Calibrating Macroprudential Policy to Forecasts of Financial Stability

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Abstract

The introduction of macroprudential responsibilities at central banks and financial regulatory agencies has created a need for new measures of financial stability. While many have been proposed, they usually require further transformation for use by policymakers. We propose a transformation based on transition probabilities between states of high and low financial stability. Forecasts of these state probabilities can then be used within a decision-theoretic framework to address the implementation of a countercyclical capital buffer, a common macroprudential policy. Our policy simulations suggest that given the low probability of a period of financial instability at year-end 2015, U.S. policymakers need not have engaged this capital buffer. However, a partial adjustment of 0.25% of affected risk-weighted assets enacted by year-end 2017 would have been sufficient to satisfy the calibrated policy thresholds for action.

Keywords: financial stability, countercyclical capital buffer, decision theory
JEL Classification: G17, G18, G28

The views expressed herein are those of the authors and do not necessarily represent those of the Federal Reserve Bank of Chicago, the Federal Reserve Bank of San Francisco, or the Board of Governors of the Federal Reserve System. We thank Òscar Jordà, Urmee Khan, Hashem Pesaran, Jan-Peter Siedlarek as well as participants at the 2016 Federal Reserve Supervisory Surveillance conference and the VieCo 2017 conference for their comments and suggestions. We thank Kevin Roberts for his exemplary research assistance.
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1 Introduction

The global financial crisis of 2007–2009 exposed an unprecedented level of systemic risk in national financial systems. The speed at which these risks developed and spread during the crisis often necessitated that central banks and financial regulatory agencies take large and immediate actions with the tools they had readily available. Subsequently, various national governments and international agencies, such as the Bank 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 face substantial challenges in implementing macroprudential policies, beginning with the identification of the current state of financial stability 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. Drehmann & 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 & Butters (2012b)). In addition, new policy tools must be designed and implemented to address these financial stability concerns, such as the countercyclical capital buffer (CCyB) developed by the BCBS (see on Banking Supervision (2010)). An example of how this tool is being employed for macroprudential policy purposes can be seen in the deliberations of the U.K.'s Financial Policy Committee, which activated its CCyB policy in March 2016 and subsequently deactivated it in July 2016 after the Brexit vote.[2]

In this paper, we focus on the application of macroprudential policy in the spirit of current and proposed CCyB policies. Along with the U.K., several European countries have implemented CCyB policies, and the U.S. had implemented their policy as well as of October 14, 2016.[3] These policies typically require setting a threshold on the level of a triggering variable that is continuously monitored. When the defined threshold is breached, increased capital requirements are put in place and must be implemented within

[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. (2016) for an overview of macroprudential policies and available policy instruments, such as the countercyclical capital buffer examined in this paper.

[2]See Financial Policy Committee (2016a,b). In particular, for their July 2016 meeting, "[t]he FPC assess the outlook for financial stability by identifying the risks faced by the financial system and weighing them against the resilience of the system."

[3]The policy was announced formally on September 8, 2016. For a full description of the policy, see Title 12 of the Code of Federal Regulations, Part 217, Appendix A.

a specified timeframe. Similarly, once the CCyB capital charges are in place, policymakers are then tasked with determining when changes in the triggering variable warrant their immediate removal; see Kowalik (2011) for further discussion. We focus here on the current U.S. policy and examine calibrated thresholds that could suggest the triggering of the CCyB policy. Underlying our efforts are econometric models that capture the probability of transitioning between states of high or low financial stability, as measured using financial stability indicators (FSIs).

Researchers have proposed several FSIs in recent years to assist policymakers in determining the current state of national financial stability.[4] However, there is little direct insight and experience on how to translate these indicators into policy actions; that is, policymakers are often provided with little or no guidance into 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 and decision processes of macroprudential policymakers. Namely, we propose that such indicators be collapsed 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 FSI in question, its removal also likely allows us to generate a clearer signal relative to the costs and benefits faced by these policymakers.[5] Notably, Brave & 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 Federal Reserve policy actions.

In particular, 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 private, nonfinancial credit to GDP (or the credit-to-GDP ratio) as proposed by the BCBS for use in CCyB policies by the Federal Reserve and other national authorities.[6] This variable has been shown to have a reasonably strong relationship with financial imbalances as per the work of Schularik & Taylor (2012), Jorda et al. (2011), and various earlier studies. We examine this variable directly within a standard

[4]See Bisias et al. (2012a) for an overview of financial stability indicators as well as Brave & Butters (2012a), Hartmann et al. (2013), and Aikman et al. (2015).

