Calibrating Macroprudential Policy to Forecasts of Financial Stability*

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Macroprudential policy is a relatively new responsibility for central banks and financial regulatory agencies, requiring new methods for analyzing previously untested policy tools like the countercyclical capital buffer. One of the first steps in this direction was the development of financial stability indicators (FSIs). While many FSIs have been proposed, they typically require further transformation for use by policymakers. We propose that a particular transformation based on transition probabilities between states of high and low financial stability be used, and demonstrate how to use these probabilities within a decision-theoretic framework to guide the implementation of U.S. countercyclical capital buffer policy.

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1. Introduction

The global financial crisis of 2007–09 exposed an unprecedented level of systemic risk in national financial systems. The speed at

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which these risks developed and spread often necessitated that central banks and financial regulatory agencies take large and immediate actions with the tools that were readily available. Subsequently, various national governments and international agencies, such as the Basel Committee on Banking Supervision (BCBS), have proposed and enacted a wide variety of new policy tools to address systemic risks and support financial stability going forward. Such policies have come to be known as macroprudential policies.[1]

Policymakers, however, face substantial challenges in implementing macroprudential policies, beginning with the early identification of financial crises and extending to the implementation of the chosen policy in a timely manner. The establishment of effective monitoring systems for financial stability is, therefore, a key element of macroprudential policymaking.[2] Furthermore, new policy tools, such as the countercyclical capital buffer (CCyB) described in Basel Committee on Banking Supervision (2010b), must be designed and then implemented to address these concerns, all with very little historical experience with which to analyze their intended (and perhaps unintended) effects.[3]

Our focus in this paper is on the application of macroprudential policy in the spirit of current and proposed CCyB policies. These policies typically require monitoring financial conditions and deciding if increased capital requirements should be implemented within a specified time frame. Once the CCyB capital charges are in place, policymakers are then tasked with determining when changes in

[1] Financial stability is defined by the European Central Bank (2013) as "a condition in which financial system intermediaries, markets, and market infrastructure can withstand shocks without major disruption in financial intermediation and, in general, supply of financial services." See Adrian et al. (2017) for an overview of macroprudential policies and available policy instruments, such as the countercyclical capital buffer examined in this paper.

[2] Drehmann and Juselius (2013) highlight the various challenges in selecting indicators of financial stability, such as the need for timely and stable policy signals; see also Brave and Butters (2012b).

[3] An example of how this tool is being employed for macroprudential policy purposes can be seen in the deliberations of the United Kingdom's Financial Policy Committee (FPC), which activated its CCyB policy in March 2016, subsequently deactivated it in July 2016 after the Brexit vote, and reactivated it in June 2017. See Financial Policy Committee (2016, 2017) for further details.

financial conditions warrant their removal.[4] Several European countries have implemented CCyB policies, and the United States implemented its policy as of October 14, 2016 with a CCyB rate of zero. We examine conditions that could suggest the raising of the U.S. CCyB rate.[5] Underlying our efforts are econometric models that capture the likelihood of a financial crisis developing over the next two years as measured using financial stability indicators (FSIs).

Researchers have proposed several FSIs to assist policymakers in determining the current state of national financial stability.[6] However, there is limited insight and experience on how to translate these indicators into policy actions; that is, policymakers are often provided with little or no guidance on how FSIs can be used in light of the decisions they must make. In this paper, we propose a transformation of FSIs that can more readily be mapped to the objective functions of macroprudential policymakers. Namely, we propose that FSIs be transformed into model-based probabilities of being in a state characterized by either high or low financial stability. While this transformation discards potentially useful information observed in the time-series dynamics of the FSIs in question, it also hopefully provides a clearer signal for policymakers' decisions.[7]

We examine a small set of FSIs currently in popular use with respect to monitoring systemic risk and macroprudential policy implementation. Our primary variable of interest is the ratio of

[4]See Kowalik (2011) for further discussion.

[5]The U.S. policy was announced on September 8, 2016. See the press release at https://www.federalreserve.gov/newsevents/pressreleases/bcreg20160908b.htm. For a full description, see Title 12 of the Code of Federal Regulations, Part 217, Appendix A (at https://www.govinfo.gov/content/pkg/CFR-2017-title12-vol2/xml/CFR-2017-title12-vol2-part217.xml). The BCBS maintains a database of national CCyB policies and policy actions at https://www.bis.org/bcbs/ccyb/.

[6]See Bisias et al. (2012) for an overview of financial stability indicators as well as Brave and Butters (2012a), Hartmann, Hubrich, and Kremer (2013), and Aikman et al. (2015). See Liang (2013) for a discussion of their use for systemic risk monitoring.

[7]See Brave and Butters (2012b) and Drehmann and Juselius (2013) for related analysis as well as Berge and Jordà (2011) for a similar approach with respect to macroeconomic indicators and the business cycle. Notably, Brave and Genay (2011) found in their analysis of Federal Reserve policy interventions during the financial crisis that persistent deviations of FSIs from their long-run averages—and not the potentially transient changes in these series—were what mattered for explaining the timing of policy actions.

private, non-financial credit to GDP (or the credit-to-GDP ratio) as proposed by the BCBS for use in national CCyB policies.[8] We examine this variable within a standard two-state Markov regime-switching model (Hamilton 1989) and then incorporate additional FSIs into our analysis using the time-varying switching probability model proposed by Diebold, Lee, and Weinbach (1994) with these series as probability-switching drivers.

The additional FSIs that we use are predominantly credit market measures, such as the corporate bond spreads described in Gilchrist and Zakrajsek (2012) and Lopez-Salido, Stein, and Zakrajsek (2015), as well as financial condition indexes as proposed by Brave and Butters (2012b). The actual objects of interest for our analysis, however, are their model-implied probability forecasts of transitioning into the state of low financial stability and remaining there for four consecutive quarters at any point over the coming two years. The variation in these probabilities across FSIs highlights the differing perspectives available to policymakers from alternative monitoring techniques. To formally account for this model uncertainty, we rank and combine the signals provided by each FSI using empirical Bayesian model averaging techniques, as described in Clyde and George (2004).

Our emphasis on probability forecasts is premised on the insights for macroprudential policy provided by Khan and Stinchcombe (2015). In their work, they propose a decision-theoretic framework that combines hazard function analysis of the arrival of an adverse event with a policymaker's objective function about whether and when to enact a costly preemptive policy action. In fact, they explicitly cite the example of a policymaker looking to maximize his or her objective function in light of a politically costly reform of a banking system, which clearly encompasses macroprudential policies in general and CCyB policies in particular. The authors characterize general first-order and second-order conditions for determining when it may be appropriate for a policymaker to act or to delay action,

[8]Basel Committee on Banking Supervision (2010b) provides the background information on the Basel-proposed CCyB policy. Note that the Federal Reserve includes the credit-to-GDP ratio among many variables that may be used to inform CCyB decisions. Similarly, the U.K. FPC is required by legislation to consider the credit-to-GDP ratio when setting its CCyB policy, but the committee has stated that "there was not a simple, mechanistic link between the buffer guide and the CCyB rate" (FPC 2016).

and we demonstrate how these conditions can be mapped directly into the CCyB decision process.

Specifically, given our estimated projections of financial stability, we describe two methods for calibrating the relative costs and benefits of CCyB policy implementation for use in a U.S. policymaker's objective function. We then conduct a pseudo out-of-sample counterfactual analysis around the U.S. implementation of its proposed CCyB policy. We examine the financial stability projections that U.S. policymakers would have faced in 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4, and provide an overview of the range of hypothetical policy actions available and the degrees of uncertainty associated with them.[9]

The choice of these four projection dates serves to highlight the effect of initial conditions on our hypothetical policy prescriptions. For example, for 2005:Q4, the model-implied starting point is projected to have a moderately high probability of entering a financial crisis. In contrast, for 2009:Q4, 2013:Q4, and 2017:Q4, a developing crisis is very unlikely. Accordingly, our estimated hazard function as of 2005:Q4 was above the calibrated threshold for policy action for almost all eight quarters of the projection horizon, suggesting that the CCyB policy should have been implemented were it available to U.S. policymakers. In contrast, our estimated hazard functions as of 2009:Q4, 2013:Q4, and 2017:Q4 were below the relevant thresholds for policy action for almost all projection quarters, suggesting that policymakers could wait to act until perhaps a clearer signal of financial instability arrived.

The remainder of the paper is structured as follows. Section 2 provides an overview of the Khan and Stinchcombe (2015) (or KS) framework and our application to U.S. CCyB policy. Section 3 presents our proposed transformations of selected FSI via Markov-switching models into the necessary hazard functions for the KS framework. Section 4 then presents two alternative calibrations of the framework and discusses their implications as of the four projection dates noted above. Section 5 concludes.

[9] Please note that we do not take into account statements of policy precommitment and their potential effect and effectiveness. For example, the U.K. FPC announced in July 2016 that "it expected to maintain a 0% U.K. countercyclical capital buffer rate until at least June 2017."

2. A Framework for Analyzing Macroprudential Policy

Macroprudential policy is a relatively new responsibility for policymakers, and certainly one that is less familiar and less examined than monetary policy. Accordingly, an important first step in analyzing macroprudential policies is developing an objective function—that is, an explicit, even if simplified, statement of the relative costs and benefits of a policy action; see, for example, Peek, Rosengren, and Tootell (2015). In general, deriving an objective function for this purpose requires detailed knowledge of the underlying decision problem.[10] However, such knowledge is not readily available in the context of macroprudential policies, as there is limited historical experience from which expected costs and benefits could be estimated.

An important first step toward developing a response to these questions was the development of financial stability indicators (FSIs) as early-warning systems for developing financial crises. As noted by Danielsson, Valenzuela, and Zer (2016), macroprudential policymakers are engaged in an active search for signals of future financial instability upon which to develop mitigating policy actions.[11] With FSIs in hand, it is possible to begin incorporating the qualitative aspects of a policymaker's decision problem into the evaluation of financial stability. As discussed by Drehmann and Juselius (2013), several studies have used a loss function that accounts for a policymaker's preferences between type I and type II errors surrounding the identification of financial crises or similar events in this way. Such loss functions are statistical in nature and based on the receiver operating characteristic (ROC) curve.

While this approach is reasonable within its own rights, it differs from the approach that we propose. Our specification of the

[10] See Pesaran and Skouras (2002) and Granger and Machina (2006) for further discussion

[11] An extensive literature on this topic related to international financial crises developed in the 1990s; see Frankel and Rose (1996), Kaminsky and Reinhart (1999), and Reinhart and Rogoff (2009) for a survey. More recent efforts, however, have focused on indicators of banking crises or credit overextension, which are more germane to the recent financial crisis; see Bisias et al. (2012) and Aikman et al. (2015).

policymaker's objective function is based instead on the work of Khan and Stinchcombe (2015), who put forth an analytical framework for deciding whether to act or delay action based on a policymaker's objective function. A key element of this framework is a hazard function of the arrival of an adverse event of interest; i.e., the policymaker generates a probability vector forecast of the adverse event arriving over a specified time horizon. This probabilistic assessment is combined with the relative costs of enacting the specified policy and used to solve for the optimal policy implementation date. The functional form of the relative costs of the policy is quite flexible and accounts for time discounting and the perceived effectiveness of the policy action taken.

KS state that "at issue is the optimal timing of a costly . . . precautionary measure: an evacuation before a hurricane landfall; or a politically painful reform of a banking system before the next financial crisis." It is the latter example that shapes our interpretation of their framework as a tool for examining macroprudential policies in general and policies regarding CCyB buffers in particular. The KS framework is applied at a decision point T when a policymaker must decide whether to enact a costly policy against the arrival of an adverse event, either immediately or in the near future after more information has been collected. The intuition is that the policymaker faces some uncertainty as to when the adverse event might arrive and must decide whether and when to act preemptively.

The authors go on to note that "the optimal hesitation before implementing expensive precautionary measures involves waiting until the [estimated] hazard function is high enough and increasing." Based on information up to time T, define t_W as the waiting time until the adverse event arrives, which has a continuous probability distribution function $f(t_w)$, a cumulative distribution function $F(t_w)$, and an associated hazard function $h(t_w) = f(t_w)/(1-F(t_w))$. The optimal decision to be made at time T regarding when to act should balance the expected benefits of waiting (i.e., inaction) with the expected costs of the event arriving after the policy implementation. Below, we discuss how this simple framework can be used in analyzing when and how to implement the CCyB policy in the United States.

2.1 The Adverse Event and Its Probability

Applying the KS framework to CCyB policy requires that we specify the adverse event that would justify its implementation. The adverse event we consider is an extended period of financial instability (or, equivalently, a financial crisis). The KS framework requires a hazard function for this adverse event, and we propose a Markov-switching model to transform the information in various FSIs into the needed probabilities of a financial crisis occurring. Several FSIs have been shown to have useful properties as leading or "early warning" indicators of adverse developments in financial and macroeconomic variables.[12] In particular, Gadea Rivas and Perez-Quiros (2015) found that aggregate credit growth is empirically correlated with the probability of financial crises and the intensity of their effect on the macroeconomy.

Accordingly, our main variable of interest is the ratio of U.S. private, non-financial credit to GDP (or the credit-to-GDP ratio), which has been proposed as the key monitoring variable for the implementation of national CCyB policies.[13] The BCBS has proposed to examine the gap between this ratio and its long-term trend, estimated using a one-sided Hodrick-Prescott filter with smoothing parameter $\lambda = 400{,}000$. Since trend specifications using this filter have important shortcomings as described by Edge and Meisenzahl (2011) and Hamilton (2018), we instead follow Brave and Butters (2012a) by transforming the ratio into growth rates, which they show produces a more reliable leading indicator of U.S. financial stability.[14]

[12]For example, Aramonte, Rosen, and Schindler (2013) found that several FSIs have short-term predictive ability with respect to stock returns and higher-frequency macroeconomic variables, such as industrial production. More relevant to our analysis, Aikman et al. (2015) found that their aggregate index Granger-causes the credit-to-GDP gap proposed for use in CCyB policies.

[13]Drehmann, Borio, and Tsatsaronis (2011) and Drehmann and Juselius (2013) helped establish this ratio as a potentially important policy variable. Subsequent work by Jordà, Schularick, and Taylor (2011), Schularick and Taylor (2012), Giese et al. (2014), Gadea Rivas and Perez-Qiros (2015), and Aikman et al. (2016) provided clear support for the hypothesis that relatively high levels of this ratio make a macroeconomy less resilient to adverse shocks.

