Online Appendixes to "Monetary Policy Transmission via Loan Contract Terms in the United States"

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Appendix A. External Instrument HFI Identification

Let $\mathbf{Z}_t$ be the vector of endogenous variables; $\mathbf{A}, \mathbf{K}$ conformable coefficient matrices; $\mathbf{B}(L)$ a lag polynomial (of order p) conformable matrix; and ϵ_t a vector of structural white-noise innovations with identity covariance matrix. The structural VAR that I consider is given by

$$\mathbf{A}\mathbf{Z}_t = \mathbf{K} + \mathbf{B}(L)\mathbf{Z}_{t-1} + \epsilon_t. \tag{A.1}$$

Assuming that the matrix $\mathbf{A}$ is invertible so that $\mathbf{S} = \mathbf{A}^{-1}$, the reduced-form representation of (A.1) is

$$\mathbf{Z}_t = \tilde{\mathbf{K}} + \tilde{\mathbf{B}}(L)\mathbf{Z}_{t-1} + \mathbf{u}_t, \tag{A.2}$$

with $\tilde{\mathbf{K}} \equiv \mathbf{S}\mathbf{K}$, $\tilde{\mathbf{B}}(L) \equiv \mathbf{S}\mathbf{B}(L)$, and the vector of reduced-form shocks $\mathbf{u}_t = \mathbf{S}\epsilon_t$. Note that the covariance matrix of the reduced-form shocks is given by

$$\Sigma = \mathbb{E}_t\left[\mathbf{u}_t\mathbf{u}_t'\right] = \mathbb{E}_t\left[\mathbf{S}\mathbf{S}'\right]. \tag{A.3}$$

Define the monetary policy indicator $z_t^p \in \mathbf{Z}_t$ as the variable in the structural representation (A.1) associated with the fundamental policy shock $\epsilon_t^p \in \epsilon_t$.[1] Note that one can write $\epsilon_t = [\epsilon_t^p \, \epsilon_t]'$ and $\mathbf{S} = \left[\mathbf{s}^p \, \tilde{\mathbf{S}}\right]$, so that $\mathbf{u}_t = \mathbf{s}^p\epsilon_t^p + \tilde{\mathbf{S}}\epsilon_t$. The column vector $\mathbf{s}^p$ captures the impact of the fundamental policy disturbance in each of the

[1] There is a distinction between the monetary policy indicator and the monetary policy instrument. The latter is the current-period federal funds rate, through which the monetary authority conducts its policy. The former is just a proxy of the stance of monetary policy.

reduced-form errors. Therefore, I interpret $s_j^p \in \mathbf{s}^p$ as an indicator of the contemporaneous *transmission* of the monetary policy shock via variable $z_j \in \mathbf{Z}$. This interpretation will allow me to quantify the relative contribution of different variables to the *transmission* of unanticipated monetary policy news.

For my purposes it suffices to identify and estimate the elements in $\mathbf{s}^p$ rather than the entire matrix $\mathbf{S}$. Consider $\mathbf{s}^p = \left[s_p^p \, \tilde{\mathbf{s}}^p\right]'$, where s_p^p captures the contemporaneous *transmission* of the monetary policy shock via the monetary policy indicator. Let IV_t be an external instrument satisfying the following two conditions:

$$\mathbb{E}\left[\mathrm{IV}_t \epsilon_t^p\right] = \gamma \neq 0 \tag{A.4}$$
$$\mathbb{E}\left[\mathrm{IV}_t \boldsymbol{\epsilon}_t\right] = \mathbf{0}. \tag{A.5}$$

Equation (A.4) implies that the external instrument must be correlated with the fundamental monetary policy disturbance (the relevance condition). Equation (A.5) requires the external instrument to be orthogonal to all the other structural disturbances (the exogeneity condition).

Given the instrument IV_t, I proceed as follows. I first estimate the reduced-form VAR in (A.2) using ordinary least squares (OLS) to obtain estimates of the parameter matrices $\widehat{\tilde{\mathbf{K}}}$ and $\widehat{\tilde{\mathbf{B}}}(L)$, the reduced-form residual vector, $\hat{\mathbf{u}}_t = \left[\hat{u}_t^p \, \widehat{\tilde{\boldsymbol{u}}}_t\right]'$ (where $\hat{u}_t^p$ is the reduced-form residual corresponding to the equation of the policy indicator), and the covariance matrix, $\widehat{\boldsymbol{\Sigma}}$. Second, I perform a two-stage least squares regression of $\widehat{\tilde{\boldsymbol{u}}}_t$ on $\hat{u}_t^p$ using the instrument IV_t:

$$\text{First Stage:} \quad \hat{u}_t^p = \beta \mathrm{IV}_t + \nu_t^p \tag{A.6}$$
$$\text{Second Stage:} \quad \widehat{\tilde{\boldsymbol{u}}}_t = \boldsymbol{\alpha}\left(\hat{\beta}\mathrm{IV}_t\right) + \tilde{\boldsymbol{\nu}}_t. \tag{A.7}$$

Given assumption (A.4), the fitted value of the first-stage regression isolates the variation of $\hat{u}_t^p$ that is due to the fundamental policy shock ϵ_t^p. Meanwhile, the second-stage regression captures the variation of the remaining residuals that is due to ϵ_t^p. The advantage of using this two-stage approach is that it identifies the vector of contemporaneous propagation coefficients, $\mathbf{s}^p$, up to a scaling factor. This is because the coefficient of the second-stage regression is given by $\boldsymbol{\alpha} = \tilde{\mathbf{s}}^p \left(s_p^p\right)^{-1}$ and its OLS estimator, $\widehat{\boldsymbol{\alpha}}$, is consistent and unbiased whenever assumption (A.5) holds. The procedure is completed by pinning down the scaling factor s_p^p. The restriction on the covariance matrix, equation (A.3), implies that s_p^p can be identified up to a sign convention.[2]

Using the estimates $\hat{s}_p^p$, $\widehat{\boldsymbol{\alpha}}$, $\widehat{\tilde{\mathbf{K}}}$, and $\widehat{\tilde{\mathbf{B}}}(L)$ along with the reduced-form representation (A.2), I can compute impulse response functions (IRFs), forecast error variances, and historical decompositions.