[5]See Brave & Butters (2012b) and Drehmann & Juselius (2013) for related analysis as well as Berge & Jorda (2011) for discussion of a similar approach with respect to macroeconomic indicators related to the business cycle.

[6]Note that the Federal Reserve includes the credit-to-GDP ratio among many variables that might be used to inform CCyB decisions. Similarly, the United Kingdom's Financial Policy Committee is reequired 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." (U.K. Financial Policy Committee (March 23, 2016))

two-state Markov regime-switching model along the line of Hamilton (1989). In order to incorporate additional FSIs into our analysis, we examine time-varying switching probability models, as proposed by Diebold et al. (1994), using these other series as probability switching drivers. The FSIs we use in our specifications are predominantly credit market measures, such as the corporate bond spreads described in Lopez-Salido et al. (2015) and Gilchrist & Zakrajsek (2012), and financial condition indexes (FCIs) as proposed by Brave & Butters (2012b).

The actual objects of interest for our analysis, however, are vector forecasts from our model specifications of transition probabilities into the state with a low degree of financial stability over the forthcoming eight quarters. The variation across these specifications in the implied state of U.S. financial stability 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 specification using empirical Bayesian model averaging techniques described in Clyde & George (2004).

Our emphasis on probability vector forecasts of the arrival of an adverse event is premised on the insights provided by Khan & Stinchcombe (2015). In their work, they propose an analytical decision framework that combines hazard function analysis of the arrival of an adverse event, such as a hurricane, with a user's objective function about whether and when to enact a costly policy, such as an evacuation. In fact, they explicitly cite the example of a policymaker looking to maximize their objective function in light of a politically painful reform of a banking system, which encompasses macroprudential policies in general and CCyB policies in particular. The authors characterize general first- and second-order conditions for determining when it may be appropriate to implement a policy or to delay action. Based on this general framework, we calibrate the policymaker's objective function for implementing the CCyB using a range of reasonable parameter values drawn from the literature and our estimated models. Our calibrated range of policy actions and implementation dates provide an overview of the opportunity sets and degrees of uncertainty that macroprudential policymakers face in their efforts.[7]

Specifically, we conduct a counterfactual analysis around the U.S. implementation of its proposed CCyB policy, which is scheduled to be fully phased in by 2019.[8] Based on the current calibration of the policy, we examine the financial stability projections that policymakers would have faced in 2007.Q4, 2011.Q4, and 2015.Q4. Defining an adverse

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

[8]The CCyB policy framework is to be phased in between October 2016 and year-end 2019.

macroprudential event as four consecutive quarters of the model-implied low financial stability state, we use GDP growth projections from our models under baseline (i.e., no policy action) and implementation scenarios to calibrate the Kahn-Stinchcombe (KS) optimal action dates. These calibrations are based on the explicit cost of action, measured in terms of the dollar value of the capital buffer of Tier 1, common equity capital for the banks subject to the policy.

These counterfactual cases illustrate the ability of our proposed framework to incorporate both current projections of financial stability and the relative costs of policy implementation as characterized by the macroprudential policymaker's loss function. While the choice of these dates is somewhat arbitrary, they serve to highlight the effect of initial conditions on the optimal policy prescriptions. For instance, for 2007.Q4, the model-implied starting point is commonly the state of low financial stability, suggesting a high probability of the adverse macroprudential event occurring over the specified projection horizon. In contrast, for 2011.Q4 and 2015.Q4, it is overwhelmingly the state of high financial stability, such that we project a very low probability of the adverse state's arrival. Accordingly, the model-weighted average hazard function as of 2007.Q4 was well above the calibrated KS policy threshold for the maximum allowable buffer for all eight quarters of the projection horizon, suggesting that the CCyB policy should have been fully implemented immediately. In contrast, the model-weighted average hazard function as of 2011.Q4 and 2015.Q4 were below the KS policy thresholds for almost all projection quarters, suggesting that policymakers could wait to act until perhaps a clearer signal of financial instability were to arrive.