[14]A one-sided Hodrick-Prescott filter produces trend estimates that are very sensitive to the arrival of new data. Edge and Meisenzahl (2011) show that the

In addition, we examine several commonly used FSIs that encompass different elements of the U.S. financial system. Our first three FSIs reflect conditions in the U.S. corporate bond market and, thus, in the overall credit environment. The series are the spread between yields on seasoned long-term Baa-rated industrial bonds and comparable maturity Treasury securities, as discussed by Lopez-Salido, Stein, and Zakrajsek (2015), and the spread and excess bond premium measures developed by Gilchrist and Zakrajsek (2012). These three series have been shown to reflect current credit market sentiment and to be correlated with near-term economic growth, both properties that meet standard criteria for use in setting macroprudential policy as per Drehmann and Juselius (2013).

The next three FSIs that we examine stem primarily from the financial conditions indexes developed by Brave and Butters (2012b) and made publicly available by the Federal Reserve Bank of Chicago.[15] The National Financial Conditions Index (NFCI) and the adjusted NFCI (ANFCI) are dynamic factors constructed from an unbalanced panel of 105 mixed-frequency indicators of U.S. financial activity, the latter of which is adjusted for prevailing economic conditions.[16] The NFCI has been shown to be 95 percent accurate in identifying U.S. financial crises contemporaneously, with a decline to 62 percent accuracy at a lead time of two years. In addition, Brave and Butters (2012b) show that disaggregating the NFCI into subcomponents can enhance the signal regarding the degree of financial stability. In particular, we examine separately the NFCI Nonfinancial Leverage subindex, which signals financial imbalances with 50 percent accuracy contemporaneously and with 83 percent accuracy with a two-year lead.

Finally, we consider the year-over-year change in the tier 1 leverage ratio for the U.S. banking system, which is defined as the aggregate sum of tier 1 capital divided by the sum of bank risk-weighted

U.S. credit-to-GDP gap has been subject to sizable ex post revisions that can be as as large as the gap itself; see also Bassett et al. (2015) for further discussion.

[15]The data and background materials are available at https://www.chicagofed.org/nfci.

[16]Research suggests that financial conditions indexes that combine FSIs perform better in terms of state identification and measurement of macroeconomic effects than individual FSIs; see Hartmann, Hubrich, and Kremer (2013).

assets. This measure focuses on developments relevant to financial stability arising within the banking system.

Our list of FSIs is admittedly far from exhaustive, but as we show in section 3, they capture well the recent historical episodes of U.S. financial stress. Rather than rely on a single FSI to guide policy decisions, we propose an empirical Bayesian model averaging method that weights the model-implied hazard function for each FSI according to its historical ability to signal financial instability.[17] This simple procedure should readily allow for our analysis to be extended to include other FSIs.

2.2 The Costs and Benefits of (In)action

Translating CCyB policy into the KS framework also requires the calibration of the costs and benefits of a policy action. Within the KS framework, we define the utility flow from present conditions as $\bar{u} > 0$, which will be at risk at $T + t_w$ unless the mitigating policy is taken prior to that time. If the policy is put in place prior to t_w at a cost of C, the utility flow declines to $\underline{u}$, such that $\bar{u} > \underline{u} > 0$. In the language of macroprudential policymakers, this definition reflects the policy intent of taking action to increase the resilience of the financial system or, equivalently, lowering the economic loss when a crisis arrives. In addition, the policy itself is designed to lower the incidence of a financial crisis as follows:

$$f_{\theta(t_w;t_1)} = \begin{cases} f(t_w) & if t_w < t_1 \\ (1-\theta)f(t_w) & if t_w \geq t_1 \end{cases};$$

i.e., the probability of a crisis declines after the policy is implemented at time t_1. The θ parameter is a measure of the perceived effectiveness of the policy and is bounded within the closed unit interval such that a fully effective policy is characterized by $\theta = 1$, while a completely ineffective policy coincides with $\theta = 0$.

The policymaker's optimal decision is to balance the cost of enacting the policy with the benefit of waiting as long as possible before doing so. The benefit of waiting is denoted rC, which is the annuitized value of the policy cost C at the discount rate r; i.e.,

[17]See the first section of the appendix for further details.

the savings from not incurring C at time T. The aggregate policy cost is the discounted value of the utility flow after enacting the policy minus its cost C, all expressed in probabilistic terms based on the hazard function as $([\theta\bar{u} + (1-\theta)\underline{u}]/r - C) * h(t_w)$.[18] Thus, the first-order condition for the optimal time to act, denoted as t_1^*, is

$$h(t_1^*) = \frac{rC}{([\theta\bar{u} + (1-\theta)\underline{u}]/r - C)}. \tag{1}$$

With respect to the second-order condition, the intuition is that the policymaker wishes to defer incurring the cost of the action as long as waiting outweighs the potential loss in utility flow, which implies $h'(t_1^*) > 0$. In other words, the policymaker should act if the event probability is high enough and increasing just before acting. Notably, these are characteristics of the empirical hazard functions for U.S. financial crises that we find in our analysis in section 3. In terms of comparative statics, the optimal time to act is increasing in both C and r (i.e., the policymaker defers longer when the policy cost is higher) and decreasing in θ (i.e., more effective policies lead to higher benefits and thus earlier implementation).

Our approach to operationalizing equation (1) is to calibrate it to the costs and benefits of CCyB policy actions for the United States. The immediate cost of enacting the policy is incurred by the affected financial institutions in raising the needed capital.[19] Thus, as a lower bound, we calibrate C in terms of the dollar cost of the capital to be raised by the affected firms as required by the CCyB policy. The current size threshold for affected firms is \$250 billion in total assets with certain exceptions. These firms would be required

[18] Note that $h(t_w)$ within the KS framework is an instantaneous hazard rate. In our work, we substitute our empirical hazard function as described in the first section of the appendix.

[19] In the Federal Reserve's CCyB framework, the affected firms are banking organizations subject to the advanced approaches capital rules, which generally apply to banking organizations with greater than \$250 billion in assets or more than \$10 billion in on-balance-sheet foreign exposures; see 12 CFR 217.11(b) (at https://www.govinfo.gov/content/pkg/CFR-2017-title12-vol2/xml/CFR-2017-title12-vol2-part217.xml). As described in 12 CFR 217.100(b), the CCyB cost will differ across firms since it is weighted based on a firm's composition of private-sector credit exposures across national jurisdictions. However, we simplify this cost to be a common ratio across all firms for our study.

to raise additional tier 1 common equity (i.e., common stock) by a specified percentage of their total risk-weighted assets related to private credit up to a maximum value of 2.5 percent.

The cost of this measure to the policymaker is zero since the firms actually incur the cost of raising this equity, but for our calibration exercises, we assume that the policymaker operates as if her cost is of equal magnitude; i.e., she internalizes the entire cost either by funding it directly or by viewing the cost to the firms as a social cost. Note that this calibration represents a lower bound on C since the policymaker may consider other costs, such as the potential macroeconomic effect of raising bank capital requirements.[20] Such indirect costs are hard to measure and capture within the KS framework. The broader macroeconomic cost of raising regulatory capital requirements also seems to vary greatly across countries, time periods, and methodological approaches.[21] For these reasons, we capture the broader welfare costs of the CCyB within the $[\underline{u}, \bar{u}]$ utility flows of the KS framework, whose calibration we discuss next.

In terms of benefits, various studies suggest that financial crises cause a significant and long-lasting reduction in GDP growth.[22] It is such declines that the policymaker hopes to avoid or, at least, mitigate with the CCyB. However, measuring this benefit in terms of the KS utility flows presents several challenges—primarily, the very limited historical experience with this policy. As a result, we present two alternative calibrations in section 4: the first an *external* calibration analysis derived from professional forecasts and estimates in the literature on the macroeconomic effects of capital increases, and

[20] See Basel Committee on Banking Supervision (2010a) and Firestone, Lorenc, and Ranish (2017) for further discussion. As an example, the U.K. FPC lowered its CCyB on banks' U.K. exposures from 0.5 percent to 0 percent in July 2016 based on the view that "the availability of banks' capital resources, and their use to absorb shocks if risks materialize, insures against a tightening of bank credit conditions" (Bank of England 2016).

[21] Edge and Meisenzahl (2011) examined the costs associated with U.S. CCyB policies, such as declines in lending volume and increased lending rates. Similarly, Berrospide and Edge (2016) found in the post-crisis period that a 1 percentage point increase in equity capital increases one-year commercial loan growth between 10 and 15 percentage points. However, the effects vary across firms and over time. Carlson, Shan, and Warusawitharana (2013) found related results for U.S. banks matched by geography and other business characteristics.

[22] For example, see Cerra and Saxena (2008), Furceri and Mourougane (2012), and Romer and Romer (2015).

the second an *internal* calibration analysis based on our Markov-switching model estimates.

The only remaining parameters in our calibration are then r and θ. The value of the discount rate r should be both a function of the horizon over which the policy decision is being made and the overall riskiness of the policy action. The horizon over which monetary policy is typically focused is two years, and it is thus reasonable to assume that such a horizon would be the case for the CCyB as well, especially since it has a built-in, one-year activation delay. Regarding the riskiness of the policy action, we assume, as above, that policymakers internalize this cost and, thus, use the risk-free discount rate.[23] For θ, defined as the perceived effectiveness of the policy in lowering the likelihood of the adverse event, we examine a range of values over the unit interval to determine the overall sensitivity of our objective function $h(t_1^*)$.

To arrive at a solution for t_1^*, we need to assume a magnitude for the increase in the CCyB, so we assume a 0.25 percent increase as a starting point. However, it is also possible to solve for the optimal CCyB rate given an assumed timing of a CCyB action. To do so, we treat a given time period as being the optimal one for a set of calibrated parameters and then solve for the CCyB rate that would satisfy the KS first-order condition. We restrict our solutions to fall between the minimum of 0 percent and maximum of 2.5 percent set forth in the parameters of the U.S. CCyB framework. Both types of solutions are examined in section 4.

3. Transforming Financial Stability Indicators into Hazard Functions

Financial stability indicators need to be transformed in order to provide sufficient context for their use by policymakers.[24] Our proposed transformation involves using a Markov-switching model to translate FSIs into arrival probabilities of a financial crisis. In this section,

[23]See Bazelon and Smetters (1999) for a discussion of public policy discount rates.

[24]For example, Brave and Butters (2012b) collapsed their FSIs into event indicators, while Aikman et al. (2015) normalized their FSIs in order to graph them in various formats, such as radar and sunburst plots.

we describe the mechanics of our estimation procedure and how to translate these probabilities into the hazard functions necessary for the KS framework.

3.1 Markov-Switching Models

As noted, the credit-to-GDP ratio is our primary variable of interest for CCyB policy decisions. Gadea Rivas and Perez-Quiros (2015) argued in their work on the effect of credit on the business cycle that "the key question for a policymaker is to what extent the level of credit-to-GDP (or its variations) observed in period t increases or not the probability of being in a recession in $t + 1$ or whether it changes the characteristics of future cyclical phases." Their results for a large panel of developed economies suggest that credit does not improve upon business cycle forecasts. Our immediate concern regarding CCyB policies, which are largely framed around the credit-to-GDP ratio, requires that we reexamine this result. In this spirit, we use an alternative model specification that allows us to incorporate our chosen FSIs.

We specify a univariate Markov-switching model, as per Hamilton (1989), capturing the joint dynamics of real GDP and credit growth in order to identify distinct states of high and low financial stability for the United States.[25] We denote these states as $\{S^+, S^-\}$, respectively, and model the transitions between them based on changes in the joint dynamics of real GDP growth $\Delta ln(GDP_t)$ and real credit growth $\Delta ln(C_t)$.[26] Our model using data from 1985:Q1 through 2017:Q4 is specified as

$$\begin{aligned} Y_t &= \alpha_S + \beta_S X_t + \epsilon_t \\ \epsilon_t &\sim N(0, \sigma^2), \end{aligned} \tag{2}$$

[25]We could alternatively specify three states of financial stability: a high state, a normal state, and a low state. However, this specification is not well identified for the United States in the univariate framework that we work with over the sample period that we examine. It may, however, be reasonable in other applications. For instance, Hubrich and Tetlow (2014) used a five-variable Markov-switching VAR (MS-VAR) model in their approach to assessing the effect of financial conditions on macroeconomic variables. The larger number of moments in such a system may, in theory, allow for three states.

[26]We deflate credit by the GDP deflator following Giese et al. (2014), who found that real credit growth performs slightly better than nominal credit growth with respect to financial crisis signals.

where $Y_t \equiv \Delta ln(GDP_t), X_t \equiv \{\Delta ln(GDP_{t-1}), \Delta ln(C_t), \Delta ln(C_{t-1}))\}$, and the state-dependent parameters are summarized in $\Theta_S \equiv \{\alpha_S, \beta_S\}$.[27] To identify the low from the high financial stability state, we associate $\alpha_{S^-} < 0$ with the former, such that real GDP growth is negative on average in this state.[28] The states of our model are assumed to follow a first-order Markov process governed by the time-varying transition probability matrix Ω_t, as per Diebold, Lee, and Weinbach (1994), such that

$$\Omega_t = \begin{bmatrix} \Phi(\delta_{S^+} + \gamma Z_t) & 1 - \Phi(\delta_{S^+} + \gamma Z_t) \\ 1 - \Phi(\delta_{S^-} + \gamma Z_t) & \Phi(\delta_{S^-} + \gamma Z_t) \end{bmatrix}, \qquad (3)$$

where Φ is the cumulative normal distribution and Z_t represents an FSI variable.

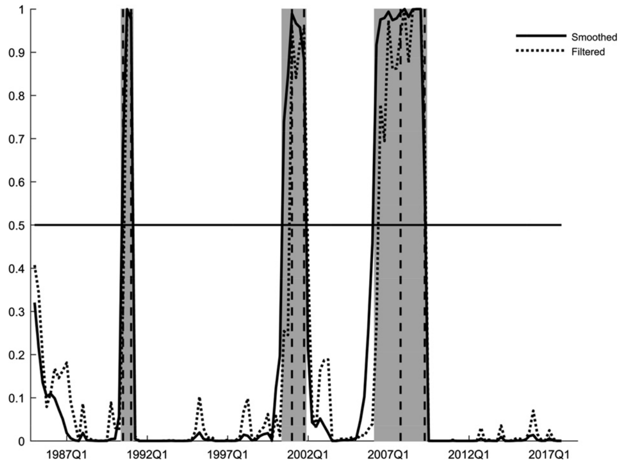
We introduce our FSIs into Z_t on an individual basis in order to limit the number of estimated parameters. For our baseline model, we do not use an FSI and set the transition probabilities to be constant. Given the small number of transitions in our data, we also find it useful to follow Amisano and Fagan (2013) and require that the slope coefficients on Z_t be common across the two states.[29] Correspondingly, our approach encompasses eight model specifications. To arrive at a single characterization of the state of financial stability,

[27]In results not reported here, we could not reject that σ was equal across states during our sample period. Increasing the length of our sample to include the early 1980s changes this result, as it captures the Great Moderation in the volatility of U.S. GDP growth post-1984. It also improves the precision of several of the other estimated parameters of equation (2), but at the cost of prohibiting the use of some of the FSIs we consider that do not have histories prior to 1984 (e.g., the tier 1 leverage ratio).