Appendix B. Forecast Error Variance Decomposition

One can use forecast error variance decomposition to quantify the contribution of different variables to the *transmission* of monetary policy shocks as follows. Consider a one-time monetary policy shock at date $t = 1$. The monetary policy shock causes a *contemporaneous change* in each VAR variable (captured by the vector $\mathbf{s}^p$). In turn, the nature of the VAR implies that the *contemporaneous change* in any of the VAR variables can cause a change in any of the other VAR variables at *any future date* (captured by the estimated coefficients of the reduced-form VAR). Therefore, for any aggregate macroeconomic variable of interest (y), the one-time monetary policy shock at date $t = 1$ leads to a change in y for any time $t > 1$. The resulting change of y at any time $t > 1$ is a consequence of the *initial change in all of the VAR variables*. The contribution of variable x to the transmission of the monetary policy shock (to variable y) can be quantified as the fraction of the total variation in y that is purely due to the initial change in variable x.

Formally, one can proceed as follows. Let $\epsilon_t = \mathbf{0}\ \forall t$ so that for any horizon h the forecast error for the vector $\mathbf{Z}_t$ is given by

$$\mathbf{Z}_{t+h} - \mathbb{E}_t\left[\mathbf{Z}_{t+h}\right] = \sum_{q=0}^{h-1} \boldsymbol{\Psi}_q \mathbf{u}_{t+h-q} = \sum_{q=0}^{h-1} \boldsymbol{\Psi}_q \mathbf{s}^p \epsilon_{t+h-q}^p, \tag{B.1}$$

with the MA coefficients defined recursively as $\boldsymbol{\Psi}_0 = \mathbf{I}$ and $\boldsymbol{\Psi}_q = \sum_{j=1}^{q} \boldsymbol{\Psi}_{q-j}\mathbf{B}_j$, $\forall q \geq 1$. Let n denote the number of variables in the vector $\mathbf{Z}$ and consider the variable $z^i \in \mathbf{Z}$, $i \in \{1, \ldots, n\}$. Denote by s_k^p the component of the vector $\mathbf{s}^p$ corresponding to variable $z^k \in \mathbf{Z}$, $k \in \{1, \ldots, n\}$ and by $\psi_q^{i,k}$ the $\left(i^{\text{th}}, k^{\text{th}}\right)$ element of the matrix $\boldsymbol{\Psi}_q$.

[2]Gertler and Karadi (2015) provide a closed-form solution that yields $\hat{s}_p^p$ as a function of the estimated parameters $\widehat{\boldsymbol{\alpha}}$ and $\widehat{\boldsymbol{\Sigma}}$.

In light of (B.1), the forecast error variance of variable z^i_{t+h} due exclusively to the fundamental monetary policy shock is given by

$$\text{FEV}_i\left(h\right) \equiv \mathbb{V}ar\left(z^i_{t+h} - \mathbb{E}_t\left[z^i_{t+h}\right]\right) = \sum_{q=0}^{h-1}\left(\sum_{k=1}^{n}\psi_q^{i,k}s_k^p\right)^2. \quad \text{(B.2)}$$

Consider a one-period horizon ($h = 1$). Since $\psi_0^{i,k} = 1$ iff $i = k$ and zero otherwise, the one-step-ahead forecast error variance is $\text{FEV}_i\left(1\right) = \left(s_i^p\right)^2$. Two things are worth pointing out. First, the $\text{FEV}_i\left(1\right)$ measures the *contemporaneous variation* of z^i_t due to an unexpected monetary policy announcement. Second, the *contemporaneous variation* of z^i_t is completely summarized by the parameter s_i^p.

Now consider a horizon longer than one period ($h > 1$) and define

$$\text{FEV}_{i,k}\left(h\right) \equiv \sum_{q=0}^{h-1}\left(\psi_q^{i,k}s_k^p\right)^2 \quad \text{(B.3)}$$

$$\text{FEV}_i^{\text{var}}\left(h\right) \equiv \sum_{k=1}^{n}\text{FEV}_{i,k}\left(h\right) \quad \text{(B.4)}$$

$$\text{FEV}_i^{\text{cov}}\left(h\right) \equiv \sum_{q=0}^{h-1}\left[\sum_{k=1}^{n}\left(\psi_q^{i,k}s_k^p\right)\sum_{r\neq k}^{n}\left(\psi_q^{i,r}s_r^p\right)\right]. \quad \text{(B.5)}$$

For any variables $z^i, z^k \in \mathbf{Z}$, $i, k \in \{1, \ldots, n\}$ and for any j such that $h \geq j \geq 1$, an unanticipated monetary policy shock at period $t + j$ results in *contemporaneous variation* in z^k_{t+j}. As discussed in the previous paragraph, this contemporaneous variation is captured entirely by the parameter s_k^p. Additionally, the change in variable z^k_{t+j} leads to variation in z^i_{t+h}. This effect of z^k_{t+j} on z^i_{t+h} is captured by the MA coefficient $\left(\psi_{h-j}^{i,k}\right)^2$. Therefore, the effect of a monetary shock on z^i_{t+h} due to the change in z^k_{t+j} is captured by the product $\left(\psi_{h-j}^{i,k}s_k^p\right)^2$. Then it is easy to see that equation (B.3) quantifies the contribution of variable z^k to the variation in z^i_{t+h} caused by a sequence of monetary shocks from $t + 1$ until $t + h$.

Equation (B.4) just adds the contribution of all variables $z^k \in \mathbf{Z}$, $k \in \{1, \ldots, n\}$ to the variation in z^i_{t+h} caused by a sequence of monetary shocks from $t + 1$ until $t + h$. Note that equation (B.4) does not quantify the *total* variation in z^i_{t+h} due to unanticipated monetary shocks—just the portion of the variation that takes place due to changes in each individual variable $z^k \in \mathbf{Z}$. To see why this is the case, consider any variables $z^k, z^r \in \mathbf{Z}$, $k, r \in \{1, \ldots, n\}$. An unanticipated monetary policy shock at period $t+j$ results in contemporaneous *individual* changes in z^k_{t+j} and z^r_{j+j}, but it also results in contemporaneous *covariation*. Within the current setup, there is no way of telling the direction of causality of the contemporaneous covariation; one can't distinguish if the change in z^k causes the change in z^r or vice versa. The term $\mathrm{FEV}^{\mathrm{cov}}_i(h)$, defined in equation (B.5), quantifies the total variation in z^i_{t+h} due to this covariance effect. Thus the total variation in variable z^i_{t+h} due to unanticipated monetary policy shocks from $t+1$ to $t+h$, equation (B.2), can be rewritten as $\mathrm{FEV}_i(h) = \mathrm{FEV}^{\mathrm{var}}_i(h) + \mathrm{FEV}^{\mathrm{cov}}_i(h)$.