The remainder of the paper is structured as follows. Section II provides an overview of the relevant literature on macroprudential policies and financial stability indicators. Section III presents our proposed transformations of the selected FSI into transition probabilities and hazard functions over the defined eight-quarter event horizon. Section IV presents the KS calibrations of simple policy objective functions as of 2007.Q4, 2011.Q4, and 2015.Q4. Section V concludes.

2 Literature review

Central banks and national governments have been given, and have taken on, financial stability responsibilities that are to be implemented using macroprudential policies. However, these new responsibilities have not been fully defined; for example, should policymakers only be concerned with guarding against financial instability among the market sectors and institutions that it is responsible for, such as the 2009 supervisory stress testing by the Federal Reserve, the commercial paper guarantees provided by the FDIC, and the TARP injections provided by the Treasury to bank holding companies? Or should they be concerned with broader events in other financial sectors, as suggested by the designation of insurance companies as systemically important financial institutions (SIFIs) by the Financial Stability Oversight Council (FSOC)? While many proposals and studies have been put forward and some legislative and regulatory steps have been taken, these policy questions remain challenging, even when direct responsibilities have been assigned.

One of the first steps toward addressing this question, proposed in the academic literature, was the development of financial stability indicators (FSIs) as early warning tools of developing financial crises. As noted by Danielsson et al. (2016), macroprudential policymakers are engaged in an active search for signals of future financial instability upon which to develop mitigating policy actions. An extensive literature around this topic related to international financial crises was initially developed in light of the international financial crises of the early 1990s; see Frankel & Rose (1996), Kaminsky & Reinhart (1999) as well as Reinhart & 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 Aikman et al. (2015) and Bisias et al. (2012b) for recent surveys.

In general, a wide variety of FSIs have been shown to have useful properties as leading or "early-warning" indicators with regards to adverse developments in financial and macroeconomic variables. For example, Aramonte et al. (2013) found that several FSIs have short-term predictive ability with respect to stock returns and higher-frequency macroeconomic variables, such as industrial production, that are of interest to policymakers. An important distinction to make in the assessment of FSIs, however, is the difference between effectively summarizing financial conditions and forecasting macroeconomic conditions. For example, Aikman et al. (2015) found that their aggregate index Granger-causes the credit-to-GDP gap used for countercyclical capital buffer policies. In addition, Gadea Rivas & Perez-Quiros (2015) note that credit growth and its transformations has been shown in various recent studies to be empirically correlated with the probability of financial crises and the intensity of their effect on the broader economy. While studies have generally examined both questions to the extent that they are separable, the former is of greater relevance to macroprudential policymakers. We describe our selected FSIs in the next section.

In general, deriving optimal empirical models for forecasting requires detailed knowledge of the underlying decision problem.[9] Such knowledge is, however, not readily available in the context of macroprudential policies, as there is limited experience from which expected costs and benefits could be estimated. Nevertheless, it is still possible to begin incorporating the qualitative aspects of a policymakers' decision problem into the evaluation procedures for FSIs. As discussed in Drehmann & 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 other defined, adverse events. Such loss functions are mainly statistical in nature and are based on the receiver operating characteristic (ROC) curve. While this approach is reasonable within its own rights, it differs from the approach we propose.

In a recent paper, Khan & Stinchcombe (2015) put forth an analytical framework for examining decision problems of whether to act or delay action that explicitly incorporates a policymaker's objective function. Among their various examples, they cite "a politically painful reform of a banking system before the next financial crisis." A key element of this framework is a hazard function of the arrival of the 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 in order to solve for the optimal implementation date. The functional form of the relative costs and benefits of the policy is quite flexible and accounts for time discounting and the relative effectiveness of the policy. We discuss the framework further with respect to our analysis in section 4. In particular, we adapt the framework for analyzing the implementation of countercyclical capital buffers.

3 Transforming financial stability indicators into hazard functions

Financial stability indicators (FSIs) need to be transformed in some way in order to provide sufficient context for use by policymakers in macroprudential policy decisions. For example, Brave & Butters (2012b) collapse their preferred FSIs into event indicators, while Aikman et al. (2015) normalize their selected FSIs in order to graph them in various formats, such as radar and sunburst plots. In this section, we describe the FSIs that we examine in the context of CCyB policies for the U.S. and their transformation into the projected hazard functions required for the Khan & Stinchcombe (2015) framework.

