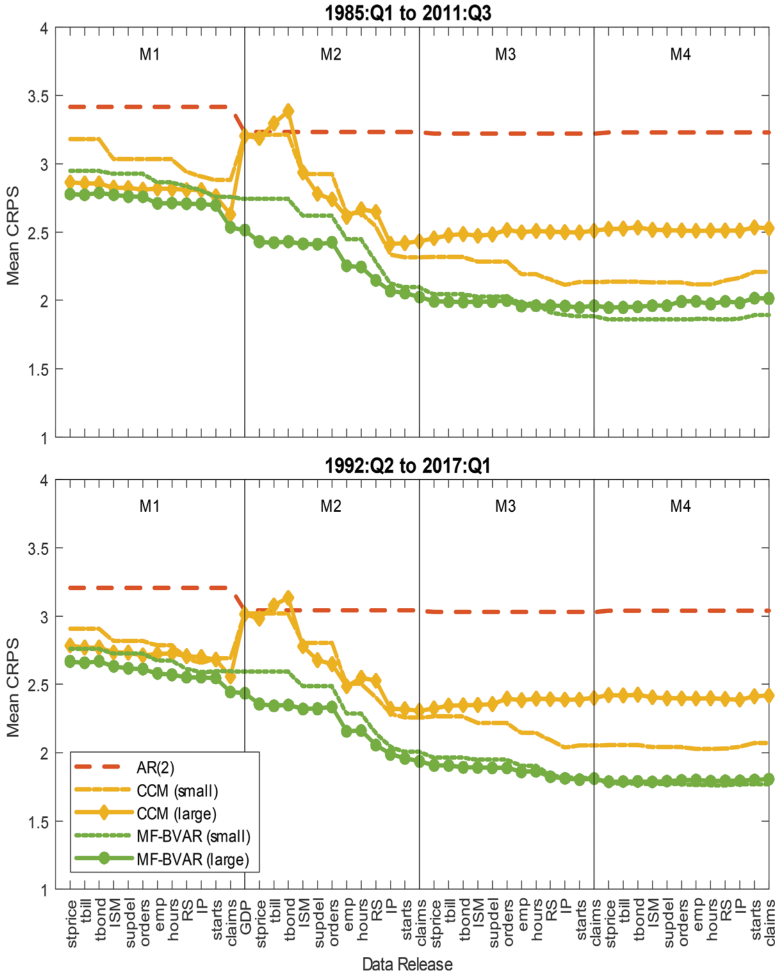
the column-model is nominally more accurate. Ratios in bold are statistically different from 1 at the 5 percent significance level. The majority of the statistically significant pairwise RMSE comparisons arise when comparing model-based forecasts to either the SPF or the BCEI. Across models, however, there are few differences that are statistically significant. The few that arise tend to do so either early or later in the quarter and simply reinforce what we observed in the figure: the small models tend to be more accurate than the large models.

In figure 3, we provide the same type of term structure but applied to mean CRPS values for each estimated model (and hence not the SPF or the BCEI) across both evaluation samples. In broad terms, the CRPS paths of all models decline as we move across forecast origins regardless of evaluation sample. Again, the exception is that both of the DMS models experience a sharp deterioration in mean CRPS values as we move into month 2. Interestingly, while the large MF-BVAR did not generally perform the best among the models in terms of RMSEs, it typically has the lowest CRPS values across all intraquarter forecast origins.