Thus one can think of the ratio $\mathrm{FEV}_{i,k}(h)/\mathrm{FEV}^{\mathrm{var}}_i(h)$ as a measure of the percent contribution of variable $z^k \in \mathbf{Z}$ to to changes in variable $z^i \in \mathbf{Z}$ caused by monetary surprises during the horizon h (i.e., from $t+1$ to $t+h$).

Appendix C. Historical Decomposition

One can also use the historical decomposition to quantify the contribution of different variables to monetary transmission. The idea is again based on the observation that the historical fluctuation in z^i_T due to a monetary policy shock realized at any period $t < T$ is a consequence of the contemporaneous change at t in *all* of the VAR variables. However, the *transmission* (i.e., contribution) via variable z^k is just the portion of the fluctuation in z^i_T caused by the change in z^k_t.

Consider the finite approximation of the moving-average representation

$$\widehat{\mathbf{Z}}_t \simeq \sum_{q=0}^{t-1} \widehat{\mathbf{\Psi}}_q \hat{\mathbf{u}}_{t-q} \simeq \sum_{q=0}^{t-1} \widehat{\mathbf{\Psi}}_q \hat{\mathbf{S}} \hat{\epsilon}_{t-q}. \tag{C.1}$$

One can quantify the *total* contribution of the monetary shocks to the fluctuations in $\widehat{\mathbf{Z}}_t$ by noting that $\hat{\epsilon}_t = \left[\hat{\epsilon}^p_t \, \widehat{\tilde{\boldsymbol{\epsilon}}}_t\right]'$ and setting (counterfactually) $\widehat{\tilde{\boldsymbol{\epsilon}}}_t = 0 \forall t$, where the hat notation refers to estimated variables. This procedure hinges on the assumption that the matrix

$\mathbf{S}$ is completely identified in the estimation procedure. Even if setting $\tilde{\boldsymbol{\epsilon}}_t = 0 \forall t$ in equation (C.1) implies that one doesn't need to know the full matrix $\tilde{\mathbf{S}}$, obtaining an estimate for the sequence of monetary policy shocks $\{\hat{\epsilon}_t^p\}_{t=0}^T$ via the relationship $\hat{\mathbf{u}}_t = \mathbf{S}\hat{\epsilon}_t$ requires knowledge of the entire matrix $\mathbf{S}$.

Fortunately I am not interested in the total contribution of monetary shocks to historical fluctuations in $\widehat{\mathbf{Z}}_t$, just in the transmission of these shocks via different variables. The HFI procedure provides a *proxy* for the sequence of monetary policy shocks $\{\hat{\epsilon}_t^p\}_{t=0}^T$ as a byproduct. To see this, consider the two-stage least squares regression in the HFI procedure. Equations (A.6) and (A.7) imply that

$$\widehat{\boldsymbol{u}}_t = \boldsymbol{\kappa}\beta \mathrm{IV}_t + \boldsymbol{\zeta}_t, \tag{C.2}$$

with $\boldsymbol{\kappa} = [1\,\boldsymbol{\alpha}]'$ and $\boldsymbol{\zeta}_t = [\nu_t^p\,\tilde{\boldsymbol{\nu}}_t]'$. Since the reduced-form errors are assumed to be a linear function of the fundamental shocks, $\mathbf{u}_t = \mathbf{s}^p\epsilon_t^p + \tilde{\mathbf{S}}\tilde{\boldsymbol{\epsilon}}_t$, as long as the relevance and exogeneity conditions—equations (A.4) and (A.5)—are satisfied, it must be the case that $\boldsymbol{\kappa}\beta\mathrm{IV}_t \propto \mathbf{s}^p\epsilon_t^p$ and $\boldsymbol{\zeta}_t \propto \tilde{\mathbf{S}}\tilde{\boldsymbol{\epsilon}}_t$. Therefore, the contribution of the monetary policy shock (up to a scaling factor) to the fluctuations in $\widehat{\mathbf{Z}}_t$ can be written as

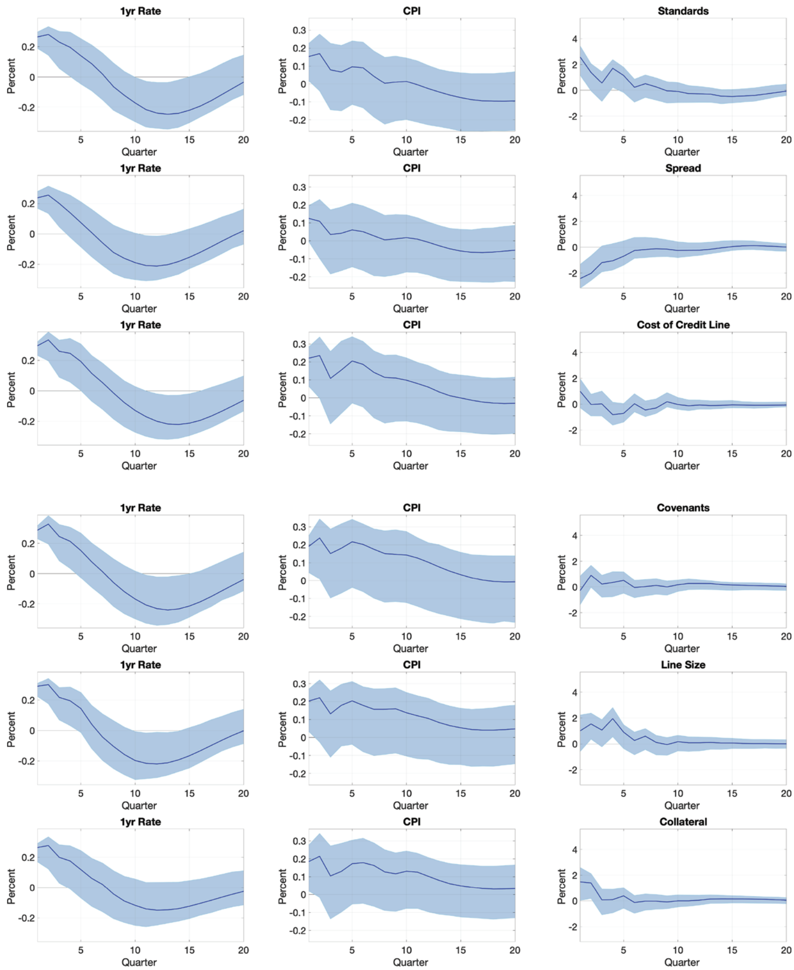
$$\widehat{\mathbf{Z}}_t^p \simeq \sum_{q=0}^{t-1} \widehat{\boldsymbol{\Psi}}_q \hat{\boldsymbol{\kappa}}\hat{\beta}\mathrm{IV}_{t-q}. \tag{C.3}$$