[9]See Granger & Machina (2006) as well as Pesaran & Skouras (2002) for further discussion

3.1 Variables of interest

Our main variable of interest is the ratio of U.S. private, nonfinancial credit to GDP (or the credit-to-GDP ratio), which has been shown to have good properties with respect to monitoring financial stability. Earlier work by Drehmann et al. (2011) as well as Drehmann & Juselius (2013) helped establish this ratio as a potentially important policy variable. Subsequent work by Schularik & Taylor (2012), Jorda et al. (2011), Gadea Rivas & Perez-Quiros (2015), and Aikman et al. (2016) provides clear empirical support for the hypothesis that relatively high levels of this ratio make a macroeconomy less resilient to the arrival of adverse economic shocks. In particular, the ratio has been proposed as the key monitoring variable for the implementation of national CCyB policies by the BCBS.[10]

The transformation proposed by the BCBS is to examine the gap between the ratio and its long-term trend, which is estimated using a one-sided Hodrick-Prescott filter with smoothing parameter $\lambda = 400,000$ in order to isolate credit cycle fluctuations.[11] We instead work with the ratio in growth rates so that we can decompose it into separate real private credit and GDP growth components.[12] Working with growth rates allows us to avoid estimating the trend in the credit-to-GDP ratio, the real-time reliability of which has been a particular source of controversy.[13] Finally, working with this ratio in growth rates as opposed to deviations from trend has also been shown to produce more reliable leading indications of financial instability for the U.S., as per Brave & Butters (2012a).

While the components of the credit-to-GDP ratio are our main variables for defining the degree of financial stability, we also examine several commonly-used FSIs that encompass different elements of the U.S. financial system. Figure 1 plots all seven of FSIs (in standard deviation units) from 1985.Q1 through 2015.Q4, the sample period for our analysis. The shaded periods in the figure correspond with the periods of low financial stability that we identify as explained in further detail below. The dashed lines within several of the shaded periods denote NBER recessions. Consistent with their purpose and

[10]Of course, the credit-to-GDP ratio cannot fully encompass the state of an economy's financial stability, and macroprudential policymakers have stated that they monitor a variety of other data series to inform and enhance their views.

[11]See Bassett et al. (2015) for a discussion of the aggregated vs. disaggregated nature of the ratio as well as a discussion of detrending issues. They highlight several important shortcomings of the one-sided HP filtering approach recommended by the BCBS. However, two-sided filters require future data and are thus not timely enough for policy purposes.

[12]Hamilton (2016b) presents an argument for why one should not use the HP filter under any circumstances. Specific to CCyB, Edge & Meisenzahl (2011) show that the U.S. credit-to-GDP gap has been subject to sizable ex-post revisions that can be as as large as the gap itself. The main source of these revisions was reported to arise from the unreliability of end-of-sample estimates of the seriesŠ trend rather than from revised estimates of the underlying data.

[13]See Edge & Meisenzahl (2011) and Bassett et al. (2015) for further discussion.

previous research, the value of each of these seven financial stability indicators for macroprudential policy is evident in the figure, with large deviations from their historical means tending to align with our estimated periods of low financial stability as well as recessions.

The first three FSIs reflect conditions in the U.S. corporate bond market and, thus, in the overall credit environment. The series are (1) the spread between yields on seasoned long-term Baa-rated industrial bonds and comparable maturity Treasury securities, as discussed by Lopez-Salido et al. (2015), and (2) the spread and (3) the excess bond premium measures described in Gilchrist & Zakrajsek (2012). The latter spread variable is quite similar to the former, while the excess bond premium is the result of removing a modeled component that captures firm-specific default information from the spread. These three series have been shown to reflect current credit market sentiment and to be correlated with near-term economic growth, meeting the criteria expressed by policymakers for justifying their use in macroprudential policy.