In table 1, the upper off-diagonal portion of each panel reports each row-model's mean CRPS as of the "hours" release relative to that of the column-model. Again, numbers greater than 1 indicate that the column-model is nominally more accurate. We find many more instances of statistically significant differences across the model-based forecasts. Clearly, while the AR(2) performs reasonably well in terms of RMSEs, the CRPS values are typically much higher than those of the other models. In addition, it is often the case that the CRPS values from the MF-BVAR models are significantly better than those from the DMS models used in CCM.[9]

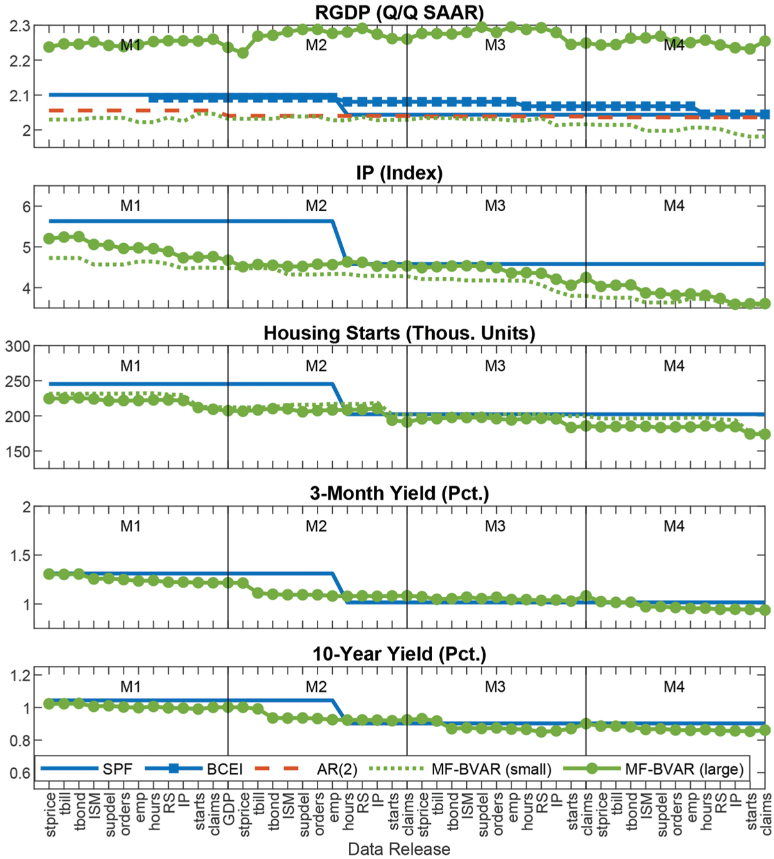
[9]In unreported results, we have investigated the role in which the additional real and financial variables affect the forecasting performance of the large MF-BVAR relative to the small MF-BVAR. We considered two alternative MF-BVAR models: one in which we add the remaining real variables to the small model and one in which we add the financial variables to the small model. In both cases we find a decline in the accuracy of the point forecasts, relative to the small model, though adding the real series is arguably worse. In contrast, in both cases we find a very modest improvement in the accuracy of the density forecasts relative to the small model.

Figure 3. CRPS Paths for GDP Growth Nowcasts



Notes: The figure depicts the average CRPS paths for nowcasts of the advance release of the GDP growth. The upper panel considers the evaluation period in CCM, while the lower panel shows the results associated with real GDP (as opposed to GNP) growth forecasting. Each tick represents a data release in the respective month.