Using equation (C.3) to quantify the transmission of monetary policy shocks to $\hat{z}_t^i$ via each variable $z^k \in \mathbf{Z}$ is straightforward. Recall that $s_k^p \in \mathbf{s}^p$ captures the *contemporaneous transmission* of the monetary policy shock via variable z^k. Given that $\hat{\boldsymbol{\kappa}}\hat{\beta}\mathrm{IV}_t \propto \mathbf{s}^p\epsilon_t^p$, the total transmission of the monetary policy shock via variable z^k is obtained by setting (counterfactually) $\hat{\kappa}_j = 0, \forall \hat{\kappa}_j \in \hat{\boldsymbol{\kappa}}, j \neq k$.

A possible concern is the effect of the scaling factor when using equation (C.3). On one hand, if the intent is to assess the total contribution of monetary policy shocks to the fluctuations in $\hat{z}_t^i \in \widehat{\mathbf{Z}}_t$, then such assessment might be biased. The bias ultimately depends on the size and sign of the scaling factor. On the other hand, if the intent is to compare the contribution of different transmission channels to the fluctuations in $\hat{z}_t^i \in \widehat{\mathbf{Z}}_t$ *relative to each other*, then the results are not affected by the scaling factor. This is because the same instrument is used for all variables in the VAR for the HFI procedure. In turn, this implies that the scaling factor is the same for all components of the vector $\hat{\boldsymbol{\kappa}}$.

Appendix D. Response for the One-Year Rate and the CPI

Figure D.1. Effect of a One-Standard-Deviation Surprise Monetary Tightening



Note: The shaded area represents the 90 percent confidence interval.

Appendix E. Forecast Error Variance Decomposition Results

Table E.1. Percent Contribution of Different Variables to Monetary Transmission

	One-Year Rate	Excess Bond Premium	Loan Contract Term
Standards	24.88	3.70	71.42
	(2.70–84.18)	(0.14–74.87)	(3.81–88.51)
Spread	18.18	0.15	81.67
	(1.58–62.32)	(0.07–53.58)	(18.71–93.67)
Cost of Line	70.54	27.51	1.96
	(8.12–98.48)	(0.22–87.57)	(0.02–30.16)
Covenants	87.71	11.39	0.90
	(16.13–98.58)	(0.16–77.95)	(0.01–30.24)
Line Size	55.26	38.94	5.80
	(6.40–97.41)	(0.41–88.62)	(0.01–40.37)
Collateral	38.08	43.16	18.76
	(4.29–88.32)	(0.43–86.52)	(0.23–76.00)

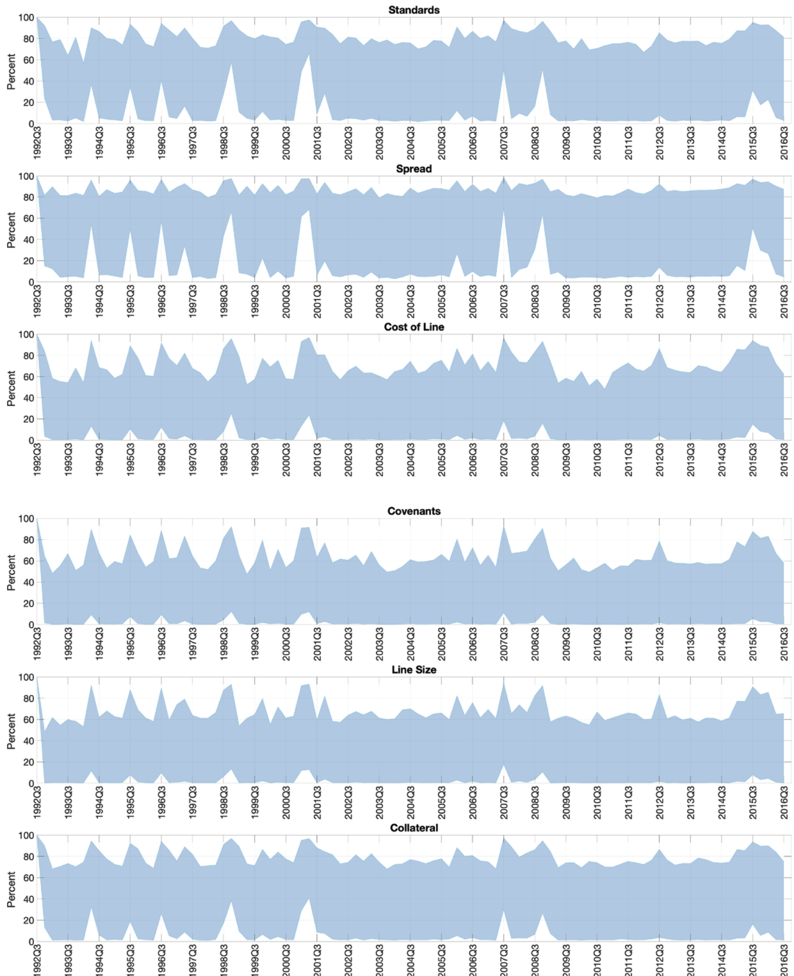
Source: Author's estimation.
Note: The 90 percent confidence intervals are given in parentheses.

Table E.1 presents the percent contribution (over a one-year horizon) of the one-year rate, the excess bond premium, and the different loan contract terms to the forecast error variance of real GDP induced by monetary policy shocks. The results correspond to the ratio $\phi_{i,j}(h) / \sum_{z_j} \phi_{i,j}(h)$ averaged over $h \in \{1, 2, 3, 4\}$, with $z_i \in$ {Real GDP}, and $z_j \in$ {One-Year Rate, EBP, SLOOS term}.[3] The *joint* contribution of the nonprice terms (proxied by changes in the standards) accounts, on average, for about 70 percent of the forecast error variance in GDP following monetary surprises. The contribution of any *individual* nonprice term (maximum line size, covenants, or collateral requirements) is not that relevant on its own, but it is largest for collateral requirements.

[3] See equation (2) in the main text.

Appendix F. Historical Decomposition Results

Figure F.1. Contribution of C&I Loan Terms to Historical Changes in Real GDP Due to Monetary Policy Shocks



Note: The shaded area represents the 90 percent confidence band.