The remaining four FSIs that we examine stem primarily from the financial conditions indexes developed in Brave & Butters (2012b) and made publicly available by the Federal Reserve Bank of Chicago. The National Financial Conditions Index (NFCI) and Adjusted NFCI (ANFCI) are dynamic factors constructed from an unbalanced panel of 105 mixed-frequency indicators of financial activity, the latter of which is adjusted for prevailing economic conditions. The NFCI has been shown to be 95% accurate in identifying U.S. financial crises contemporaneously, with a decline to 80% accuracy at a lead of up to one year.[14] In addition, Brave & Butters (2012b) show that disaggregating the NFCI into subcomponents can enhance the nature of the signal provided regarding the degree of financial stability. In particular, the NFCI Nonfinancial Leverage subindex signals financial imbalances at leads of up to two years with close to 80% accuracy; correspondingly, we examine this variable in isolation as well. 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 sum of Tier 1 capital divided by the sum of bank risk-weighted assets.

3.2 Transition probabilities from Markov-switching models

In their work on the effect of credit on the business cycle, Gadea Rivas & Perez-Quiros (2015) argue 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

[14]Research, such as Hartmann et al. (2013), suggests that financial conditions indexes that combine a variety of FSIs perform better in terms of state identification and measurement of macroeconomic effects, especially relative to individual FSIs.

phases." While 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 that have been largely framed around the credit-to-GDP ratio requires that we re-examine this result. In this spirit, we develop an alternative transformation of the credit-to-GDP ratio and various FSIs for the U.S. into policy-relevant information.

Our first step in this process is to 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 U.S.[15] We denote these states as $\{S^+, S^-\}$, respectively. The motivation for our model can be seen in the following decomposition of the growth rate of the credit-to-GDP ratio (approximated by log first differences, denoted by Δln).[16]

$$\Delta ln(\frac{\text{Credit}}{\text{Nominal GDP}}) = \underbrace{\Delta ln(\text{Credit}) - \Delta ln(\text{Price Level})}_{\text{Real Private Credit Growth}} - \underbrace{\Delta ln(\text{Real GDP})}_{\text{Real GDP Growth}}$$

We make use of this convenient expression, modeling transitions between states of low and high financial stability according to changes in the underlying dynamics of real GDP growth, $\Delta ln(GDP_t)$, and real credit growth, $\Delta ln(C_t)$.

Our baseline model can then be summarized as

$$\begin{aligned} Y_t &= \alpha_S + \beta_S X_t + \epsilon_t \qquad (1) \\ \epsilon_t &\sim N(0, \sigma^2), \end{aligned}$$

where $Y_t \equiv \Delta ln(GDP_t)$ and $X_t \equiv \{\Delta ln(GDP_{t-1}), \Delta ln(C_t), \Delta ln(C_{t-1}))\}$ with the model's state-dependent parameters summarized in $\Theta_{S_t} \equiv \{\alpha_{S_t}, \beta_{S_t}\}$.[17] Our specification differs slightly from that of Gadea Rivas & Perez-Quiros (2015), in that we do not restrict the contemporaneous or lagged impact of real credit growth, captured in β_S, on the conditional mean of real GDP growth in either state. As such, it is a more flexible parameterization of the growth rate of the credit-to-GDP ratio, allowing for potentially richer joint dynamics of real GDP and credit growth across states of financial stability.

[15] In contrast, Hubrich & Tetlow (2014) use a five-variable Markov-switching VAR (MS-VAR) model in their approach to assessing the effect of financial conditions on macroeconomic variables.

[16] We deflate both GDP and private credit by the GDP deflator.

[17] In results not reported here, we also tested to see whether or not allowing σ to vary across states provided any additional information. We could not reject the null hypothesis that σ was equal across states, and, therefore, restricted it to be state-invariant.

The states, however, are not sign invariant in our framework. Therefore, in order to identify the low from the high financial stability state, we restrict $\alpha_{S^-} < 0$, so that real GDP growth is negative on average in this state. The states are then also assumed to follow a first-order Markov process with a constant transition probability matrix Ω with elements p_{ij} denoting the transition probability from state i to state j. The elements of this matrix are given by

$$Pr(S_t = S^- | S_{t-1} = i, X_t, \Theta_i) \quad = \quad \Phi(\delta_i) \quad i = S^+, S^-, \tag{2}$$

where Φ is the cumulative normal.[18]

To introduce the FSIs into our analysis, we instead use the time-varying transition probability model proposed by Diebold et al. (1994) that allows the transition probabilities of the first-order Markov process to depend on the covariates Z_t. The transition probability matrix in this case is specified as

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

where we introduce our selected FSIs into Z_t on an individual basis in order to limit the number of parameters that must be estimated.[19] Given the small number of transitions in our data, we also find it useful to follow the precedent in Amisano & Fagan (2013) and require that the slope coefficients on Z_t are common across the two states.