[28]Our specification differs slightly from Gadea Rivas and Perez-Quiros (2015) in that we do not restrict the effects of real credit growth in either state. As such, it allows for potentially richer joint dynamics within the two financial stability states. Note that Ajello et al. (2015) also used a contemporaneous credit growth variable in their specification of a crisis transition probability.

[29]The MATLAB MSREGRESS package of Perlin (2015) extended to the time-varying transition probability case by Ding (2012) was used for estimation with thirty-six random initializations of each model used to pick the one that achieves the highest likelihood. For models with additional FSIs, we centered our initializations around the converged parameter estimates of our baseline model. For instances where convergence was first not achieved, we continued to draw random initializations until convergence.

Figure 1. Smoothed and Filtered Probabilities of the Low Financial Stability State



Notes: The sample period is 1985:Q1 through 2017:Q4. The shaded periods reflect quarters in which the Bayesian model weighted-average smoothed probabilities of the low financial stability state are greater than 50 percent. The dashed vertical lines within the shaded periods denote National Bureau of Economic Research (NBER) recessions.

we combine these specifications using empirical Bayesian model averaging techniques as described in Clyde and George (2004).[30] This framework weights each model by a measure of its fit of the data, giving more weight in relative terms to models that better capture the estimated transitions in the U.S. data; see the first section of the appendix for further details.

3.2 States of Financial Stability

Figure 1 shows the one-sided (filtered) and two-sided (smoothed) estimates of the model-implied probability of the low financial stability state, weighted across our eight specifications, for our full sample period. The shaded regions in the figure denote quarters where our model-weighted average (smoothed) probability of the

[30] Lo Duca and Peltonen (2013) also combined their FSIs in similar fashion, but in their case within a multivariate discrete choice model.

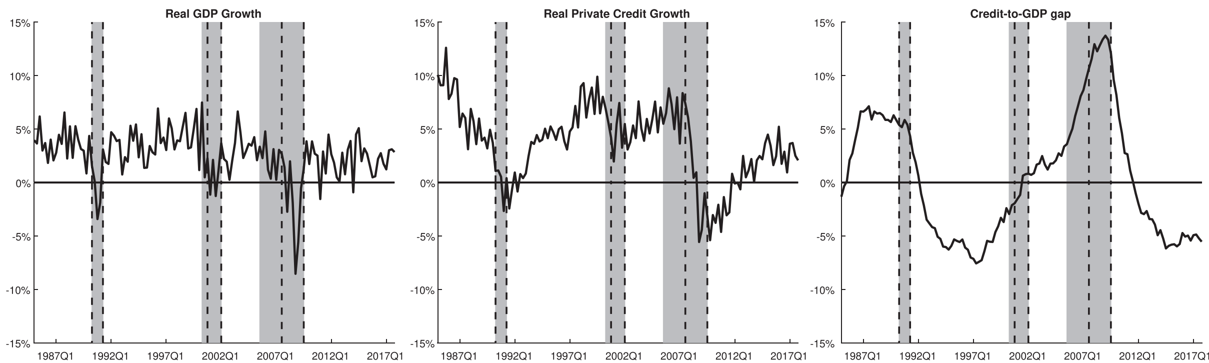
low financial stability state exceeds 50 percent. The three periods of low financial stability are 1990:Q3–1991:Q1, 2000:Q3–2001:Q4, and 2006:Q2–2009:Q2. Each corresponds with well-known periods of U.S. financial stress; i.e., the latter stages of the S&L crisis and the credit crunch of the early '90s, the dot-com stock market bubble, and the recent global financial crisis. A fourth period of financial stress associated with the early stages of the S&L crisis in the mid-1980s falls somewhat below our 50 percent cutoff but is also apparent in the figure.

Figure 2 further summarizes the low and high states of financial stability identified by our models relative to real GDP and credit growth. For the sake of comparison, the figure also includes the credit-to-GDP gap. Generally speaking, the figure shows that periods of jointly decelerating GDP and real credit growth tend to align with the low financial stability state. Furthermore, our models also capture well turning points in the credit-to-GDP gap. This can be seen by the ranges of the three shaded regions in the figure (denoted with dashed lines) corresponding to NBER recessions. Our low financial stability state clearly leads several recessions. In particular, we identify the low financial stability state two quarters prior to the 2001 recession and six quarters in advance of the 2008–09 recession.

This leading signal can also be seen in the FSIs shown in figure 3.[31] Consistent with previous research, large deviations in each of them from their historical means tend to align with our estimated periods of low financial stability as well as recessions. This is particularly true for the NFCI Nonfinancial Leverage subindex, which can be seen in the very large weight (84 percent) given to it by our Bayesian model averaging procedure in table 1. Only one other FSI (the leverage ratio) receives a non-trivial weight (8 percent), suggesting that much of the timing of transitions between high and low states of financial stability can be captured exclusively by these two FSIs as well as the joint dynamics of real credit and GDP growth captured in our baseline model (8 percent). To more rigorously examine this result, we next take a closer look at our estimated model parameters.

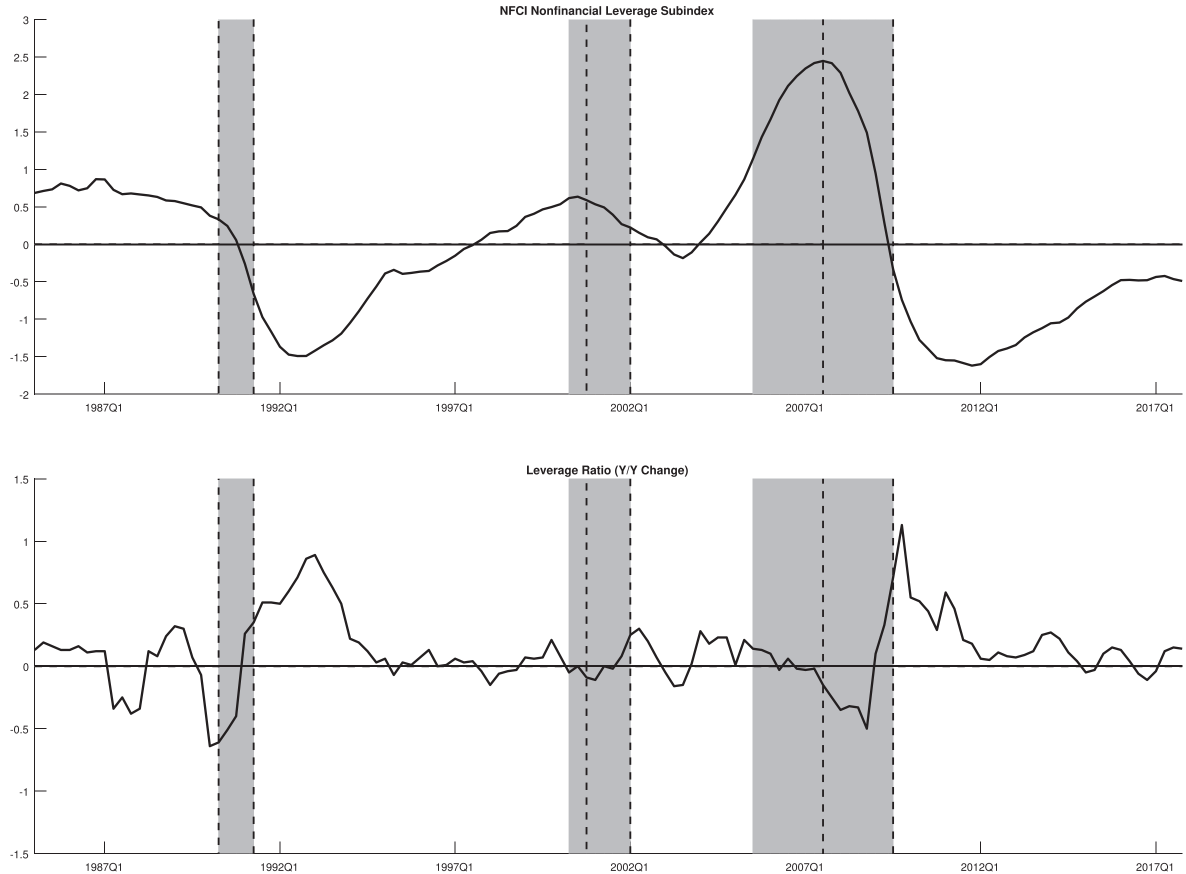
[31] All of our FSIs are shown in figure 9 in the appendix.

Figure 2. Annual Real GDP Growth, Annual Private Credit Growth, and the Credit-to-GDP Gap as a Percent Deviation from Its BCBS-Recommended Trend



Notes: The shaded periods reflect quarters in which the Bayesian model weighted-average smoothed probabilities of the low financial stability state are greater than 50 percent. The dashed vertical lines within the shaded periods denote NBER recessions.

Figure 3. Financial Stability Indicators (FSIs), Presented in Standard Deviation Units



Notes: The shaded periods reflect quarters in which the Bayesian model weighted-average smoothed probabilities of the low financial stability state are greater than 50 percent. The dashed vertical lines within the shaded periods denote NBER recessions.

Table 1 presents the estimated coefficients for our eight model specifications for our longest estimation period from 1985:Q1 through 2017:Q4.[32] The top row of each column reports the model weights assigned by our Bayesian model averaging procedure. The transition probability parameters are then reported in the next set of rows. The δ_1 estimates govern the probability of remaining in the high stability state, while the δ_2 estimates govern the transition from the low stability state to the high stability state. The effect of the FSIs on these probabilities is summarized in our γ estimates. Focusing on the baseline model, we find that the probability of remaining in the high stability state is roughly 97 percent, while the probability of transitioning from the low stability back to the high stability state is about 16 percent. The introduction of the other FSIs tends to generate negative γ estimates (except for the leverage ratio), most prominently for the NFCI Nonfinancial Leverage subindex that received a model weight of 84 percent. This negative coefficient suggests that as non-financial leverage increases over time, the probability of transitioning into the low financial stability state next period increases.

These parameters are then followed in the table by those governing the co-movement of real GDP and real credit growth in our high (S^+) and low (S^-) financial stability states. Here, the estimated parameters vary importantly across the two states but are similar across model specifications. The high stability state exhibits a positive and significant α_1 constant, while the α_2 constant for the low stability state is negative and insignificant. In contrast, the estimated coefficients on the lagged value of GDP growth are not statistically significant, though they are generally more negative in the low stability state, indicating a faster pace of mean reversion.

Across the two states, the coefficients on both contemporaneous and lagged credit growth are generally significant, suggesting an

[32] To check the stability of our models, parameter estimates obtained by truncating our sample period initially to 2005:Q4 and adding back one year's worth of data at a time—namely, spanning 2005:Q4 through 2016:Q4—can be found in similar tables in the last section of the appendix. While there is some variation across time periods that is evident in these tables, their overall impact on assessing the state of financial stability is small once our Bayesian model averaging procedure is employed, as discussed in section 4.

Table 1. Markov Regime-Switching Models Estimated up through 2017:Q4

	Baseline	**Baa Spread**	**GZ Spread**	**EBP**	**NFCI**	**ANFCI**	**NFCI-nfl**	**Leverage Ratio**
Weight	0.08	0.00	0.00	0.00	0.00	0.00	0.84	0.08
Transition Probabilities:								
δ_1	1.83***	1.83***	1.73***	1.58***	1.78***	1.79***	2.03***	2.22***
	(0.35)	(0.38)	(0.36)	(0.51)	(0.37)	(0.41)	(0.54)	(0.62)
δ_2	−1.01***	−1.01***	−0.70*	−0.00	−0.84***	−0.72**	−0.18	−0.95
	(0.37)	(0.43)	(0.45)	(0.60)	(0.42)	(0.44)	(0.66)	(0.78)
γ^{FSI}	—	−0.00	−0.29	−0.65*	−0.20	−0.40	−1.24*	0.78**
	—	(0.26)	(0.26)	(0.43)	(0.25)	(0.43)	(0.82)	(0.44)
GDP Growth (S^+):								
α_1	2.41***	2.41***	2.43***	2.45***	2.42***	2.42***	2.35***	2.42***
	(0.32)	(0.33)	(0.34)	(0.37)	(0.34)	(0.33)	(0.33)	(0.33)
β_1^{GDPt-1}	−0.00	−0.00	−0.00	−0.00	−0.00	−0.00	0.02	−0.00
	(0.10)	(0.10)	(0.10)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)
β_1^{Ct}	−0.06	−0.06	−0.06	−0.00	−0.06	−0.06	−0.07	−0.07
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
β_1^{Ct-1}	0.26***	0.26***	0.25***	0.17***	0.25***	0.25***	0.27***	0.25***
	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.08)
GDP Growth (S^-):								
α_2	−2.79***	−2.79***	−2.63***	−2.41**	−2.76***	−2.82***	−2.79***	−2.71***
	(1.12)	(1.12)	(1.18)	(1.26)	(1.17)	(1.13)	(0.99)	(0.97)
β_2^{GDPt-1}	−0.32	−0.32	−0.30	−0.22	−0.33	−0.35	−0.34	−0.31
	(0.35)	(0.36)	(0.36)	(0.39)	(0.36)	(0.33)	(0.27)	(0.27)
β_2^{Ct}	0.70***	0.70***	0.71***	0.73***	0.71***	0.71***	0.68***	0.69***
	(0.12)	(0.13)	(0.12)	(0.14)	(0.13)	(0.13)	(0.12)	(0.13)
β_2^{Ct-1}	0.15	0.15	0.10	0.01	0.14	0.15	0.16	0.12
	(0.27)	(0.27)	(0.28)	(0.31)	(0.28)	(0.26)	(0.22)	(0.23)
σ_ε^2	2.49***	2.49***	2.47***	2.59***	2.48***	2.48***	2.45***	2.48***
	(0.41)	(0.41)	(0.42)	(0.49)	(0.41)	(0.41)	(0.42)	(0.40)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2017:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

effect of credit growth on real activity. For the high financial stability state, the lagged credit growth coefficient $\beta_1^{C_{t-1}}$ is positive and significant, while the contemporaneous coefficient is not. This result suggests that credit growth's contribution to GDP growth is milder and lagged during normal times. In contrast, in the low financial stability state, the $\beta_2^{C_t}$ coefficients are larger, positive, and significant contemporaneously while the lagged credit growth coefficients are not. It is predominately this property of the data (e.g., the contemporaneous positive co-movement of real credit and GDP growth) that provides a leading indication of slipping into the state of low financial stability in our models.