Figure 4. RMSE Paths for Four-Quarter-Ahead Forecasts

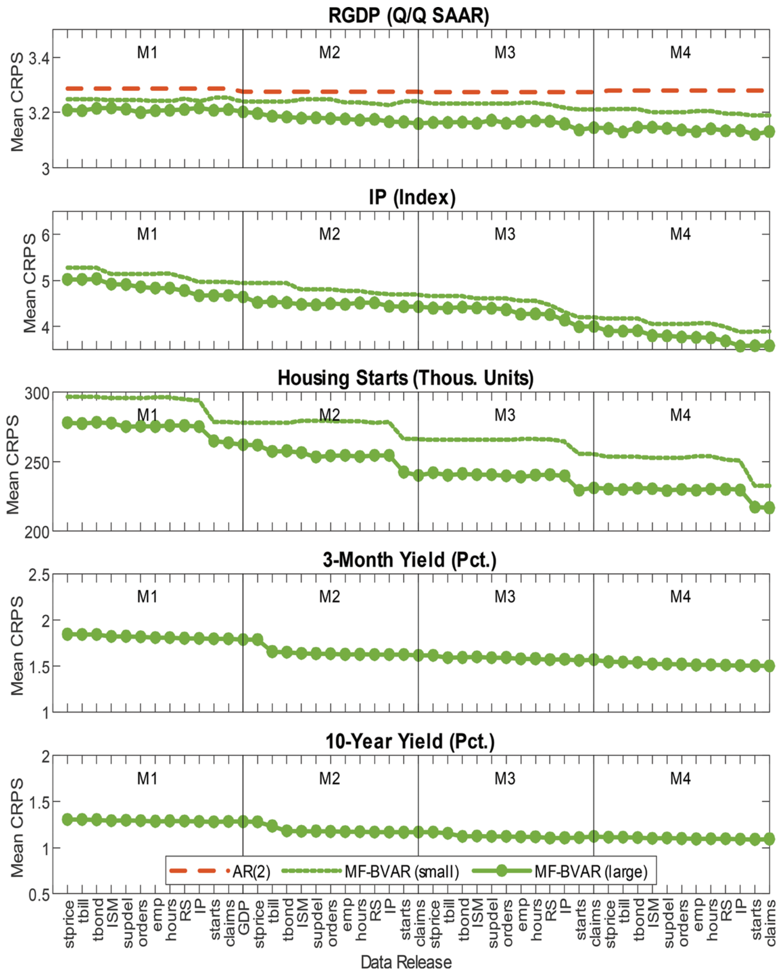


Notes: The figure depicts the RMSE paths for four-quarter-ahead forecasts for the evaluation period of 1992:Q2–2017:Q1. The quarterly AR(2) model is included for real GDP growth only. Each tick represents a data release in the respective month.

4.2 Four-Quarter-Ahead Forecasts

In figures 4 and 5, we provide the term structure of RMSE and CRPS values for four-quarter-ahead forecasts. In contrast to the nowcasting results, we now use the MF-BVARs to forecast a wider range of series consisting of GDP growth, industrial production, housing starts, and both the 3-month and 10-year Treasury yields.

Figure 5. CRPS Paths for Four-Quarter-Ahead Forecasts



Notes: The figure depicts the average CRPS paths for four-quarter-ahead forecasts for the evaluation period of 1992:Q2–2017:Q1. The quarterly AR(2) model is included for real GDP growth only. Each tick represents a data release in the respective month.

For comparison, we consider SPF forecasts of all five series. In addition, we include BCEI and AR(2) forecasts of GDP growth.[10] When applicable, the RMSE paths include forecasts from the MF-BVARs, SPF, BCEI, and the AR(2); the CRPS paths only include forecasts from the AR(2) and the MF-BVARs. Because CCM do not consider longer horizons forecasts, we do not include the DMS forecast in the comparison.

The top panel of figure 4 shows that the SPF and BCEI point forecasts for real GDP growth exhibit similar accuracy at the four-quarter-ahead horizon. The AR(2) outperforms the surveys in month 1, and early in month 2, but they eventually equalize in performance. The small MF-BVAR performs similar to, and sometimes a bit better than, the AR(2), especially in month 4. The large MF-BVAR is considerably worse than all of the alternatives at the four-quarter-ahead horizon. In contrast, the lower four panels of figure 4 show that the models outperform the SPF for variables other than GDP growth—in particular, industrial production and housing starts—at some intraquarter forecast origins. Four-quarter-ahead forecasts of industrial production and housing starts are as good as or better than the SPF at almost all forecast origins other than those late in the second calendar month. Relative to the SPF, model-based forecasts of yields are a bit better for the 10-year than the 3-month but, in both cases, they track the RMSEs of the SPF fairly closely.