From the policymaker's perspective, this still leaves open the question of which model to base decision-making upon. Our approach here is to instead combine the relevant information across the models we consider using a Bayesian model averaging framework.[20] To do so, we weight an object of interest for each model (e.g. state probabilities) by a measure of the model's fit of the data. Defining the set of model specifications as Ξ, the posterior probability $p(\Xi_m | Y, X, Z)$ assigned to each of our $m = 8$ specifications is

[18] Please note that the estimation was done in Matlab using the MSREGRESS package of Perlin (2015) extended to the time-varying transition probability case by Ding (2012).

[19] Similarly, we limit their inclusion to only contemporaneous values. In future work, we plan to explore in greater detail possible lead/lag relationships that could be exploited as well.

[20] As discussed in Lo Duca & Peltonen (2013), several studies have found that multivariate discrete choice models outperform stand-alone indicators as well as univariate models both in-sample and out-of-sample. Our model averaging procedure draws on this result as its motivation.

$$p(\Xi_m|Y,X,Z) \;=\; \frac{p(\Xi_m)exp(-0.5 * BIC(\Xi_m))}{\sum_m p(\Xi_m)exp(-0.5 * BIC(\Xi_m))}, \tag{4}$$

where BIC is the Bayesian information criterion and $p(\Xi_m)$ is a uniform prior.[21]

Figure 2 summarizes the low and high states of financial stability identified by our models for real GDP and private credit growth. For the sake of comparison, the figure also includes the credit-to-GDP gap. The shaded regions in each panel denote quarters where our weighted average smoothed (two-sided) probability of the low financial stability state exceeds 50%. Four periods of low financial stability stand out in this figure: $1986.Q1 - 1986.Q4$, $1990.Q3 - 1991.Q1$, $2000.Q3 - 2001.Q4$, and $2005.Q4 - 2009.Q2$. Each of these correspond with well-known periods of financial stress, i.e. the early stages of the S&L crisis, the credit crunch of the early '90s, the dot-com stock market bubble, and the recent global financial crisis.

Below, we take a closer look at the driving forces behind transitions from high to low stability states. Generally speaking, however, it is clear from figure 2 that periods of jointly decelerating real credit and GDP growth tend to align with low financial stability. Furthermore, although we use the growth rate of the credit-to-GDP ratio in our model, our methodology also does quite well at capturing elevated values of the credit-to-GDP gap in signaling potential financial vulnerabilities. This can be further seen by the ranges within three of the four shaded regions in the figure (denoted with dashed lines) corresponding to NBER recessions. Our low stability state clearly leads several recessions.[22] In particular, we identify the occurrence of the low financial stability state two quarters prior to the 2001 recession and eight quarters in advance of the 2008-2009 recession. In both instances, this leading signal can also be seen in the NFCI Nonfinancial Leverage subindex in figure 1.

The leading indicator nature of our estimated low financial stability state is useful for our purpose of guiding macroprudential policy. To more closely examine its source, we next take a closer look at our model weights and estimated parameters. Table 1 presents the estimated coefficients for our eight model specifications for three quarters of interest - namely, $2007.Q4$, $2011.Q4$, and $2015.Q4$. The top row of each panel reports the model weights assigned by our Empirical Bayesian procedure. The model rankings are consistent across the three periods we examine. Notably, the model including the

[21]This Empirical Bayesian procedure and its benefits are described in greater detail in Clyde & George (2004). One could substitute the BIC criterion for the likelihood of each model by simply eliminating the penalty that the BIC imposes on model complexity. In our case, this makes little difference as the number of estimated parameters is identical across models.

[22]This is true whether or not we use two- or one-sided probability estimates from our models.

NFCI Nonfinancial Leverage subindex receives the largest weight, ranging from 57% to 87%, which is in line with the findings of Brave & Butters (2012b). The baseline model with just real credit and GDP growth receives a weight of 38% for the $2007.Q4$ period and much lower values of 8% and 6% for the others. Together, these two models account for 90% of the model weights and will be the focus of our discussions below; however, we use the full set of models and weights in our subsequent analysis.