Figure F.1 shows the 90 percent confidence band for the contribution of adjustments in the credit conditions (triggered by monetary policy shocks) to historical changes in real GDP. These results correspond to the ratio $|\tilde{z}^i_{c_j,t}|/\sum_{z_j}|\tilde{z}^i_{c_j,t}|$, with $z_i \in$ {Real GDP}, $z_j \in$ {One-Year Rate, EBP, SLOOS term}, and $\tilde{z}^i_{c_j,t}$ obtained via the historical decomposition counterfactual.[4]

The confidence intervals are rather wide and not too informative for most of the sample period. However, there are a few exceptions: the late 1990's and early 2000's, the financial crisis of 2007–08, and the mid-2010's. As can be seen from these periods, changes in the non-price terms (proxied by changes in the standards) account for at least 40 percent of the change in GDP triggered by monetary surprises. The contribution of changes in *all* three nonprice terms is important, but it is largest for collateral requirements.

Appendix G. Robustness: Other Indicators of Credit Conditions

I use VAR specifications that include the C&I loan rate spread instead of the excess bond premium as the indicator of the overall credit conditions.[5] The spread is measured as the difference between the aggregated lending rate for all C&I loans and the 1YR (or 2YR) government bond.[6]

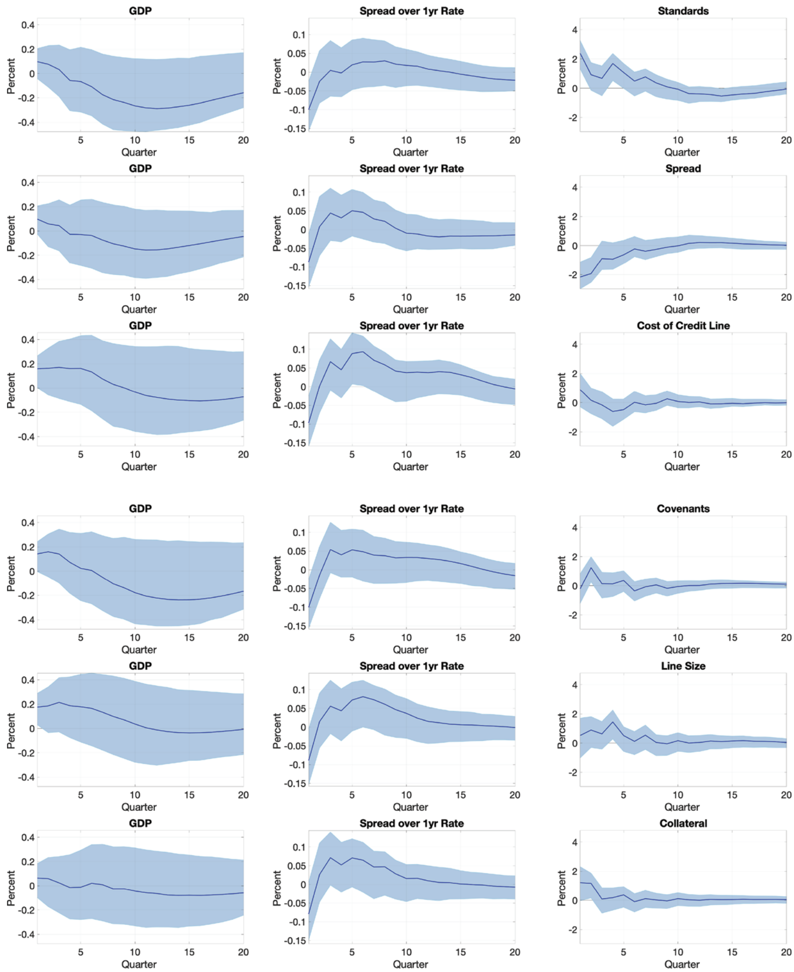
Figure G.1 presents the IRFs of real GDP (left pane), the interest rate spread (middle pane), and the SLOOS net percent of banks tightening the specified C&I loan contract term (right pane) after a surprise monetary contraction. The GDP responses are qualitatively similar to the baseline responses in the main text (left column in figure 3), but smaller in magnitude. This is not surprising considering the excess bond premium contains *more* relevant information about the economy than the loan spreads (and than most other credit indicators). The response of the SLOOS variables remains unchanged relative to the baseline responses in the main text (right column in figure 3); the nonprice terms (standards, covenants, line size, and collateral requirements) tighten and the spread relaxes for about five quarters after the shock. The response of the *actual* spread

[4]See equation (3) in the main text.

[5]The conclusions hold when using the mortgage spread or the commercial paper spread.

[6]The average maturity of C&I loans during the sample period was about 1.6 years.

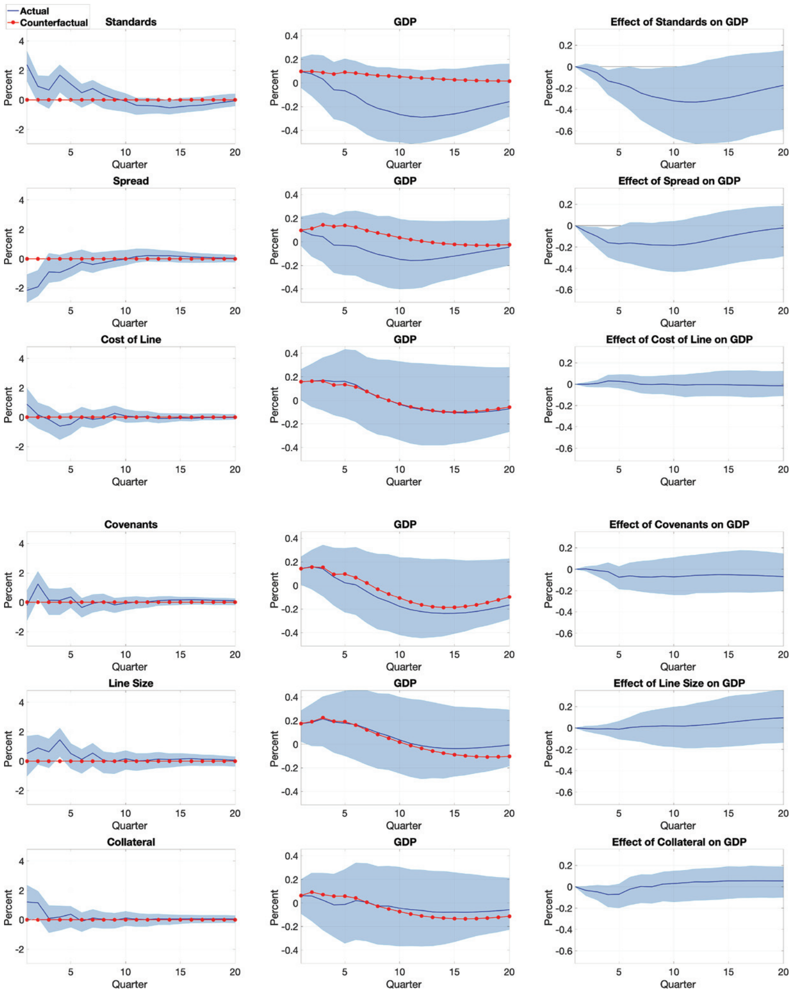
Figure G.1. Effect of a One-Standard-Deviation Surprise Monetary Tightening when the Spread over the One-Year Yield Is Used instead of the Excess Bond Premium