In figure 5, we plot the mean CRPS values as in figure 3, but for the four-quarter-ahead horizon. As was the case before, the values generally decline as we move across the intraquarter forecast origins. This is most evident for industrial production, but also for housing starts. Across all forecast origins and each of the three relevant series (i.e., GDP, industrial production, and housing starts), the large MF-BVAR has a lower CRPS value than that of the small model.

As we did for the GDP nowcasts in table 1, table 2 reports the nominal and relative measures of accuracy for four-quarter-ahead

[10] Note that, for this exercise, we do not consider the BCEI forecasts available prior to the Employment Situation Report in the first calendar month of quarter $t+1$. Given our timing conventions, there are few observations associated with the requisite five-quarter-ahead forecasts.

Table 2. RMSEs and Mean CRPSs of Four-Quarter-Ahead Forecasts of GDP Growth for the 1992:Q2 to 2017:Q1 Sample

		SPF	BCEI	AR(2)	MF-BVAR (Small)	MF-BVAR (Large)
M1	SPF	2.10\NA				
	BCEI	1.00	2.09\NA			
	AR(2)	0.98	0.98	2.06\3.29	**1.01**	1.02
	MF-BVAR (Small)	0.96	0.97	0.98	2.02\3.24	1.01
	MF-BVAR (Large)	1.07	1.08	**1.10**	**1.11**	2.25\3.21
M2	SPF	2.04\NA				
	BCEI	1.02	2.08\NA			
	AR(2)	1.00	0.98	2.04\3.28	**1.01**	1.03
	MF-BVAR (Small)	0.99	0.97	0.99	2.03\3.24	1.02
	MF-BVAR (Large)	1.12	1.10	1.12	**1.12**	2.28\3.17
M3	SPF	2.04\NA				
	BCEI	1.01	2.07\NA			
	AR(2)	1.00	0.99	2.04\3.28	**1.01**	**1.03**
	MF-BVAR (Small)	0.99	0.98	0.99	2.03\3.24	1.02
	MF-BVAR (Large)	1.12	1.11	**1.12**	**1.13**	2.29\3.17
M4	SPF	2.04\NA				
	BCEI	1.00	2.04\NA			
	AR(2)	1.00	1.00	2.04\3.28	**1.02**	**1.04**
	MF-BVAR (Small)	0.98	0.98	0.99	2.01\3.20	1.02
	MF-BVAR (Large)	1.10	1.10	**1.11**	**1.12**	2.26\3.14

Notes: The table shows the RMSEs (below the slash) and mean CRPSs (above the slash) of each model on the diagonal. The lower off-diagonal portion of each panel in the table reports the ratio of RMSEs in the row-model to the column-model. The upper off-diagonal portion of each panel reports the ratio of average CRPS in the row-model to the column-model. The results are as of the "hours" release in each month. Off-diagonal numbers greater than 1 indicate that the column-model is nominally more accurate. Ratios in bold are statistically different from 1 at the 5 percent significance level.

GDP growth forecasts. Values in bold are ratios for which a pairwise test of equal accuracy indicates statistical significance at the 5 percent level. In general, the results are statistically insignificant; however, in accordance with figures 4 and 5, the small MF-BVAR is significantly more accurate than the large MF-BVAR in terms of point forecasting, while simultaneously being less accurate in terms of density forecasting.[11]

Table 3 reports the accuracy measures and tests of equal predictive accuracy from table 2 but for forecasts of industrial production, housing starts, and 3-month and 10-year yields. In many instances, especially for the 3-month and 10-year yields, differences in accuracy are statistically insignificant. Significant differences do arise when comparing the MF-BVAR density forecasts of industrial production and housing starts. In addition, while not uniform across forecast origins, both MF-BVARs provide statistically significant improvements over the SPF for point forecasts of industrial production.