The transition probability parameters for the models are reported in the next set of panel rows. As the results are most readily interpretable for the baseline model, we examine them directly and find that they and their implied probabilities differ only slightly across the three time periods. The δ_1 estimates govern the probability of remaining in the high stability state, which rises slightly from 93% in $2007.Q4$ to 96% in $2015.Q4$. Similarly, the δ_2 estimates govern the transition from the low stability to the high stability state, and the implied probability increases from 13% to 16%, respectively. The introduction of the FSI variables into the transition probability equations lead to negative γ estimates across our specifications, most prominently for our best performing model using the NCFI Nonfinancial Leverage subindex. This negative coefficient means that as nonfinancial leverage increases, the probability of being in the high stability state next next period decreases.

Focusing on the state dynamics for GDP growth, the estimated parameters vary importantly across the two states, but are similar across model specifications and time periods. The high stability state exhibits a positive constant (α_1), which declines notably from 3.38% in $2007.Q4$ to 2.50% in $2015.Q4$. This decline reflects both the magnitude of the 2008-2009 recession and the subsequent moderate recovery, and can also be seen in the constant for the low stability state (α_2) going from -0.8% in $2007.Q4$ to -2.69% in $2015.Q4$. In contrast, the coefficient on the lagged value of GDP growth is not statistically significant, though it is generally more negative in the low stability state indicating a faster pace of mean reversion. Turning to the state dynamics for credit growth, the coefficients on both contemporaneous and lagged credit growth are generally significant. For the high stability state, the lagged credit growth coefficient 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 periods of financial stability. In contrast, in the low stability state the coefficient on credit growth is larger, positive, and significant contemporaneously. It is predominately this property that provides a leading indication of slipping into the state of low financial stability in our model.

3.3 Projecting state probabilities over the policy horizon

The next step in our process is to project out the financial state probabilities over the policy horizon of interest. Based on the notation presented in Hamilton (2016a), we discuss here the construction of the projected state probabilities needed for our policy exercise, which we denote as hazard functions. Gadea Rivas & Perez-Quiros (2015) note that the effects of credit growth on the business cycle are notable in-sample, but that there are no significant gains in forecasting business cycle turning points. However, given our particular need for such forecasts and the evidence presented above, we proceed under the assumption that the transformation of our estimated state probabilities should be a useful input to the policymaking process.

The relevant output from the selected Markov-switching model are the transition probabilities between states of financial stability and instability, summarized as

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

To summarize the state of the process under analysis, denote ξ_T as a (2x1) vector whose q^{th} element is unity when $S_T = q$ and is zero otherwise. For the estimated Markov models, we then have

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

where the elements $\hat{p}_{i1}$ and $\hat{p}_{i2}$ sum to one. For forecasting purposes, we define the matrix P as one 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 is then $E[\xi_{T+1} | \xi_T] = P\xi_T$, and the k-step-ahead forecast is $E[\xi_{T+k} | \xi_T] = P^k \xi_T$. We generate the forecasts for our weighted average hazard based on the individual model $\hat{\xi}_T$ estimates.

This framework allows us to generate the forecasted state probabilities over the number of quarters in the policymakers' decision horizon. The forecasted probabilities can then be used as building blocks to construct vector probability forecasts for a defined event of interest, which we denote as conditional hazard functions. For example, assume that the policymaker is concerned with entry into the financial instability state at any point over the eight quarter forecast horizon.[23] Using the notation above,

$$H_T(k) = E[Pr(S_{T+k} = 2)|\xi_T] = (P^k \xi_T)_{(2,1)}, \tag{5}$$

which refers to element $(2, 1)$ in the product for each value of $k, k \in [1, 8]$.[24]

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 potential interest to policymakers is the probability of being in the adverse state for a consecutive number of quarters.[25] For example, implementation of the CCyB may be phased in over a one-year horizon such that policymakers would likely value the probability or remaining in the adverse state in the quarters after the policy's enactment. In this paper, we assume that policymakers are concerned with the probability of four consecutive quarters of financial instability, which corresponds to S^- as defined above.

In particular, we frame the policymaker's problem as projecting out the vector probability forecast (or hazard function) at time T of four consecutive quarters of S^- over the two-year horizon $T + k$, $k \in [1, 8]$. Note that the policymaker will have in hand the state probabilities in 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 an overall hazard function for each of our eight Markov model specifications. From there, we then weight across the hazard functions of each model as described above to obtain a single vector probability forecast.