Note: The shaded area represents the 90 percent confidence interval.

is mostly consistent with the response of the SLOOS net percent of banks tightening the spread (second row). In particular, both experience a decrease right after the contractionary shock (although it is marginally statistically significant for the actual spread).

Figure G.2. Contribution of C&I Loan Terms to Monetary Policy Transmission when the Spread over the One-Year Yield Is Used instead of the Excess Bond Premium



Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Figure G.2 presents the IRF counterfactual described in section 4.2 of the paper. The *joint* contribution of the nonprice terms to monetary policy transmission remains economically and statistically relevant.

Appendix H. Summary Statistics for the First-Stage Regression

Table H.1. First-Stage Regression Summary Statistics

	A. Baseline VAR Specification with Four Lags					
	Standards	**Spread**	**Cost of Line**	**Covenants**	**Line Size**	**Collateral**
Observations	97	97	97	97	97	97
Adj. R^2	0.10	0.10	0.12	0.13	0.11	0.08
F-statistic	12.14	9.34	16.93	13.37	10.73	9.22
	B. VAR Specification with Two Lags					
	Standards	**Spread**	**Cost of Line**	**Covenants**	**Line Size**	**Collateral**
Observations	99	99	99	99	99	99
Adj. R^2	0.13	0.14	0.13	0.14	0.14	0.12
F-statistic	12.28	10.22	14.79	12.66	11.34	13.33

Source: Author's estimation.

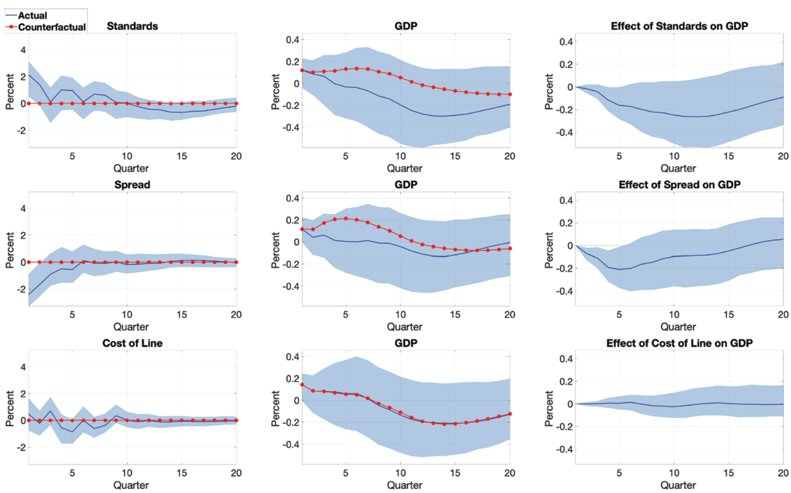
Table H.1 provides summary statistics for the first-stage regression of the VAR residuals on the external instrument FF_3. I follow the criteria proposed by Stock, Wright, and Yogo (2002) to rule out the weak instrument problem and use an F-statistic threshold value of 10.[7] As can be seen from panel A, the robust F-statistic for the baseline VARs is either well beyond the specified threshold or sufficiently close. To alleviate the concerns even further, panel B shows that the robust F-statistic is well beyond the specified threshold in *all* cases for the VAR specifications with two lags (appendix J shows the results remain robust under the specifications with two lags).

[7]An instrument is strong when it ensures that a 5 percent hypothesis test rejects no more than 15 percent of the time. Table 1 in Stock, Wright, and Yogo (2002) shows that for the case of one instrument (which is my case), the F-statistic threshold is 8.96.

Appendix I. Robustness: Instrument Choice

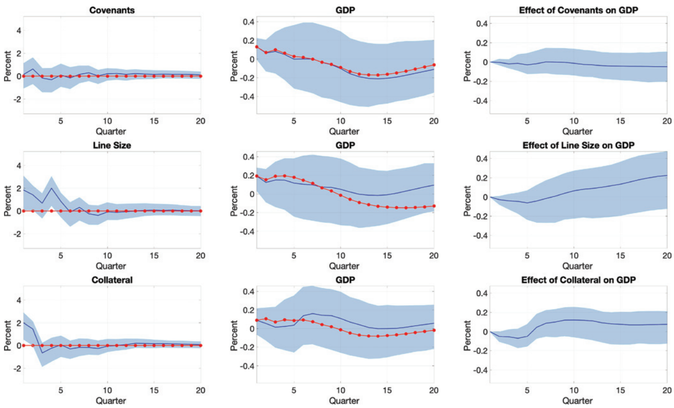
Figures I.1 and I.2 present the IRF counterfactual described in the paper (section 4.2) when using FF_0 as the external instrument. The sample period is restricted to 1990:Q1–2012:Q2 due to the limited availability of the instrument. The figures show that the response and contribution of the different C&I loan terms to monetary policy transmission remain unchanged relative to the baseline specification. In particular, the *joint* contribution of the nonprice terms (lending standards) to monetary policy transmission remains (marginally) statistically significant.