3.3 Forecasts of Financial Stability

The next step in transforming our selected FSIs into tools relevant to macroprudential policy is to project the financial stability state probabilities out over a forecast horizon of interest in order to generate the hazard function of the KS framework. This procedure, derived from Hamilton (2016) and detailed in the first section of the appendix, allows us to generate the forecasted state probabilities over the number of quarters in the policymakers' decision horizon. For example, assume that the policymaker is concerned with entry into the low financial stability state at any point over an eight-quarter forecast horizon. The forecasted probabilities are then used to construct vector probability forecasts for this defined event of interest, which we denote as the conditional hazard function $H_T(k)$ for $k = 1, 2, .., 8$ quarters ahead. While straightforward to calculate, the usefulness of this event to a policymaker is likely limited. That is, a single quarter in the low financial stability state may not be sufficient to warrant a policy action, either because of uncertainty about the state itself or the overall effects of the policy occurring over more than one quarter.

An alternative event of greater interest to policymakers is the probability of being in the low financial stability state for a consecutive number of quarters.[33] For example, the CCyB in the

[33]Edge and Meisenzahl (2011) discussed different ways for policymakers to frame the policy threshold for implementing the CCyB, but none are based on financial stability projections as we propose. The authors instead discuss a policy threshold that is a high percentile, say 90 percent, of the credit-to-GDP gap.

United States is required to be phased in over a one-year period after announcement. Accordingly, policymakers would likely need to assess the probability of remaining in the low financial stability state in the next four quarters in the absence of their policy action. We thus assume that U.S. policymakers are concerned with the probability of *four consecutive* quarters of financial instability and project our hazard function at time T for this event over an eight-quarter horizon.

The choice of an eight-quarter horizon for our work is based on the political realities of the U.S. CCyB policy, which mandates a four-quarter delay between announcement and implementation. Drehmann and Juselius (2013) provided support for this choice since they argue that FSI signals should have appropriate timing to be useful for macroprudential policy responses. In particular, they suggest that the signal arrive at least 1.5 years before a financial crisis, but not more than five years before.[34] The early warning indicator nature of several of our FSIs should, therefore, be useful for guiding CCyB policy decisions over this time horizon.

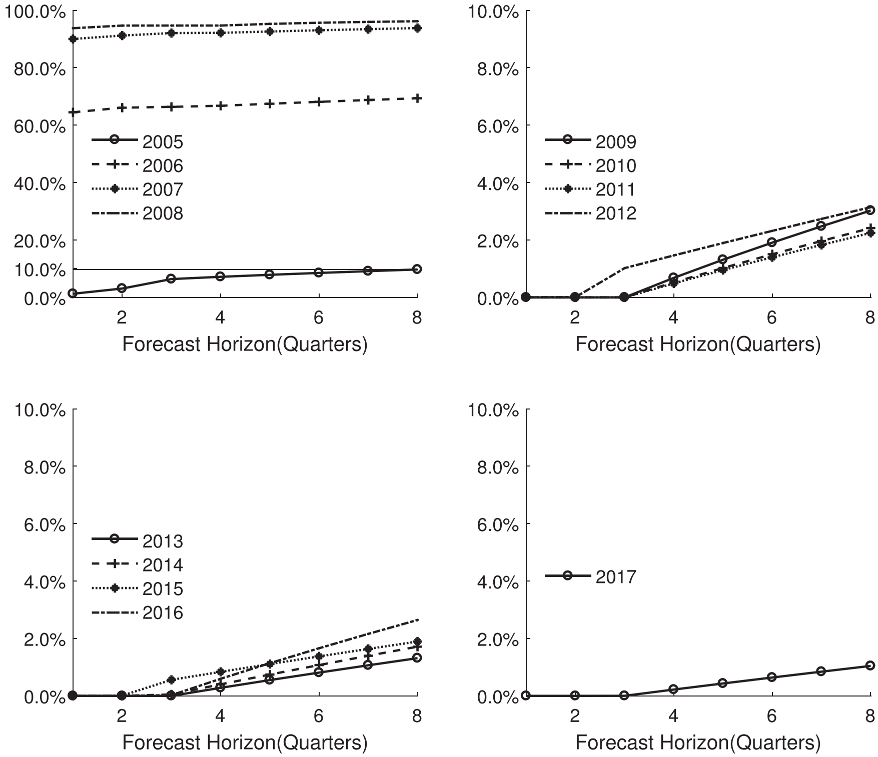
To test this, we consider a pseudo out-of-sample exercise where we estimate $H_T(k)$ by truncating our sample period initially to 2005:Q4 and then adding back one year's worth of data at a time—namely, spanning 2005:Q4 through 2017:Q4. The result of this exercise can be seen in figure 4. Each of the four panels contain hazard functions for four data samples over projection quarters (PQ) 1 through 8 with the exception of the bottom-right panel, which only contains the 2017:Q4 hazard values. The upper-left panel of the figure demonstrates quite clearly the effectiveness of our methodology in providing an early warning signal for the recent financial crisis.[35] Here, our hazard estimates begin in 2005:Q4 by signaling a maximum probability for our four-quarter adverse event of 10 percent at PQ8 before jumping rapidly to 60 percent, 90 percent, and 95 percent in PQ1 for 2006:Q4, 2007:Q4, and 2008:Q4, respectively.[36]

[34] Lo Duca and Peltonen (2013) examined a horizon of six to eight quarters.

[35] Lo Duca and Peltonen (2013) have a similar figure in spirit, but it represents just their interest in PQ6.

[36] It should be noted, however, that we are using revised data. Given the large revisions that some of our data series experienced during this period, we are likely somewhat overstating this result. Using real-time data vintages for each estimation sample instead would eliminate this concern, but is precluded by the limited availability of such data for several of the FSIs that we examine.

Figure 4. Year-End Model-Weighted Average Hazard Functions 2005:Q4–2017:Q4



Note: Note the change of scale from the top-left panel to the other three panels.

After 2008:Q4, our hazard functions shift markedly lower, with each four-year period demonstrating progressively lower maximum values until 2017:Q4, where at PQ8 the maximum remains below 2 percent.

Table 1 and the tables in the appendix report the weights given to each of our eight specifications for each year-end hazard function shown in figure 4. The model rankings are largely consistent over the latter half of our sample. Notably, from 2007:Q4 on, the model including the NFCI Nonfinancial Leverage subindex receives the largest weight, which is in line with the findings of Brave and Butters (2012b). The only other FSI that demonstrates an increase over time in its weight is the leverage ratio, although its weight has also been declining since 2010:Q4. In contrast, the weights given to the other specifications fall over time, largely due to their reduced ability to provide a leading indication of the global financial crisis and recession.

In many respects, our most recent hazard estimates are very much defined by the characteristics of the last crisis, just as our hazard estimates for 2005:Q4, with their heavy reliance on corporate bond spread measures, were for the early 2000s' financial market disruptions. It is, therefore, reassuring for the early detection of future crises that despite these shortcomings, our methodology still provides an early warning signal for the last crisis. Our methodology is also flexible enough that subjective information on this dimension could also be incorporated. For example, we use a very agnostic prior in our Bayesian model averaging procedure. A more informative prior could instead be used if there were indications that a particular model was no longer working as intended. We do not consider this possibility here, but simply raise it as a possibility that could enhance the discussion of macroprudential policy recommendations.

4. Transforming Hazard Functions into Policy Recommendations

In this section, we provide additional context for our financial crisis hazard functions for the United States in terms of judging in hindsight whether or not hypothetical CCyB policy actions would have been warranted. As above, we consider a pseudo out-of-sample exercise where we now estimate the optimal timing and level of the CCyB according to alternative calibrations of the KS framework by truncating our sample period initially to 2005:Q4 and then adding back one year's worth of data up through 2017:Q4. For the sake of brevity, we focus in this section only on the results for 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4. The first quarter of analysis corresponds to the run-up to the financial crisis, while the latter three correspond to periods that are relatively more stable, although with slightly different probabilities of entering a financial crisis.

It is important to note that the projections used in the subsequent analysis are conditional on the data available at time T over the projection horizon $T + \tau$. They are not structured to take into account the interactive adjustments in the economy subsequent to the CCyB policy actions and, as such, fall subject to the usual Lucas critique. While this limitation is obvious, designing a structural model characterizing the response to the implementation of CCyB policies is beyond the scope of this work. Instead, our approach provides conditional projections using available data in a real-time setting that should provide key operational insights to policymakers. In addition, if structural model simulations are available that capture such interactive adjustments, they could easily be folded into our methodology for estimating the hazard functions described in the first section of the appendix.

4.1 External Calibration Analysis

Table 2 presents the values used for our external calibration analysis as of our four selected year-end quarters. Our calibration risk-free discount rate, r, is the two-year Treasury rate, as reported in the table. The calibration of C is the required increase in bank capital, which is based on the total risk-weighted assets (RWA) for the affected firms. The details of this calculation can be found in the second section of the appendix.

Our $[\underline{u}, \bar{u}]$ parameters in this calibration are based on real GDP projections from the Survey of Professional Forecasters (SPF) and studies conducted by the Macroeconomic Assessment Group (MAG) established by the Financial Stability Board and the BCBS to examine the economic effect of the proposed Basel III capital requirements.[37] In their analysis, the MAG implemented ninety-seven different models to examine the effect of increased capital requirements on national GDP growth. They presented a range of model outcomes, and in our work, we use their 20th and 80th percentile values to establish a range of possible $\underline{u}$ values. For a 1 percentage point increase in bank capital, they found that real GDP growth declined

[37] See Macroeconomic Assessment Group (2010a, 2010b).

Table 2. External Calibration Parameters for KS Policy Projections

	2005:Q4	**2009:Q4**	**2013:Q4**	**2017:Q4**
KS Parameters:				
RWA for Top Twelve BHCs ($b)	$4,807	$6,829	$6,348	$6,750
CCyB Ratio	0.25%	0.25%	0.25%	0.25%
CCyB Cost ($b)	$12.0	$17.1	$15.9	$16.9
Two-Year Treasury Rate	4.41%	1.14%	0.38%	1.89%
GDP at Year-End	$14,373	$14,542	$15,794	$17,287
SPF Real GDP Growth Rate	3.40%	2.40%	2.60%	2.50%
$\bar{u}$ ($b)	$994	$706	$832	$875
μ_{20pct}	3.32%	2.32%	2.52%	2.42%
$\underline{u}_{20pct}$($b)	$970	$682	$806	$846
μ_{80pct}	3.38%	2.38%	2.58%	2.48%
$\underline{u}_{80pct}$ ($b)	$988	$700	$825	$867
KS Values:				
$\theta = 0.00$	1.37%	2.63%	2.02%	2.11%
$\theta = 0.25$	1.36%	2.60%	2.01%	2.09%
$\theta = 0.50$	1.35%	2.58%	1.99%	2.08%
$\theta = 0.75$	1.34%	2.56%	1.98%	2.06%
$\theta = 1.00$	1.33%	2.53%	1.96%	2.04%

Notes: Dollar values are expressed in 2009 dollars using the U.S. GDP deflator. Growth rates used to calculate $\bar{u}$ and $\underline{u}$ are presented as annual percent rates, as is the SPF real GDP growth rate.

by −17 and −4 basis points at the one-year horizon for these two percentiles, respectively.[38] We calibrate $\bar{u}$ based on the two-year compounding of that year's SPF one-year forecast and then $\underline{u}$ as the two-year compounding of that year's SPF one-year forecast minus the two MAG percentiles noted.

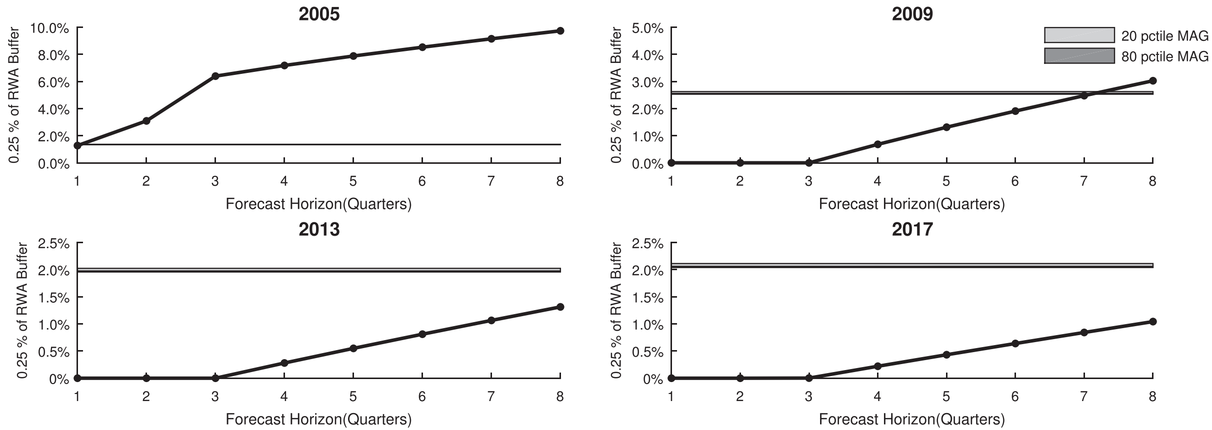
[38] Firestone, Lorenc, and Ranish (2017) suggest a decrease in real GDP growth within the range of $(-27, -8)$ basis points for a 1 percentage point increase in bank capital; see their table 12.