4.3 Scenario Forecasting

The previous subsections indicate that point forecasts from the surveys are difficult to beat in terms of RMSEs. Even so, there is one thing our model can do that the surveys cannot—produce scenario forecasts designed to guide hypothetical policies. While perhaps not immediately obvious, the block structure of the MF-BVAR permits scenarios other lower-frequency models cannot. In this section, we provide two examples of high-frequency, policy-oriented scenarios and compare their implementation using the MF-BVAR to that of a quarter BVAR with quarterly averaged monthly variables.

In both examples, we consider a central bank that uses a high-frequency interest rate to conduct monetary policy. The goal of the policy is to influence a low-frequency series such as GDP. In a purely

[11]To get a feel for the differential performance of the small and large MF-BVARs for real GDP growth at the four-quarter-horizon, we again considered two alternative MF-BVARs: one in which we add the remaining real variables to the small model and one in which we add the financial variables to the small model. In unreported results, we find that including the financial variables leads to a sharp deterioration of the point forecasts but has little impact on the density forecasts. Adding the real variables has the opposite effect: a sharp improvement of the density forecasts with little impact on the accuracy of the point forecasts.

Table 3. RMSEs and Mean CRPSs of Four-Quarter-Ahead Forecasts of Select Monthly Variables for the 1992:Q2 to 2017:Q1 Sample

		Industrial Production			Housing Starts		
		SPF	**MF-BVAR (Small)**	**MF-BVAR (Large)**	**SPF**	**MF-BVAR (Small)**	**MF-BVAR (Large)**
M1	SPF	5.63\NA			245.39\NA		
	MF-BVAR (Small)	**0.82**	4.64\5.15	**1.06**	**0.95**	232.13\296.33	**1.07**
	MF-BVAR (Large)	**0.88**	1.07	4.96\4.84	0.91	0.96	222.67\275.90
M2	SPF	4.58\NA			202.24\NA		
	MF-BVAR (Small)	0.95	4.33\4.78	1.06	1.07	217.03\279.15	**1.10**
	MF-BVAR (Large)	1.01	1.07	4.63\4.51	1.03	0.96	208.29\253.81
M3	SPF	4.58\NA			202.24\NA		
	MF-BVAR (Small)	0.91	4.17\4.55	1.07	1.00	202.63\266.56	**1.11**
	MF-BVAR (Large)	0.95	1.05	4.37\4.27	0.97	0.97	196.00\240.45
M4	SPF	4.58\NA			202.24\NA		
	MF-BVAR (Small)	**0.81**	3.73\4.07	**1.08**	0.98	197.42\253.90	**1.10**
	MF-BVAR (Large)	**0.83**	1.02	3.81\3.75	0.92	0.94	185.80\230.32

		3-Month Yield		10-Year Yield	
		SPF	**MF-BVAR (Large)**	**SPF**	**MF-BVAR (Large)**
M1	SPF	1.31\NA		1.04\NA	
	MF-BVAR (Large)	0.95	1.24\1.81	0.96	1.01\1.29
M2	SPF	1.02\NA		0.90\NA	
	MF-BVAR (Large)	1.06	1.08\1.63	1.02	0.92\1.17
M3	SPF	1.02\NA		0.90\NA	
	MF-BVAR (Large)	1.03	1.04\1.58	0.96	0.87\1.12
M4	SPF	1.02\NA		0.90\NA	
	MF-BVAR (Large)	0.94	0.96\1.51	0.96	0.86\1.10

Notes: The table shows the RMSEs (below the slash) and mean CRPSs (above the slash) of each model on the diagonal. The lower off-diagonal portion of each panel in the table reports the ratio of RMSEs in the row-model to the column-model. The upper off-diagonal portion of each panel reports the ratio of average CRPS in the row-model to the column-model. The results are as of the "hours" release in each month. Off-diagonal numbers greater than 1 indicate that the column-model is nominally more accurate. Ratios in bold are statistically different from 1 at the 5 percent significance level.

quarterly model, the high-frequency policy rate would likely be averaged across all three months of the quarter, leaving the timing of the rate change obscured.[12] Instead, the MF-BVAR can explicitly account for the timing of the policy rate change within the quarter as well as capture the impact of any intraquarterly data that may have been released.