Figure I.1. IRF Counterfactual for Standards, Spreads, and Cost of Line when Using FF_0 as the External Instrument



Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Figure I.2. IRF Counterfactual for Covenants, Line Size, and Collateral when Using FF_0 as the External Instrument



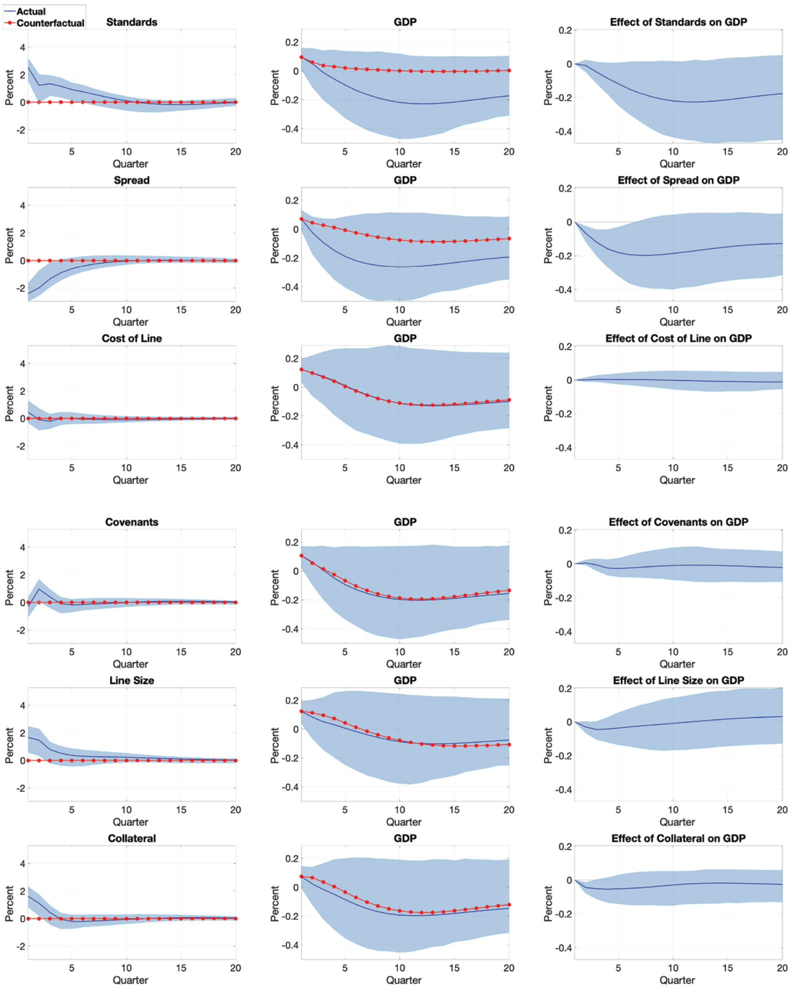
Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Appendix J. Robustness: Number of Lags

Figure J.1 presents the IRF counterfactual described in the paper (see section 4.2) for VAR specifications that include only two lags instead of four. The figure shows that the response of the different C&I loan terms remains unchanged relative to the baseline specification. However, there are some slight changes in terms of the contribution of the loan terms to monetary transmission. First, the contribution of the lending standards is no longer statistically significant. Second, the contribution of the tightening in collateral requirements becomes statistically significant. These results would suggest the changes in lending standards no longer relevant for monetary transmission.

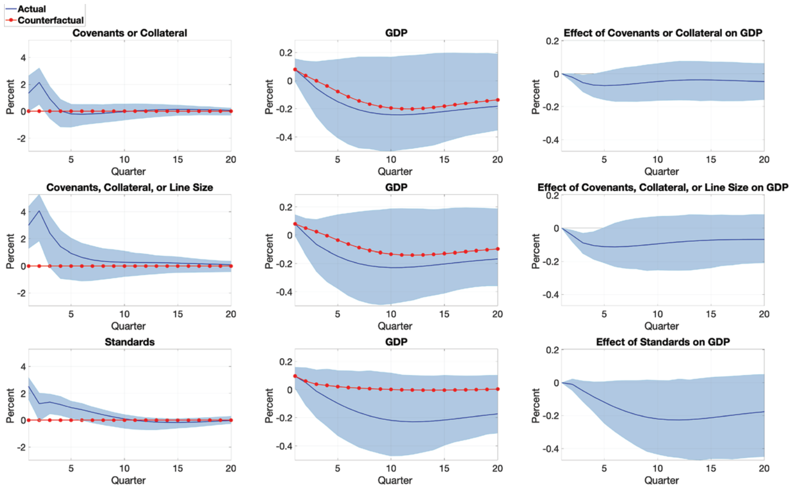
Nonetheless, figure J.2 presents the responses of the specifications that account for *simultaneous* changes in covenants, collateral requirements, and the maximum line size. As it can be seen from the figure, the effect of the nonprice terms on GDP is still statistically significant when thinking about them collectively (note that it is larger in magnitude and "more" statistically significant than the isolated effect of collateral changes). Altogether, these results

Figure J.1. IRF Counterfactual for Contract Terms when VAR Specifications Include Only Two Lags instead of Four



Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Figure J.2. IRF Counterfactual for Covenants, Collateral, and Line Size when VAR Specifications Include Only Two Lags instead of Four



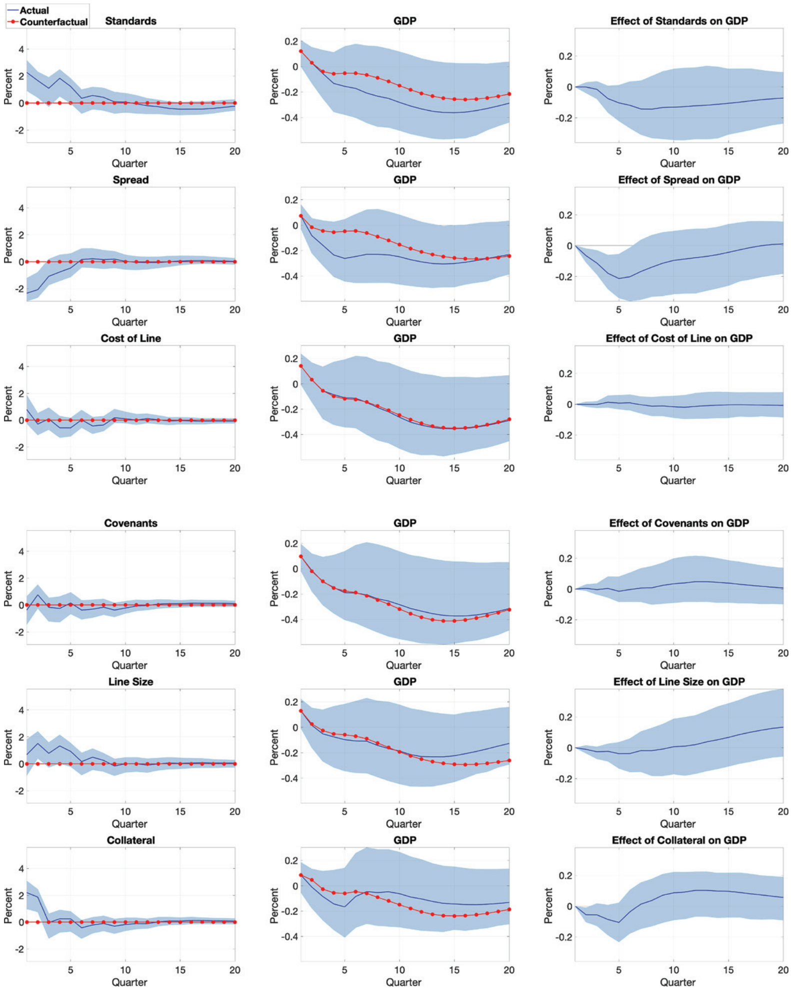
Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

suggest that the nonprice terms (particularly collateral requirements) are relevant for monetary transmission and account for significant changes in GDP following monetary surprises.