The bottom rows of table 2 show the estimated hazard values that optimize the KS first-order condition for various calibrations of θ and across our four projection points. These values are the recommended policy implementation thresholds, expressed as probabilities and based on the total capital to be raised by the affected banks under a 0.25 percent implementation of the CCyB policy. Over all four projection points, they range from 1.33 percent to 2.63 percent, which is a relatively low threshold for action in each case. The policy intuition here is that the cost of the CCyB capital raise in this calibration is quite low relative to the overall potential benefit of avoiding a decline in real GDP. Based on these threshold probabilities, we can identify calibrated policy implementation dates that incorporate both the policymaker's objective function and current financial stability projections.

The calibrated implementation quarters for our four projection points and model-weighted average hazard functions are shown in figure 5. For the policymaker at 2005:Q4, the hazard function suggests that the CCyB should be enacted within the four-quarter implementation period after announcement; i.e., the threshold values depicted at the very bottom of the graph are breached by the hazard values after PQ1. Given the relative policy costs, seven of our eight models suggest that the policymaker should consider implementing the CCyB policy given the projected financial stability conditions.

The policymakers at 2009:Q4, 2013:Q4, and 2017:Q4 face a contrasting set of conditions with a near-zero hazard value for the first three projection quarters. At 2009:Q4, a much lower initial level and slope of the hazard function than in 2005:Q4 keeps it below the threshold for action until PQ8. This is the case despite six of the eight specifications suggesting CCyB implementation in PQ4 through PQ6. A similar pattern is observed for 2013:Q4 and 2017:Q4, with the KS threshold values for several models suggesting implementation in PQ4–PQ7. For all three periods, the NFCI Nonfinancial Leverage subindex that dominates our Bayesian model averaging procedure has a hazard value that is quite low, causing the model-weighted average hazard not to exceed the KS thresholds until PQ8 or later. This policy recommendation illustrates how even a relatively low-cost policy might not be reasonably implemented when facing a benign projection for financial instability.

Figure 5. Model-Weighted Average Hazard Functions and KS Thresholds Based on the External Calibration as of 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4



Note: Note the differing scales for 2005 and 2009 relative to 2013 and 2017.

Table 3. Internal Calibration Parameters for KS Policy Projections

	2005:Q4	**2009:Q4**	**2013:Q4**	**2017:Q4**
KS Parameters:				
RWA for Top Twelve BHCs ($b)	$4,807	$6,829	$6,348	$6,750
CCyB Ratio	0.25%	0.25%	0.25%	0.25%
CCyB Cost ($b)	$12.0	$17.1	$15.9	$16.9
Two-Year Treasury Rate	4.41%	1.14%	0.38%	1.89%
GDP at Year-End	$14,373	$14,542	$15,794	$17,287
$\bar{u}$ ($b)	$1,110	$1,051	$1,080	$1,121
μ_+	3.79%	3.55%	3.36%	3.19%
$\underline{u}$ ($b)	$430	$282	$147	$125
μ_-	1.48%	0.97%	0.46%	0.36%
KS Values:				
$\theta = 0.00$	3.14%	6.58%	12.20%	16.29%
$\theta = 0.25$	2.23%	3.82%	4.39%	4.91%
$\theta = 0.50$	1.73%	2.69%	2.68%	2.89%
$\theta = 0.75$	1.41%	2.07%	1.93%	2.05%
$\theta = 1.00$	1.19%	1.69%	1.50%	1.59%

Notes: Dollar values are expressed in 2009 dollars using the U.S. GDP deflator. Growth rates used to calculate $\bar{u}$ and $\underline{u}$ are presented as annual percent rates.

4.2 Internal Calibration Analysis

Table 3 presents the values used for our internal calibration analysis. Both the calibration of r and C are the same as above. However, our model-based utility flows $[\underline{u}, \bar{u}]$ are instead defined in this case over the projection horizon as the long-term expectations of GDP *growth* conditional upon both the financial stability state and average credit *growth*, as detailed in the second section of the appendix. Table 3 highlights that we set the utility flows as $\bar{u} = GDP_T * \mu_+$ and $\underline{u} = GDP_T * \mu_-$, where GDP_T is the end-of-sample *level* of real GDP and $\mu_{\{+,-\}}$ are our state-dependent GDP growth expectations. Measured in this way, we interpret the difference between $\bar{u}$ and $\underline{u}$ as the counterfactual lost output from a financial crisis.

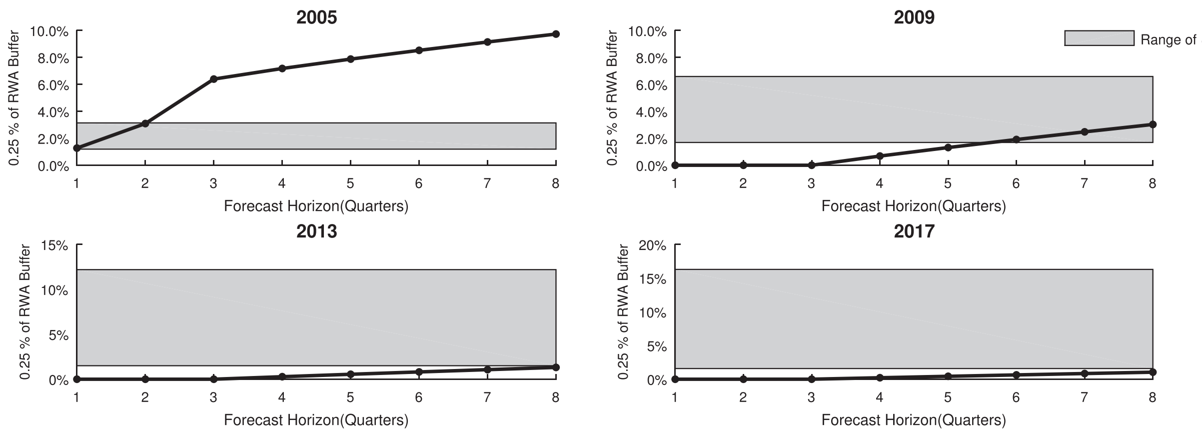
The bottom rows of table 3 show the hazard values that optimize the KS first-order condition for various values of θ across our four sample periods. As before, these values are the recommended policy implementation thresholds based on the total capital to be raised by the affected banks under a 0.25 percent implementation of the CCyB policy. Over all four sample periods, the calibrated probability values range from 1.19 percent to 16.29 percent, which is a relatively wide range due to the relatively large differences in state-contingent utility flows that arise from our parameter estimates. The policy intuition here is that the relative cost of the CCyB capital raise is quite sensitive to its perceived effectiveness (i.e., the calibrated value of θ) since the spread between $[\underline{u}, \bar{u}]$ is much larger.

The calibrated implementation quarters for our four projection points and model-weighted average hazard functions are shown in figure 6. As before, for the policymaker at 2005:Q4, the hazard function suggests that the CCyB policy should be enacted within the four-quarter implementation period after announcement regardless of the perceived effectiveness of the policy; i.e., the threshold values depicted in the bottom of the gray range in figure 6 are breached by the weighted average hazard value in PQ1 and those at the top of the gray range are breached in PQ2. Given the relatively low cost of the required capital raise, implementing the policy within the coming year would be warranted based on the projected financial stability conditions of six of the eight models.

The decision to be made is more nuanced for the policymaker at 2009:Q4, where the threshold for action is not breached until PQ6, and even then only in the case where the policy is assumed to be highly effective (i.e., for a large value of θ). The policymakers at 2013:Q4 and 2017:Q4 face a contrasting set of conditions. The KS lower threshold values for most models fall between PQ4 and PQ8. However, since the highest weight is placed on the specification using the NFCI Nonfinancial Leverage subindex whose threshold date is beyond PQ8, the weighted average hazard values do not meet the thresholds for action over the projection horizon for any value of θ.

These results highlight the importance of defining the $[\underline{u}, \bar{u}]$ calibration parameters in the KS objective function. Both our external and internal calibrations provide insight into the policymaker's decision process, albeit along different dimensions. While our two

Figure 6. Model-Weighted Average Hazard Functions and KS Thresholds Based on the Internal Calibration as of 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4



Note: Note the differing scales for 2013 and 2017 relative to 2005 and 2009.

chosen calibrations may be quite different in this regard, their similar conclusions are reassuring of the robustness of our methodology and highlight the potential value of the KS framework for policy discussions; i.e., the framework organizes various components of the CCyB decision process into a format that enhances policy discussion.

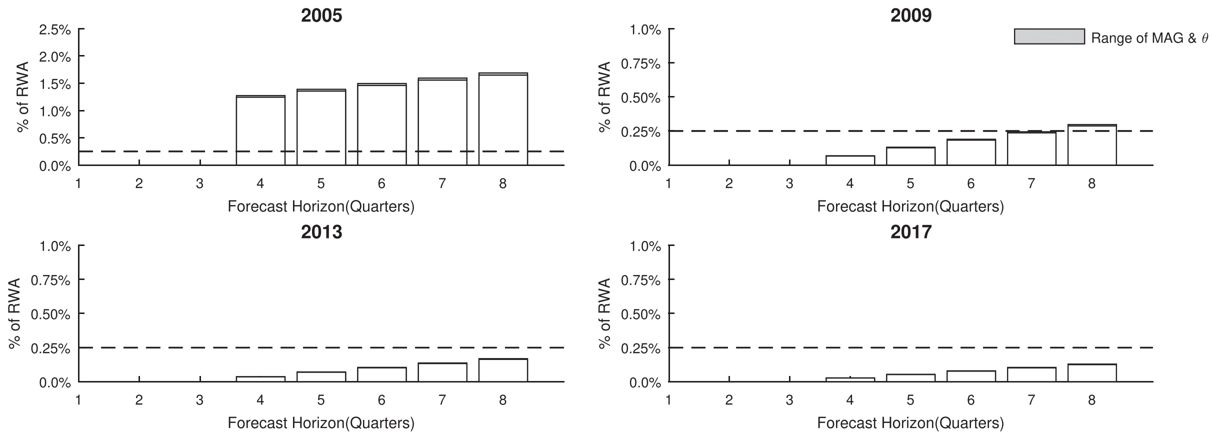
4.3 Calibration of the CCyB Rate

The policy recommendations discussed above are based on whether or not to enact the CCyB policy using the rate of 0.25 percent at the beginning of a projection quarter. An alternative policy analysis that can be conducted within this framework is to ask today what CCyB rate should be enacted in a particular projection quarter. In terms of the KS notation, instead of setting all of the calibration parameters to see at what date it would be reasonable to act, this alternative analysis fixes the policy enactment date and examines what the policy rate should be relative to the KS first-order condition at each date.

Figures 7 and 8 present this analysis for our four projection points and the two utility calibrations. Given that the CCyB is to be implemented over the four quarters after its announcement, we present our implied CCyB rates only for PQ4 through PQ8. As of year-end 2005 when there was a high probability of tipping into a financial crisis, the clear policy recommendation from both calibrations is that a CCyB rate in excess of 0.25 percent should be put in place, with the optimal rate rising from about 1 percent to roughly 2 percent depending on the MAG and θ values across our calibrations.

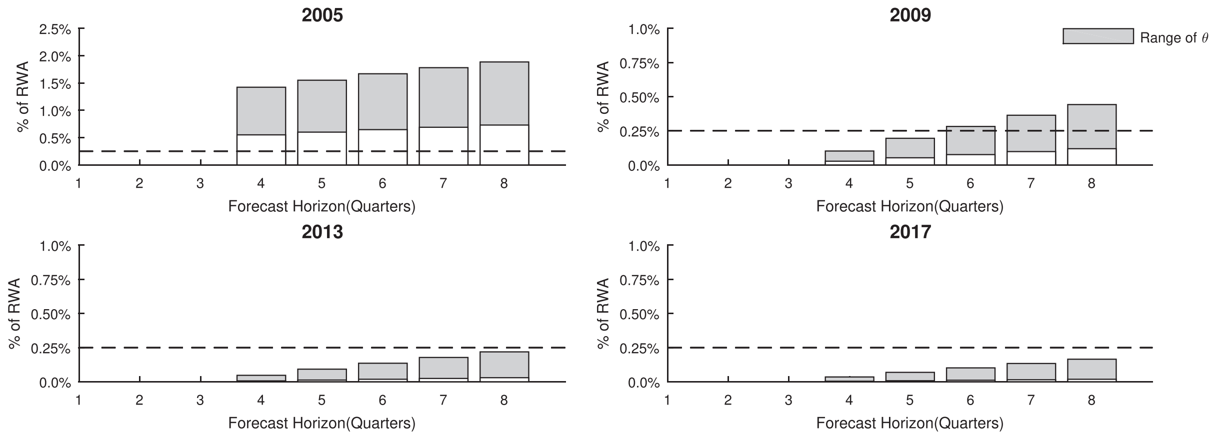
The other three sample periods provide more nuanced answers. If the policymaker wanted to maintain a non-zero CCyB rate, it would be in effect in PQ4. The policymakers in 2013:Q4 and 2017:Q4 would not need to act at all since the optimal CCyB rate does not exceed our defined 0.25 percent minimum. However, a policymaker at year-end 2009 may prefer to just barely act at PQ6–PQ8 if the θ value was close to one in the internal calibration and at PQ7–PQ8 in the external calibration. In both cases, the policymaker need not act immediately given the relatively low hazard values, but instead may delay action for a few quarters hoping for a clearer signal of potential financial instability.

Figure 7. Model-Weighted Average Countercyclical Capital Buffer Proposals Based on the External Calibration as of 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4



Note: Note the change of scale from the top-left panel to the other three panels.

Figure 8. Model-Weighted Average Countercyclical Capital Buffer Proposals Based on the Internal Calibration as of 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4



Note: Note the change of scale from the top-left panel to the other three panels.

5. Conclusion

The introduction of macroprudential responsibilities and policies at central banks and financial regulatory agencies has created a need for new methods of analyzing previously untested policy tools, like the countercyclical capital buffer (CCyB). We proposed for this purpose a transformation of financial stability indicators (FSIs) based on transition probabilities between states of high and low financial stability estimated from Markov-switching models. We then demonstrated how probabilities could be used within the Khan and Stinchcombe (KS, 2015) decision-theoretic framework to examine when to implement a CCyB rate increase.

We provided calibrated examples for the United States using data as of 2005:Q4, 2009:Q4, 2013:Q4, and 2017:Q4 that illustrated how this framework allows for macroprudential policy recommendations that incorporate both policymakers' objective functions and financial stability projections. For 2005:Q4, we found that a moderate likelihood of deteriorating financial stability according to our measures and the relatively low cost of raising CCyB capital amounts suggested that policymakers should have considered implementation of the CCyB immediately if this macroprudential tool would have been available to them at that time. For the other three projection dates, the opposite pattern holds, with the suggested implementation dates generally beyond our two-year projection horizon.