The specifics of both experiments, and their associated scenarios, are adapted from the pattern of federal funds rate changes made by the Federal Open Market Committee (FOMC) throughout 2017 but, to maintain consistency across sections of the paper, we use the three-month Treasury yield as the policy rate. For example, suppose that on the last business day of January 2017, a scenario forecast is made that assumes the three-month Treasury yield remains constant throughout February but rises 25 basis points (bps) in March (e.g., at the March FOMC meeting). It then remains unchanged until June, at which time it rises another 25 bps. It is then assumed to remain constant throughout much of the year before rising another 25 bps in December and stays constant until the end of the year.

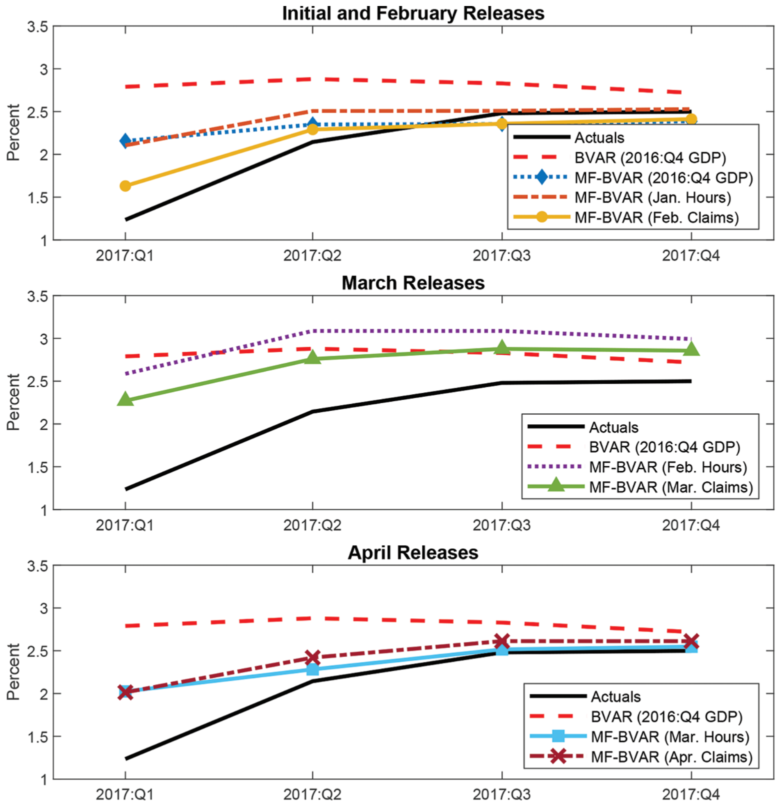
In the MF-BVAR, implementing this scenario is straightforward. We map the month-to-month changes in the policy rate directly into specific variables in the large MF-BVAR: the first, second, and third three-month Treasury yields. For the quarterly BVAR, we first form quarterly averages of the scenario and then form conditional forecasts using this low-frequency approximation to the high-frequency scenario.

In our first experiment, we address two issues related to scenario forecasting. First, holding the forecast origin constant, are there substantive differences between the MF-BVAR and quarterly BVAR forecasts? Second, are there substantive differences among the MF-BVAR forecasts as we receive high-frequency intraquarter information?

In figure 6, we plot multiple scenario forecasts of *total* annualized real GDP growth (cumulative sum of quarter on quarter growth rates) from 2016:Q4 for quarterly horizons 1 through 4. Total—rather than quarter-to-quarter—growth is reported in order to align our forecasts with the fixed-event forecasts used by the FOMC. Each

[12] See Knotek and Zaman (2019) for an exception.