Appendix K. Robustness: SLOOS Demand

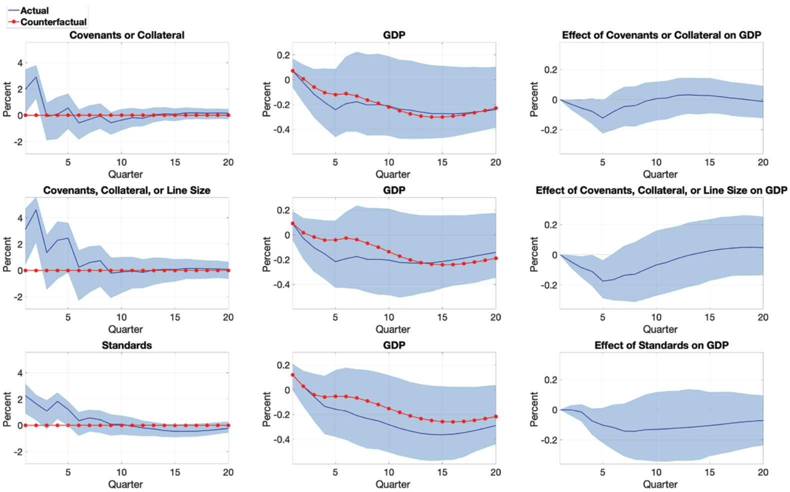
Figures K.1 and K.2 show the IRF counterfactuals described in the paper (see section 4.2) for VAR specifications that do not include the SLOOS demand control. Just as in appendix J, these results suggest that the nonprice terms (particularly collateral requirements) are relevant for monetary transmission and account for significant changes in GDP following monetary surprises.

Figure K.1. IRF Counterfactual for Contract Terms when VAR Specifications Do Not Include Demand Controls



Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Figure K.2. IRF Counterfactual for Covenants, Collateral, and Line Size when VAR Specifications Do Not Include Demand Controls

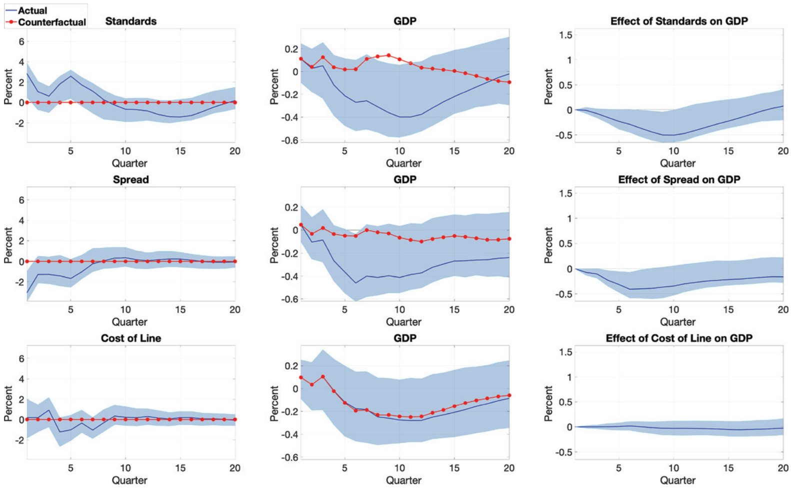


Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Appendix L. Robustness: Pre-crisis Period

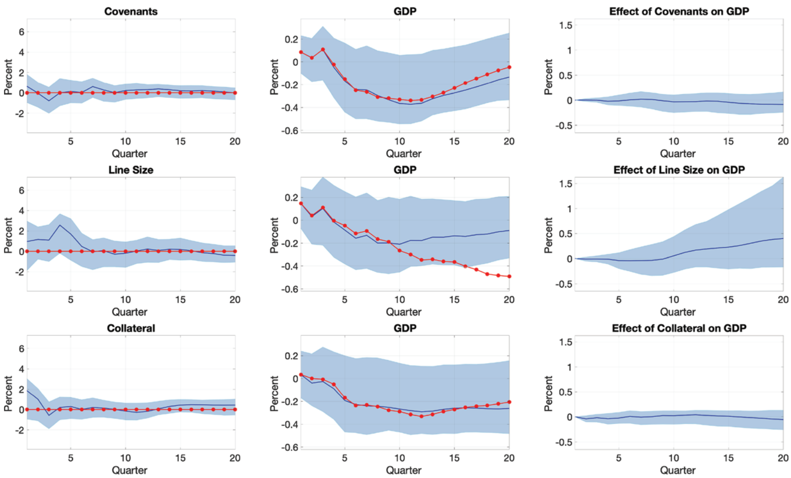
Figures L.1 and L.2 present the IRF counterfactual described in the paper (see section 4.2) when restricting the sample period to 1990:Q1–2007:Q4. The figures show that the response of the different loan terms is consistent with a contraction in loan supply that can account for significant changes in GDP following a monetary surprise. The results also show that the *joint* contribution of the nonprice terms (lending standards) to monetary policy transmission remains statistically significant. Furthermore, not only is the contribution of the nonprice terms (lending standards) statistically significant, but it almost doubles in magnitude relative to the baseline case.

Figure L.1. IRF Counterfactual for Standards, Spreads, and Cost of Line when Using the Restricted Sample Period (1990:Q1–2007:Q4)



Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

Figure L.2. IRF Counterfactual for Covenants, Line Size, and Collateral when Using the Restricted Sample Period (1990:Q1–2007:Q4)



Notes: The IRFs correspond to one standard deviation of the monetary policy shock. The shaded area represents the 90 percent confidence interval.

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