The calibration exercises demonstrate how our proposed analytical framework could be used constructively for macroprudential policymaking. By combining projected policy costs and benefits with reasonably estimated hazard functions of financial crises, the KS approach would provide policymakers with a concrete framework for assessing if and when to act. Clearly, a variety of research questions remain to be addressed regarding the exact nature of the policy tool of interest, the specification of the projected hazard functions and their associated financial stability measures, and the policy costs and benefits. However, by providing a straightforward analytical framework for approaching this problem, we hope to contribute to the effective design, ongoing implementation, and assessment of CCyB policies. For example, the framework could be used to examine the reasonableness of the current four-quarter implementation lag as well as the current 2.5 percent cap on the CCyB rate.

Appendix

Projecting Hazard Functions over the Policy Horizon

Based on the notation presented in Hamilton (2016), we demonstrate here the construction of the hazard functions needed for our pseudo out-of-sample exercise. The relevant output from our Markov-switching models is the end-of-sample (T) transition probability matrix characterizing expected transitions between our financial stability states, summarized as

$$\hat{\pi}_T = \begin{pmatrix} \hat{p}_{11} & (1-\hat{p}_{11}) \\ (1-\hat{p}_{22}) & \hat{p}_{22} \end{pmatrix} = \begin{pmatrix} \hat{p}_{11} & \hat{p}_{12} \\ \hat{p}_{21} & \hat{p}_{22} \end{pmatrix},$$

where $\hat{p}_{ij}$ is the estimated transition probability from state i at time T to state j at time $T+1$. To summarize the model-implied state, denote ξ_T as a (2×1) vector that uses a value of one to indicate the true, but unobservable, state and a value of zero otherwise. For our estimated Markov-switching models, we generate

$$E[\hat{\xi}_T | S_{T-1} = i, \Omega_T] = \begin{pmatrix} Pr(S_T = 1 | S_{T-1} = i) \\ Pr(S_T = 2 | S_{T-1} = i) \end{pmatrix} = \begin{pmatrix} \hat{p}_{i1} \\ \hat{p}_{i2} \end{pmatrix},$$

where the elements $\hat{p}_{i1} + \hat{p}_{i2} = 1$, $i = 1$ corresponds to our high financial stability state S^+, and $i = 2$ corresponds to our low financial stability state S^-.

For forecasting purposes, define the matrix P whose (j, i) element corresponds to p_{ij}, such that each column sums to 1; i.e.,

$$P = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix}.$$

The one-step-ahead forecast of our model-implied state is then $E[\xi_{T+1} | \hat{\xi}_T] = P\hat{\xi}_T$, and the k-step-ahead forecast is $E[\xi_{T+k} | \hat{\xi}_T] = P^k \hat{\xi}_T$. We generate forecasts in this manner for each of our eight Markov-switching model specifications based on their estimates of $\hat{\xi}_T$. The forecasted probabilities for each specification are then used to construct vector probability forecasts for a defined adverse event of interest, which we denote in the main text as the conditional hazard function $H_T(k)$. Using the notation above,

$$H_T(k) = E[Pr(S_{T+k} = 2) | \hat{\xi}_T] = (P^k \hat{\xi}_T)_{(2,1)},$$

which refers to the $(2,1)$ element in the product for each value of $k \in [1,8]$.[39]

As noted in the main text, the usefulness of this event to a policymaker is likely limited. Therefore, we instead frame the policymaker's problem as projecting out the hazard function at time T of experiencing *four consecutive* quarters of the low financial stability state S^- over the eight-quarter forecast horizon. Note that the policymaker will have in hand the model-implied state probabilities of the three quarters leading up to the projection point T (i.e., quarters $T-2$ through T), which inform the probability of the *four-quarter* adverse event occurring in quarter $T+1$. With three conditional in-sample quarters and eight out-of-sample quarters to project over, we have $2,048 (= 2^{11})$ state paths to consider. For each path, we determine the probability of the *four-quarter* adverse event occurring, and the likelihood of each path is then used to weight them into a corresponding *four-quarter* hazard function for each of our eight model specifications.

To obtain a single hazard function for our policy exercise, we use our empirical Bayesian model averaging procedure, weighting each specification by a measure of its model fit. Defining the set of model specifications as Ξ, the posterior probability $p(\Xi_m|Y,X,Z)$ assigned to each of one of our $m = 1, 2, ..., 8$ specifications is given by

$$p(\Xi_m|Y,X,Z) = \frac{p(\Xi_m)exp(-0.5 * BIC(\Xi_m))}{\sum_m p(\Xi_m)exp(-0.5 * BIC(\Xi_m))},$$

where $BIC(\Xi_m)$ is the Bayesian information criterion and $p(\Xi_m)$ is a uniform prior.

Additional Details for Our Calibration Exercises

To calculate the required capital increase, we used the variable BHCK A223 (total risk-weighted assets) from the consolidated Y-9C reporting forms. Note that the current U.S. proposal suggests that the CCyB rate be applied only to firms' private-sector credit exposures, which is a subset of total RWA and thus a lower number

[39]For the time-varying probability models, the out-of-sample projections could be conditioned on projections for Z_{t+k}. In the main text, we instead treat these variables as fixed at their end-of-sample values.

than the one we used here. In addition, the applicable CCyB amount for a banking organization is equal to the weighted average of CCyB amounts established by the Board of Governors for the national jurisdictions where the banking organization has private-sector credit exposures.

As proposed, the CCyB policy applies only to banking organizations subject to the advanced capital rules, which generally are those with greater than $250 billion in assets or more than $10 billion in on-balance-sheet foreign exposures. For the twelve banking firms that met this threshold as of 2017:Q4, their total RWA was $7.7 trillion dollars, which suggests a 0.25 percent CCyB need of $19.25 billion. Note that this capital amount must be raised within one calendar year of policy enactment. We assume that the *number* of affected firms would be the same for 2005:Q4, 2009:Q4, and 2013:Q4. Thus, in 2005:Q4, we calibrate C as 0.25 percent of $4.5 trillion, which is $11.25 billion. The corresponding amount then for both 2009:Q4 and 2013:Q4 is $17.0 billion.

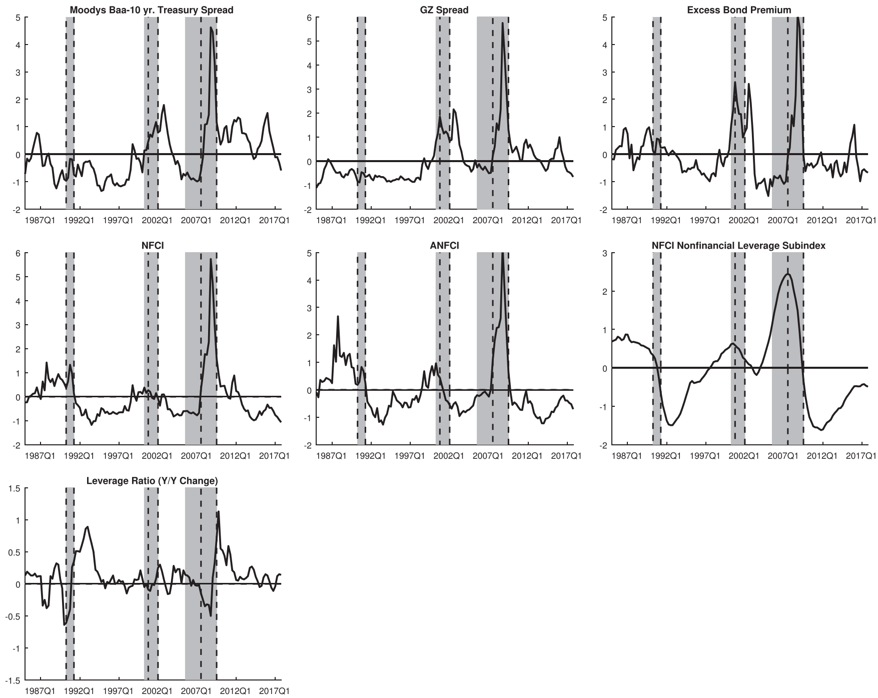
For our internal calibration exercise, we define our model-based utility flows based on our state-dependent long-term expectations of GDP *growth* conditional on average credit growth. In the notation of equation (2) of the text, this expectation in state S^i with $i = \{+, -\}$ is

$$\hat{\mu}_i = \frac{\hat{\alpha}_{S^i} + (\hat{\beta}_{S^i,C_t} + \hat{\beta}_{S^i,C_{t-1}}) * \mu_{C_t}}{(1 - \hat{\beta}_{S^i,GDP_{t-1}})},$$

where the $\hat{\alpha}_{S^i}$ and $\hat{\beta}_{S^i}$ terms correspond to the estimated Bayesian model averaged parameters of our Markov-switching models and μ_{C_t} is the sample average of credit growth.

Additional Results

Figure 9. Financial Stability Indicators (FSIs), Presented in Standard Deviation Units



Notes: The shaded periods reflect quarters in which the Bayesian model weighted-average smoothed probabilities of the low financial stability state are greater than 50 percent. The dashed vertical lines within the shaded periods denote NBER recessions.