Figure 6. Policy-Rate-Based Scenario Forecasts



Notes: The figure depicts total real GDP growth forecasts conditional on an assumed path of an interest rate. Each figure shows the forecasts from a quarterly BVAR as well as the actual realized value. Each panel further shows forecasts from the large MF-BVAR. (.) represents the release of a variable the forecast is conditioned on.

forecast is generated using the relevant real-time vintage of data exactly as we did for the one- and four-quarter-ahead forecasting exercises in the previous subsection. Actuals are reported using data from the advance release of 2017:Q4 GDP. It is useful to keep in mind that forecasts from the MF-BVAR will evolve as we obtain intraquarter information, while those from the quarterly BVAR will not.

In the first panel, we report forecasts from both quarterly and MF-BVAR models made from the same end-of-January forecast origin. At this origin, the quarterly BVAR forecasts are uniformly higher than those from the mixed-frequency BVAR. These differences are as large as 75 bps at the one-quarter horizon but narrow substantially at the four-quarter horizon. We then update the MF-BVAR forecast twice as we move across February. The first update aligns with the Employment Situation Report, while the second aligns with the claims report (and hence we observe all February releases). The first of these remains relatively close to the path predicted by the initial MF-BVAR forecast while the latter, in particular, reduces the near-term forecast of GDP growth sharply.

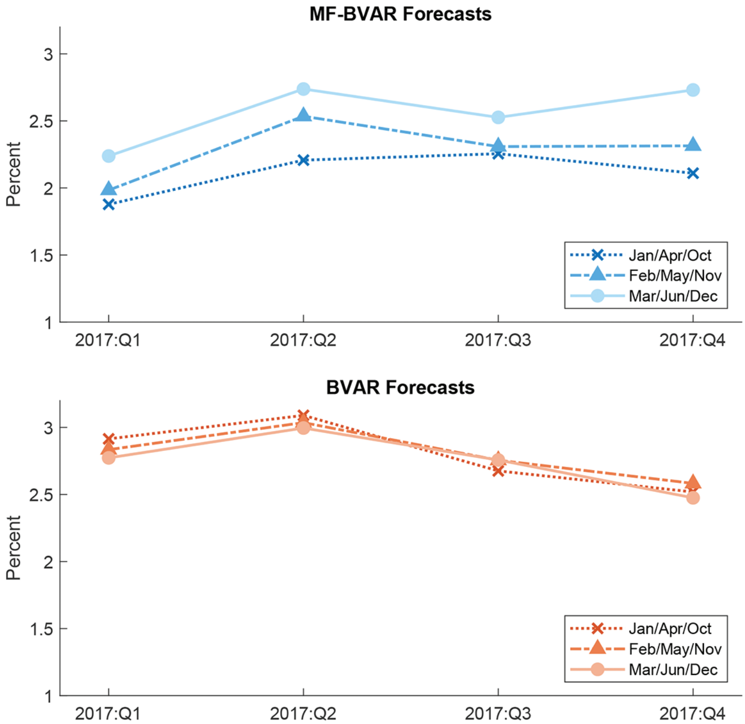
The second panel reports comparably updated forecasts from the MF-BVAR moving across March. Not surprisingly, given the strong employment report in early March 2017, the first March revision shifts the forecasts upwards and is now much more in line with that of the quarterly BVAR—at least for horizons greater than one quarter. Even so, as further data arrives in March, this shift moderates.

The final panel again reports updated forecasts from the MF-BVAR but this time as we move across April. In contrast to March, reported employment growth fell sharply. As a consequence, the scenario paths both decline and are again closely in line with the realized values of total GDP growth—at least relative to those from the quarterly BVAR, which does not get updated as we move across the quarter.