Table 4. Markov Regime-Switching Models Estimated up through 2005:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.19	0.00	0.04	0.70	0.01	0.00	0.04	0.02
Transition Probabilities:								
δ_1	1.56***	1.60***	1.42***	1.50**	1.71*	1.63***	1.76***	2.36**
	(0.55)	(0.61)	(0.70)	(0.85)	(1.11)	(0.67)	(0.68)	(1.23)
δ_2	−0.88**	−0.81	−0.07	−0.29	−0.70	−0.88**	−0.81*	−0.68
	(0.50)	(0.63)	(0.72)	(0.68)	(0.54)	(0.51)	(0.52)	(0.90)
γ^{FSI}	—	−0.28	−0.63	−0.65	−0.51	−0.16	−0.89*	0.83
	—	(0.43)	(0.58)	(0.73)	(0.90)	(0.42)	(0.59)	(0.85)
GDP Growth (S^+):								
α_1	3.40***	3.21***	3.37***	3.46***	3.33***	3.35***	3.43***	3.14***
	(0.67)	(0.65)	(0.59)	(0.64)	(0.64)	(0.66)	(0.62)	(0.59)
β_1^{GDPt-1}	−0.15	−0.04	−0.15	−0.18	−0.13	−0.13	−0.19	−0.08
	(0.14)	(0.17)	(0.14)	(0.14)	(0.13)	(0.14)	(0.14)	(0.12)
β_1^{Ct}	−0.07	−0.04	−0.05	−0.08	−0.06	−0.07	−0.08	−0.06
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.15)	(0.12)
β_1^{Ct-1}	0.25***	0.15	0.23***	0.27***	0.22**	0.23**	0.31***	0.20**
	(0.12)	(0.13)	(0.12)	(0.11)	(0.12)	(0.12)	(0.14)	(0.11)
GDP Growth (S^-):								
α_2	−0.86	−2.03	−1.08	−0.84	−1.00	−0.93	−0.71	−1.34
	(1.00)	(1.91)	(1.85)	(0.88)	(0.99)	(1.07)	(0.77)	(1.19)
β_2^{GDPt-1}	−0.07	−0.22	−0.11	−0.08	−0.10	−0.09	−0.08	−0.07
	(0.36)	(0.20)	(0.50)	(0.35)	(0.45)	(0.37)	(0.28)	(0.71)
β_2^{Ct}	0.30	0.38*	0.36	0.27	0.31	0.31	0.27	0.25
	(0.28)	(0.24)	(0.29)	(0.23)	(0.32)	(0.30)	(0.20)	(0.48)
β_2^{Ct-1}	0.19	0.53***	0.16	0.20	0.20	0.20	0.22	0.22
	(0.41)	(0.27)	(0.45)	(0.36)	(0.49)	(0.43)	(0.29)	(0.96)
σ_ε^2	2.27***	2.41***	2.24***	2.14***	2.33***	2.32***	2.19***	2.41***
	(0.64)	(0.52)	(0.73)	(0.67)	(0.64)	(0.66)	(0.56)	(0.54)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2005:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 5. Markov Regime-Switching Models Estimated up through 2006:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.44	0.03	0.07	0.15	0.01	0.01	0.28	0.02
Transition Probabilities:								
δ_1	1.40***	1.18***	1.26***	1.31***	1.40***	1.42***	1.67***	1.83***
	(0.41)	(0.60)	(0.57)	(0.51)	(0.52)	(0.51)	(0.63)	(0.88)
δ_2	−0.97**	−0.33	−0.41	−0.39	−0.88*	−0.96**	−0.90**	−0.76
	(0.51)	(0.61)	(0.60)	(0.69)	(0.55)	(0.52)	(0.51)	(0.73)
γ^{FSI}	—	−0.51	−0.56	−0.65**	−0.23	−0.08	−0.99*	0.56
	—	(0.41)	(0.49)	(0.33)	(0.35)	(0.30)	(0.68)	(0.61)
GDP Growth (S^+):								
α_1	3.45***	3.40***	3.45***	3.47***	3.42***	3.43***	3.40***	3.20***
	(0.68)	(0.64)	(0.63)	(0.66)	(0.67)	(0.68)	(0.61)	(0.64)
β_1^{GDPt-1}	−0.18	−0.19	−0.17	−0.17	−0.16	−0.17	−0.19	−0.09
	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.14)	(0.13)	(0.13)
β_1^{Ct}	−0.07	−0.07	−0.06	−0.07	−0.06	−0.07	−0.08	−0.05
	(0.14)	(0.13)	(0.13)	(0.12)	(0.14)	(0.14)	(0.15)	(0.12)
β_1^{Ct-1}	0.28***	0.28***	0.25***	0.27***	0.26***	0.27***	0.31***	0.19**
	(0.12)	(0.13)	(0.12)	(0.11)	(0.12)	(0.12)	(0.14)	(0.11)
GDP Growth (S^-):								
α_2	−0.69	−0.79	−0.79	−0.66	−0.73	−0.71	−0.72	−1.04
	(0.78)	(0.88)	(1.08)	(0.83)	(0.82)	(0.82)	(0.81)	(1.02)
β_2^{GDPt-1}	−0.10	−0.10	−0.11	−0.08	−0.11	−0.11	−0.13	−0.10
	(0.32)	(0.40)	(0.43)	(0.34)	(0.34)	(0.33)	(0.29)	(0.47)
β_2^{Ct}	0.37**	0.39**	0.42**	0.31*	0.38*	0.38**	0.37***	0.40
	(0.21)	(0.23)	(0.24)	(0.22)	(0.23)	(0.22)	(0.19)	(0.34)
β_2^{Ct-1}	0.11	0.08	0.07	0.12	0.10	0.11	0.13	0.08
	(0.27)	(0.29)	(0.29)	(0.33)	(0.32)	(0.28)	(0.24)	(0.47)
σ_ε^2	2.18***	2.14***	2.17***	2.15***	2.22***	2.20***	2.17***	2.37***
	(0.61)	(0.58)	(0.65)	(0.54)	(0.61)	(0.62)	(0.55)	(0.60)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2006:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 6. Markov Regime-Switching Models Estimated up through 2007:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.40	0.01	0.04	0.04	0.01	0.00	0.48	0.02
Transition Probabilities:								
δ_1	1.44***	1.30***	1.27***	1.36***	1.42***	1.45***	1.55***	1.82***
	(0.41)	(0.47)	(0.47)	(0.42)	(0.43)	(0.45)	(0.57)	(0.69)
δ_2	−1.12***	−0.87**	−0.75*	−0.97**	−1.07***	−1.10***	−1.00***	−0.98*
	(0.46)	(0.47)	(0.47)	(0.55)	(0.48)	(0.48)	(0.51)	(0.59)
γ^{FSI}	—	−0.29	−0.52	−0.46*	−0.19	−0.11	−1.09	0.57
	—	(0.32)	(0.40)	(0.32)	(0.33)	(0.29)	(0.79)	(0.52)
GDP Growth (S^+):								
α_1	3.44***	3.47***	3.50***	3.54***	3.43***	3.42***	3.39***	3.25***
	(0.64)	(0.63)	(0.61)	(0.64)	(0.63)	(0.64)	(0.58)	(0.62)
β_1^{GDPt-1}	−0.19*	−0.20*	−0.19	−0.21*	−0.18	−0.17	−0.19*	−0.10
	(0.13)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.12)
β_1^{Ct}	−0.07	−0.07	−0.07	−0.08	−0.06	−0.06	−0.07	−0.05
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.14)	(0.12)
β_1^{Ct-1}	0.29***	0.30***	0.27***	0.30***	0.27***	0.27***	0.31***	0.20**
	(0.12)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)	(0.13)	(0.11)
GDP Growth (S^-):								
α_2	−0.75	−0.75	−0.72	−0.59	−0.75	−0.76	−0.79	−0.97
	(0.73)	(0.76)	(0.87)	(0.65)	(0.71)	(0.76)	(0.81)	(0.91)
β_2^{GDPt-1}	−0.13	−0.13	−0.12	−0.12	−0.13	−0.13	−0.15	−0.12
	(0.31)	(0.34)	(0.36)	(0.30)	(0.32)	(0.32)	(0.29)	(0.43)
β_2^{Ct}	0.41***	0.42***	0.43***	0.39***	0.41***	0.42***	0.41***	0.45**
	(0.19)	(0.19)	(0.19)	(0.17)	(0.19)	(0.20)	(0.18)	(0.27)
β_2^{Ct-1}	0.08	0.07	0.05	0.07	0.08	0.08	0.10	0.04
	(0.22)	(0.23)	(0.24)	(0.24)	(0.24)	(0.24)	(0.22)	(0.35)
σ_ε^2	2.08***	2.04***	2.05***	2.04***	2.09***	2.10***	2.07***	2.25***
	(0.52)	(0.53)	(0.54)	(0.48)	(0.52)	(0.53)	(0.50)	(0.54)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2007:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 7. Markov Regime-Switching Models Estimated up through 2008:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.34	0.01	0.05	0.02	0.01	0.01	0.50	0.07
Transition Probabilities:								
δ_1	1.61***	1.37***	1.35***	1.44***	1.54***	1.60***	1.55***	1.92***
	(0.39)	(0.42)	(0.44)	(0.40)	(0.43)	(0.43)	(0.52)	(0.62)
δ_2	−1.17***	−0.84**	−0.67	−0.92**	−1.02***	−1.04***	−0.73	−1.03
	(0.41)	(0.45)	(0.48)	(0.48)	(0.49)	(0.53)	(0.70)	(0.80)
γ^{FSI}	—	−0.40	−0.74*	−0.50*	−0.39	−0.34	−1.02	0.67
	—	(0.31)	(0.47)	(0.31)	(0.43)	(0.50)	(0.75)	(0.48)
GDP Growth (S^+):								
α_1	3.10***	3.24***	3.29***	3.29***	3.06***	2.97***	3.00***	3.05***
	(0.54)	(0.57)	(0.58)	(0.58)	(0.57)	(0.56)	(0.56)	(0.58)
β_1^{GDPt-1}	−0.09	−0.16	−0.14	−0.16	−0.08	−0.06	−0.10	−0.08
	(0.12)	(0.13)	(0.14)	(0.14)	(0.13)	(0.13)	(0.13)	(0.12)
β_1^{Ct}	−0.03	−0.04	−0.04	−0.04	−0.03	−0.03	−0.03	−0.03
	(0.13)	(0.14)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.12)
β_1^{Ct-1}	0.20**	0.24***	0.21**	0.24***	0.19**	0.19*	0.23**	0.18**
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
GDP Growth (S^-):								
α_2	−2.26***	−2.12***	−2.06***	−2.08***	−2.37***	−2.49***	−2.41***	−2.43***
	(1.03)	(0.97)	(1.02)	(0.98)	(1.10)	(1.17)	(1.14)	(1.10)
β_2^{GDPt-1}	−0.34	−0.32	−0.30	−0.31	−0.36	−0.38	−0.38	−0.37
	(0.32)	(0.30)	(0.28)	(0.29)	(0.32)	(0.33)	(0.31)	(0.31)
β_2^{Ct}	0.69***	0.67***	0.70***	0.66***	0.69***	0.70***	0.67***	0.69***
	(0.15)	(0.13)	(0.14)	(0.13)	(0.16)	(0.16)	(0.15)	(0.17)
β_2^{Ct-1}	0.09	0.08	0.04	0.07	0.10	0.12	0.12	0.09
	(0.27)	(0.24)	(0.27)	(0.24)	(0.28)	(0.29)	(0.27)	(0.30)
σ_ε^2	2.48***	2.38***	2.41***	2.38***	2.46***	2.47***	2.41***	2.48***
	(0.47)	(0.49)	(0.50)	(0.49)	(0.48)	(0.48)	(0.49)	(0.48)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2008:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 8. Markov Regime-Switching Models Estimated up through 2009:Q4