In the first experiment, the hypothetical, high-frequency scenario was held fixed and we investigated the impact of intraquarterly data releases on the subsequent forecast of the low-frequency variable. In our second experiment, we do the opposite: We hold the forecast origin constant and investigate whether or not changes to the intraquarterly timing of the high-frequency scenario affect forecasts of the low-frequency variable. For example, note that in 2017, each of the changes to the policy rate came in the third calendar month of the respective quarter. With this in mind, in our second experiment we hold the forecast origin constant at the end-of-January forecast origin and compare three distinct scenarios. The first continues to maintain that the 25 bps changes are made in the third month of the quarter, but for the other two scenarios we allow the same 25 bps changes to come in the first and second months of the quarter.[13]

[13] Recall that, in the MF-BVAR model, "tbill" is the monthly average of daily values for the three-month Treasury yield. As such, the precise date for the policy

Figure 7. Policy-Rate-Timing Scenario Forecasts



Notes: The figure depicts total real GDP growth forecasts conditional on three different assumed paths of an interest rate: (i) 25 bps increases in January, April, and October 2017, (ii) 25 bps increases in February, May, and November 2017, and (iii) 25 bps increases in March, June, and December 2017. The top panel shows the forecasts from the large MF-BVAR and the bottom panel shows the forecasts from a quarterly BVAR.

Akin to those provided in figure 6, in figure 7 we plot one- through four-quarter-ahead forecasts of total annualized real GDP growth but based on the three distinct scenarios. In the first panel we report

change matters for the average. For the first experiment we assumed that the policy rate changed mid-month, and hence the 25 bps change in the policy rate was spread out over the current and subsequent month. For the second experiment we assume that the policy rate was changed on the first business day of the month, and hence the monthly average of the three-month Treasury yield increases the full 25 bps within that month.

forecasts from the MF-BVAR, while in the second panel we report forecasts from the BVAR. In the first panel we find a clear pattern within the forecasts made by the MF-BVAR model: later policy rate changes lead to higher forecasts of growth. This is in contrast to those generated by the BVAR model in the second panel. Here we find little evidence that the timing of the policy rate changes matters for the forecasts.

While these are only two examples of scenario forecasts, both are realistic, policy-oriented scenarios that suggest some advantages to using the MF-BVAR when modeling mixed frequencies. First, the mixed frequency allows the user to implement detailed high-frequency scenarios that low-frequency models cannot. In addition, since the model is readily revised as high-frequency data is released, we are able to track how the scenario forecasts evolve within a quarter and, by implication, evolve as new data are observed between policy meetings.

5. Conclusion

In this paper, we investigate the usefulness of a particular type of mixed-frequency VAR, delineated by Ghysels (2016), in the context of real-time forecasting. In this model, multiple high-frequency intraquarter observations are treated as distinct quarterly observations, and a standard VAR is formed based on these series. Because this leads to a high-dimensional VAR, we estimate the parameters using standard shrinkage-based Bayesian methods. In addition, since the model is just a Bayesian VAR, existing methods developed by Waggoner and Zha (1999) can be used to produce end-of-quarter forecasts as well as intraquarter forecasts that account for high-frequency data releases.

In terms of both point and density forecasts, we find that the iterated multistep approach to mixed-frequency nowcasting of real GDP growth performs as well as direct multistep variants developed in Carriero, Clark, and Marcellino (2015) and, depending on the specific version of our model, can be as accurate as the SPF and BCEI at certain very short horizons. One advantage of the MF-BVAR model is that the same model can be used for both near- and longer-horizon forecasting. As such, we also compare the forecasting performance of our model to the survey forecasts at the four-quarter horizon. At this longer horizon we find that the small-scale MF-BVAR model is as good as or better than the SPF and BCEI when forecasting real GDP growth. In addition, the MF-BVAR generally outperforms the SPF when forecasting monthly variables such as industrial production, housing starts, and, to a lesser extent, 3-month and 10-year Treasury yields. Finally, we discuss the usefulness of the model for central bank-type scenario forecasting when the scenario is delineated using high-frequency observables, but the object of interest is only observed at the lower frequency.

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