	Baseline	**Baa Spread**	**GZ Spread**	**EBP**	**NFCI**	**ANFCI**	**NFCI-nfl**	**Leverage Ratio**
Weight	0.17	0.00	0.01	0.01	0.00	0.00	0.69	0.11
Transition Probabilities:								
δ_1	1.62***	1.48***	1.31***	1.39***	1.53***	1.57***	1.61***	2.00***
	(0.38)	(0.41)	(0.43)	(0.41)	(0.41)	(0.40)	(0.47)	(0.62)
δ_2	−1.01***	−0.80**	−0.42	−0.68*	−0.85***	−0.82***	−0.64	−1.02
	(0.37)	(0.44)	(0.43)	(0.44)	(0.41)	(0.41)	(0.64)	(0.76)
γ^{FSI}	—	−0.21	−0.62**	−0.57**	−0.23	−0.34	−1.12	0.77*
	—	(0.30)	(0.35)	(0.31)	(0.31)	(0.45)	(0.78)	(0.49)
GDP Growth (S^+):								
α_1	2.79***	2.98***	3.07***	3.13***	2.85***	2.80***	2.80***	2.87***
	(0.44)	(0.49)	(0.51)	(0.50)	(0.50)	(0.48)	(0.47)	(0.49)
β_1^{GDPt-1}	−0.00	−0.06	−0.07	−0.10	−0.02	−0.00	−0.02	−0.02
	(0.12)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
β_1^{Ct}	−0.04	−0.03	−0.02	−0.03	−0.03	−0.03	−0.04	−0.04
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
β_1^{Ct-1}	0.19*	0.20**	0.18*	0.20**	0.18*	0.18*	0.21**	0.18*
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
GDP Growth (S^-):								
α_2	−2.63***	−2.45***	−2.39***	−2.31***	−2.61***	−2.72***	−2.64***	−2.59***
	(1.10)	(1.10)	(1.09)	(0.99)	(1.17)	(1.18)	(1.03)	(0.91)
β_2^{GDPt-1}	−0.30	−0.27	−0.25	−0.24	−0.30	−0.33	−0.32	−0.29
	(0.34)	(0.32)	(0.32)	(0.29)	(0.35)	(0.35)	(0.28)	(0.26)
β_2^{Ct}	0.70***	0.69***	0.71***	0.68***	0.70***	0.71***	0.68***	0.69***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)
β_2^{Ct-1}	0.13	0.09	0.06	0.07	0.11	0.13	0.14	0.10
	(0.26)	(0.26)	(0.25)	(0.23)	(0.27)	(0.27)	(0.22)	(0.21)
σ_ε^2	2.53***	2.48***	2.44***	2.43***	2.51***	2.51***	2.47***	2.52***
	(0.51)	(0.52)	(0.53)	(0.52)	(0.51)	(0.51)	(0.51)	(0.48)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2009:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 9. Markov Regime-Switching Models Estimated up through 2010:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.15	0.00	0.01	0.01	0.00	0.00	0.71	0.12
Transition Probabilities:								
δ_1	1.66***	1.58***	1.41***	1.44***	1.58***	1.60***	1.70***	2.04***
	(0.38)	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)	(0.50)	(0.63)
δ_2	−1.02***	−0.90***	−0.53	−0.69*	−0.87***	−0.82***	−0.59	−0.99
	(0.37)	(0.44)	(0.43)	(0.43)	(0.40)	(0.41)	(0.64)	(0.73)
γ^{FSI}	—	−0.13	−0.54**	−0.57**	−0.21	−0.35	−1.16	0.79*
	—	(0.30)	(0.32)	(0.31)	(0.31)	(0.45)	(0.83)	(0.49)
GDP Growth (S^+):								
α_1	2.89***	3.04***	3.17***	3.24***	2.97***	2.91***	2.95***	2.98***
	(0.42)	(0.45)	(0.47)	(0.47)	(0.47)	(0.45)	(0.45)	(0.46)
β_1^{GDPt-1}	−0.00	−0.04	−0.08	−0.10	−0.02	−0.01	−0.02	−0.03
	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)
β_1^{Ct}	−0.05	−0.04	−0.03	−0.03	−0.04	−0.04	−0.05	−0.05
	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)
β_1^{Ct-1}	0.18*	0.18*	0.18*	0.19**	0.18*	0.17*	0.20**	0.18**
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.12)	(0.11)
GDP Growth (S^-):								
α_2	−2.61***	−2.47***	−2.40***	−2.30***	−2.58***	−2.70***	−2.61***	−2.57***
	(1.05)	(1.05)	(1.08)	(0.96)	(1.12)	(1.13)	(1.00)	(0.86)
β_2^{GDPt-1}	−0.30	−0.28	−0.26	−0.24	−0.30	−0.33	−0.31	−0.29
	(0.32)	(0.31)	(0.31)	(0.28)	(0.33)	(0.33)	(0.27)	(0.25)
β_2^{Ct}	0.70***	0.70***	0.71***	0.68***	0.70***	0.71***	0.68***	0.69***
	(0.12)	(0.11)	(0.11)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)
β_2^{Ct-1}	0.12	0.09	0.06	0.06	0.11	0.13	0.13	0.10
	(0.25)	(0.25)	(0.25)	(0.22)	(0.26)	(0.26)	(0.22)	(0.20)
σ_ε^2	2.44***	2.41***	2.35***	2.35***	2.42***	2.43***	2.40***	2.43***
	(0.46)	(0.47)	(0.48)	(0.48)	(0.46)	(0.46)	(0.47)	(0.44)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2010:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 10. Markov Regime-Switching Models Estimated up through 2011:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.12	0.00	0.00	0.01	0.00	0.00	0.75	0.11
Transition Probabilities:								
δ_1	1.68***	1.63***	1.48***	1.46***	1.61***	1.63***	1.75***	2.08***
	(0.37)	(0.39)	(0.39)	(0.39)	(0.38)	(0.39)	(0.52)	(0.63)
δ_2	−1.03***	−0.95***	−0.60	−0.72**	−0.89***	−0.82***	−0.50	−0.97
	(0.37)	(0.44)	(0.43)	(0.43)	(0.40)	(0.41)	(0.61)	(0.72)
γ^{FSI}	—	−0.09	−0.48*	−0.58**	−0.19	−0.35	−1.23*	0.80*
	—	(0.29)	(0.31)	(0.31)	(0.30)	(0.45)	(0.85)	(0.49)
GDP Growth (S^+):								
α_1	2.88***	2.96***	3.09***	3.16***	2.93***	2.89***	2.93***	2.92***
	(0.39)	(0.41)	(0.43)	(0.43)	(0.42)	(0.41)	(0.40)	(0.41)
β_1^{GDPt-1}	−0.05	−0.07	−0.11	−0.13	−0.06	−0.05	−0.07	−0.06
	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)
β_1^{Ct}	−0.04	−0.04	−0.03	−0.03	−0.04	−0.04	−0.05	−0.04
	(0.12)	(0.12)	(0.11)	(0.12)	(0.12)	(0.11)	(0.12)	(0.11)
β_1^{Ct-1}	0.21***	0.22***	0.21***	0.23***	0.21***	0.20***	0.24***	0.21***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)
GDP Growth (S^-):								
α_2	−2.53***	−2.46***	−2.33***	−2.25***	−2.54***	−2.66***	−2.57***	−2.57***
	(1.00)	(0.98)	(0.93)	(0.91)	(1.05)	(1.12)	(1.00)	(0.89)
β_2^{GDPt-1}	−0.28	−0.27	−0.24	−0.23	−0.29	−0.32	−0.31	−0.29
	(0.30)	(0.29)	(0.27)	(0.26)	(0.31)	(0.32)	(0.27)	(0.25)
β_2^{Ct}	0.69***	0.69***	0.70***	0.67***	0.70***	0.70***	0.67***	0.69***
	(0.12)	(0.12)	(0.11)	(0.11)	(0.12)	(0.13)	(0.11)	(0.12)
β_2^{Ct-1}	0.11	0.09	0.05	0.06	0.10	0.12	0.13	0.10
	(0.24)	(0.24)	(0.22)	(0.21)	(0.25)	(0.26)	(0.22)	(0.21)
σ_ε^2	2.53***	2.51***	2.45***	2.44***	2.51***	2.51***	2.47***	2.53***
	(0.47)	(0.48)	(0.48)	(0.48)	(0.47)	(0.48)	(0.48)	(0.46)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2011:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 11. Markov Regime-Switching Models Estimated up through 2012:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.12	0.00	0.00	0.01	0.00	0.00	0.76	0.10
Transition Probabilities:								
δ_1	1.70***	1.70***	1.52***	1.49***	1.65***	1.66***	1.82***	2.09***
	(0.37)	(0.40)	(0.38)	(0.39)	(0.38)	(0.40)	(0.52)	(0.64)
δ_2	−1.02***	−1.02***	−0.64*	−0.68*	−0.90***	−0.80**	−0.39	−0.95
	(0.37)	(0.44)	(0.43)	(0.42)	(0.41)	(0.42)	(0.62)	(0.75)
γ^{FSI}	—	−0.00	−0.42*	−0.56**	−0.16	−0.35	−1.26*	0.79*
	—	(0.29)	(0.29)	(0.30)	(0.28)	(0.44)	(0.85)	(0.49)
GDP Growth (S^+):								
α_1	2.61***	2.61***	2.83***	2.90***	2.64***	2.61***	2.65***	2.67***
	(0.36)	(0.38)	(0.40)	(0.40)	(0.39)	(0.38)	(0.37)	(0.38)
β_1^{GDPt-1}	−0.00	−0.00	−0.07	−0.09	−0.01	−0.00	−0.02	−0.02
	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
β_1^{Ct}	−0.05	−0.05	−0.04	−0.04	−0.05	−0.04	−0.06	−0.05
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
β_1^{Ct-1}	0.23***	0.23***	0.22***	0.24***	0.23***	0.22***	0.26***	0.23***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.09)
GDP Growth (S^-):								
α_2	−2.66***	−2.66***	−2.35***	−2.29***	−2.64***	−2.75***	−2.67***	−2.61***
	(1.10)	(1.10)	(1.03)	(0.97)	(1.15)	(1.17)	(1.01)	(0.95)
β_2^{GDPt-1}	−0.30	−0.30	−0.24	−0.24	−0.31	−0.34	−0.32	−0.29
	(0.34)	(0.34)	(0.30)	(0.28)	(0.35)	(0.34)	(0.27)	(0.27)
β_2^{Ct}	0.70***	0.70***	0.71***	0.67***	0.70***	0.71***	0.67***	0.69***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.13)	(0.13)	(0.12)	(0.13)
β_2^{Ct-1}	0.13	0.13	0.05	0.07	0.12	0.14	0.15	0.11
	(0.26)	(0.26)	(0.24)	(0.23)	(0.27)	(0.27)	(0.22)	(0.22)
σ_ε^2	2.55***	2.55***	2.49***	2.47***	2.54***	2.54***	2.50***	2.55***
	(0.47)	(0.48)	(0.48)	(0.48)	(0.47)	(0.48)	(0.48)	(0.46)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2012:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 12. Markov Regime-Switching Models Estimated up through 2013:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.10	0.00	0.00	0.01	0.00	0.00	0.80	0.09
Transition Probabilities:								
δ_1	1.74***	1.74***	1.60***	1.54***	1.69***	1.70***	1.88***	2.13***
	(0.36)	(0.39)	(0.37)	(0.39)	(0.38)	(0.40)	(0.53)	(0.63)
δ_2	−1.02***	−1.02***	−0.67*	−0.66*	−0.89***	−0.78***	−0.32	−0.95
	(0.37)	(0.44)	(0.44)	(0.41)	(0.41)	(0.42)	(0.62)	(0.75)
γ^{FSI}	—	−0.00	−0.37	−0.56***	−0.17	−0.37	−1.28*	0.79**
	—	(0.28)	(0.28)	(0.28)	(0.27)	(0.45)	(0.85)	(0.47)
GDP Growth (S^+):								
α_1	2.57***	2.57***	2.73***	2.82***	2.60***	2.58***	2.61***	2.64***
	(0.35)	(0.37)	(0.38)	(0.38)	(0.38)	(0.37)	(0.36)	(0.37)
β_1^{GDPt-1}	−0.00	−0.00	−0.05	−0.08	−0.01	−0.00	−0.02	−0.02
	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
β_1^{Ct}	−0.05	−0.05	−0.04	−0.04	−0.05	−0.05	−0.06	−0.05
	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)
β_1^{Ct-1}	0.24***	0.24***	0.23***	0.25***	0.23***	0.23***	0.27***	0.23***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
GDP Growth (S^-):								
α_2	−2.72***	−2.72***	−2.50***	−2.37***	−2.70***	−2.78***	−2.69***	−2.65***
	(1.10)	(1.10)	(1.11)	(0.98)	(1.15)	(1.14)	(0.99)	(0.93)
β_2^{GDPt-1}	−0.31	−0.31	−0.27	−0.25	−0.32	−0.34	−0.32	−0.30
	(0.34)	(0.34)	(0.33)	(0.29)	(0.35)	(0.33)	(0.27)	(0.26)
β_2^{Ct}	0.70***	0.70***	0.71***	0.68***	0.70***	0.71***	0.67***	0.69***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)
β_2^{Ct-1}	0.14	0.14	0.08	0.08	0.13	0.14	0.15	0.11
	(0.27)	(0.27)	(0.26)	(0.23)	(0.27)	(0.26)	(0.22)	(0.22)
σ_ε^2	2.50***	2.50***	2.45***	2.43***	2.49***	2.49***	2.44***	2.49***
	(0.45)	(0.45)	(0.46)	(0.46)	(0.45)	(0.45)	(0.46)	(0.44)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2013:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 13. Markov Regime-Switching Models Estimated up through 2014:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.08	0.00	0.00	0.01	0.00	0.00	0.82	0.08
Transition Probabilities:								
δ_1	1.75***	1.75***	1.60***	1.54***	1.70***	1.71***	1.91***	2.16***
	(0.35)	(0.38)	(0.37)	(0.38)	(0.37)	(0.40)	(0.55)	(0.62)
δ_2	−1.02***	−1.02***	−0.66*	−0.69**	−0.88***	−0.77**	−0.30	−0.96
	(0.37)	(0.43)	(0.44)	(0.41)	(0.41)	(0.42)	(0.61)	(0.74)
γ^{FSI}	—	−0.00	−0.39	−0.58***	−0.19	−0.38	−1.31*	0.79**
	—	(0.28)	(0.28)	(0.29)	(0.27)	(0.45)	(0.87)	(0.46)
GDP Growth (S^+):								
α_1	2.67***	2.67***	2.82***	2.90***	2.70***	2.69***	2.71***	2.71***
	(0.35)	(0.36)	(0.38)	(0.38)	(0.38)	(0.37)	(0.36)	(0.37)
β_1^{GDPt-1}	−0.04	−0.04	−0.08	−0.12	−0.05	−0.05	−0.07	−0.06
	(0.10)	(0.11)	(0.11)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)
β_1^{Ct}	−0.08	−0.08	−0.06	−0.07	−0.07	−0.07	−0.08	−0.07
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
β_1^{Ct-1}	0.27***	0.27***	0.26***	0.29***	0.27***	0.26***	0.31***	0.26***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)
GDP Growth (S^-):								
α_2	−2.61***	−2.61***	−2.40***	−2.28***	−2.61***	−2.70***	−2.62***	−2.60***
	(1.03)	(1.03)	(1.06)	(0.95)	(1.09)	(1.11)	(0.99)	(0.94)
β_2^{GDPt-1}	−0.29	−0.29	−0.25	−0.24	−0.30	−0.32	−0.31	−0.29
	(0.32)	(0.32)	(0.31)	(0.27)	(0.33)	(0.32)	(0.27)	(0.26)
β_2^{Ct}	0.69***	0.69***	0.70***	0.67***	0.70***	0.70***	0.66***	0.69***
	(0.12)	(0.12)	(0.12)	(0.11)	(0.12)	(0.13)	(0.12)	(0.13)
β_2^{Ct-1}	0.12	0.12	0.06	0.07	0.11	0.12	0.14	0.10
	(0.25)	(0.25)	(0.25)	(0.22)	(0.26)	(0.25)	(0.22)	(0.22)
σ_ε^2	2.56***	2.56***	2.51***	2.48***	2.55***	2.55***	2.49***	2.56***
	(0.45)	(0.46)	(0.47)	(0.46)	(0.45)	(0.45)	(0.46)	(0.44)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2014:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 14. Markov Regime-Switching Models Estimated up through 2015:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.09	0.00	0.00	0.00	0.00	0.00	0.82	0.08
Transition Probabilities:								
δ_1	1.78***	1.78***	1.63***	1.55***	1.72***	1.74***	1.96***	2.18***
	(0.35)	(0.38)	(0.37)	(0.39)	(0.37)	(0.40)	(0.55)	(0.62)
δ_2	−1.02***	−1.02***	−0.67*	−0.66*	−0.87***	−0.75**	−0.25	−0.95
	(0.37)	(0.43)	(0.44)	(0.42)	(0.41)	(0.43)	(0.63)	(0.76)
γ^{FSI}	—	−0.00	−0.36	−0.57***	−0.19	−0.39	−1.28*	0.79**
	—	(0.27)	(0.27)	(0.29)	(0.27)	(0.45)	(0.85)	(0.46)
GDP Growth (S^+):								
α_1	2.54***	2.54***	2.70***	2.79***	2.58***	2.57***	2.58***	2.61***
	(0.34)	(0.35)	(0.37)	(0.38)	(0.37)	(0.36)	(0.35)	(0.36)
β_1^{GDPt-1}	−0.02	−0.02	−0.07	−0.10	−0.03	−0.03	−0.04	−0.04
	(0.10)	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
β_1^{Ct}	−0.07	−0.07	−0.05	−0.05	−0.06	−0.06	−0.07	−0.06
	(0.11)	(0.11)	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)	(0.10)
β_1^{Ct-1}	0.26***	0.26***	0.25***	0.27***	0.26***	0.25***	0.29***	0.26***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
GDP Growth (S^-):								
α_2	−2.66***	−2.66***	−2.41***	−2.23***	−2.65***	−2.74***	−2.69***	−2.63***
	(1.03)	(1.08)	(1.08)	(0.97)	(1.14)	(1.14)	(1.00)	(0.96)
β_2^{GDPt-1}	−0.30	−0.30	−0.25	−0.22	−0.31	−0.33	−0.32	−0.29
	(0.33)	(0.34)	(0.32)	(0.28)	(0.34)	(0.33)	(0.27)	(0.27)
β_2^{Ct}	0.69***	0.69***	0.71***	0.67***	0.70***	0.71***	0.67***	0.69***
	(0.12)	(0.13)	(0.12)	(0.11)	(0.13)	(0.13)	(0.12)	(0.13)
β_2^{Ct-1}	0.13	0.13	0.06	0.05	0.12	0.13	0.15	0.11
	(0.26)	(0.26)	(0.26)	(0.23)	(0.27)	(0.26)	(0.22)	(0.22)
σ_ε^2	2.56***	2.56***	2.52***	2.49***	2.55***	2.55***	2.51***	2.56***
	(0.45)	(0.45)	(0.46)	(0.46)	(0.44)	(0.45)	(0.45)	(0.43)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2015:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

Table 15. Markov Regime-Switching Models Estimated up through 2016:Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	NFCI-nfl	Leverage Ratio
Weight	0.09	0.00	0.00	0.01	0.00	0.00	0.82	0.08
Transition Probabilities:								
δ_1	1.81***	1.81***	1.70***	1.56***	1.76***	1.77***	2.01***	2.20***
	(0.35)	(0.38)	(0.36)	(0.52)	(0.37)	(0.41)	(0.54)	(0.63)
δ_2	−1.01***	−1.01***	−0.70*	−0.00	−0.85***	−0.73**	−0.21	−0.95
	(0.37)	(0.43)	(0.45)	(0.62)	(0.42)	(0.44)	(0.66)	(0.78)
γ^{FSI}	—	−0.00	−0.29	−0.65*	−0.19	−0.39	−1.25*	0.78**
	—	(0.27)	(0.26)	(0.45)	(0.26)	(0.44)	(0.84)	(0.45)
GDP Growth (S^+):								
α_1	2.43***	2.43***	2.47***	2.48***	2.43***	2.43***	2.38***	2.44***
	(0.33)	(0.34)	(0.35)	(0.38)	(0.35)	(0.34)	(0.34)	(0.34)
β_1^{GDPt-1}	−0.00	−0.00	−0.01	−0.00	−0.00	−0.00	−0.01	−0.00
	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)
β_1^{Ct}	−0.06	−0.06	−0.05	−0.00	−0.05	−0.05	−0.06	−0.06
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
β_1^{Ct-1}	0.25***	0.25***	0.24***	0.17**	0.24***	0.24***	0.26***	0.24***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)
GDP Growth (S^-):								
α_2	−2.77***	−2.77***	−2.60***	−2.40***	−2.75***	−2.81***	−2.77***	−2.69***
	(1.14)	(1.14)	(1.19)	(1.29)	(1.19)	(1.16)	(1.02)	(1.00)
β_2^{GDPt-1}	−0.32	−0.32	−0.29	−0.21	−0.32	−0.35	−0.33	−0.30
	(0.36)	(0.36)	(0.36)	(0.41)	(0.37)	(0.34)	(0.27)	(0.28)
β_2^{Ct}	0.70***	0.70***	0.71***	0.73***	0.71***	0.72***	0.68***	0.69***
	(0.13)	(0.13)	(0.13)	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)
β_2^{Ct-1}	0.15	0.15	0.10	0.01	0.13	0.14	0.16	0.12
	(0.27)	(0.27)	(0.29)	(0.32)	(0.28)	(0.27)	(0.23)	(0.23)
σ_ε^2	2.56***	2.56***	2.53***	2.67***	2.55***	2.55***	2.52***	2.56***
	(0.44)	(0.44)	(0.45)	(0.52)	(0.44)	(0.44)	(0.45)	(0.43)

Notes: Each column reports the estimated parameters and their standard deviations from our eight model specifications over the period from 1985:Q1 to 2016:Q4. Statistical significance at the 5 percent, 10 percent, and 15 percent level is noted with ***, **, and *, respectively. The "Weight" row refers to the model weights generated via the empirical Bayesian technique described in the text.

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