Figure 3 presents weighted average hazard functions across our eight model speci-

[23]The choice of an eight-quarter horizon for our work is based on other studies as well as the specifics of the countercyclical capital buffer policy. Drehmann & Juselius (2013) 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. Lo Duca & Peltonen (2013) examine a projection horizon of six to eight quarters.

[24]Technically, for the time-varying transition probability models, the out-of-sample projections for the transition probabilities should be conditioned on Z_{t+k}. At this point, we treat the variables as fixed at their end-of-sample values, but in future work, we will examine the sensitivity of our results to this assumption.

[25]Edge & Meisenzahl (2011) discuss different ways for policymakers to frame their event of interest or policy threshold for implementing the CCyB, but none are based on defined financial stability projections as we propose. The authors discuss a policy threshold that is a high percentile, say 90%, of the credit-to-GDP gap.

fications for our three projection points extending outward over projection quarters (PQ) one through eight. Turning first to the 2007.Q4 projection, the weighted-average hazard function starts at the relatively high value of roughly 90%, suggesting that the adverse event has likely already occurred. The hazard function then rises slightly to around 95% by PQ8. This result is consistent with the available evidence on the value of these FSIs as leading indicators of financial instability.[26] A contrasting pattern is observed for our projections as of 2011.Q4 and 2015.Q4. In both cases, our results suggest very little likelihood of the adverse event having already occurred, with the weighted average hazard functions increasing only very slowly from essentially zero at PQ1 to near 1.5% in PQ8 for the 2011.Q4 case and 2% for the 2015.Q4 case.

4 Transforming hazard functions into policy recommendations

Macroprudential policy is a relatively new responsibility for policymakers, and certainly one that is less familiar and examined than monetary policy. Yet, by law, policymakers must enact and implement these policies either within their own jurisdictions or in collaboration with international bodies, such as the Basel Committee for Bank Supervision (BCBS) and the European Banking Authority. In order to analyze and conduct these policies, an objective function would be a useful tool to have; that is, an explicit, even if simplified, statement of the costs and benefits of action should enrich the understanding and measurement of the available policy tools. Khan & Stinchcombe (2015) provides just such an analytical framework, as we outline in this section.

4.1 KS first- and second-order conditions

As Khan & Stinchcombe (2015) (KS) state, "[a]t 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 countercyclical capital buffers in particular. The KS framework can be applied at a decision point in time, say T, when a policymaker must decide whether to enact a costly policy against the arrival of an adverse event, either immediately or at some point in the near future after more information about the event arrival has been collected. The intuition is that the policymaker faces a hazard function of when the adverse event might arrive, as discussed above.

[26]Lo Duca & Peltonen (2013) has a figure similar in spirit, but represents just their interest in the PQ6 result.

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 specified adverse event arrives, which has a continuous probability distribution function $f(t_w)$ and a cumulative distribution function $F(t_w)$. The associated hazard function is denoted as $h(t_w) = f(t_w)/(1 - F(t_w))$. 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 having taken a mitigating action.

Within the KS framework, define the present utility flow $\bar{u} > 0$, which will decline to 0 at $T + t_w$ unless the precautionary measure was taken prior to that. If the measure is instead put in place prior to t_w at a cost of C, the utility flow declines to $\underline{u} > 0$, such that $\bar{u} > \underline{u} > 0$. In the language of macroprudential policy, this definition reflects the policy intent of taking action to increase the resilience of the financial system or, equivalently, lowering economic loss when a crisis arrives. In addition, the precautionary measure lowers the incidence of a financial crisis (i.e., the probability of the event actually occurring). This condition alters the probability of a crisis as follows

$$f_{\theta(t_w;t_1)} = \left\{ \begin{array}{cc} f(t_w) & \textit{if}\, t_w < t_1 \\ (1-\theta)f(t_w) & \textit{if}\, t_w \geq t_1 \end{array} \right\};$$

that is, the probability of the event occurring declines after the measure is implemented at time t_1. The θ parameter is a measure of the effectiveness of the policy action and is bounded within the closed unit interval; i.e., a fully effective policy has $\theta = 1$, while a completely ineffective policy has $\theta = 0$.

Within the KS framework, 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 is denoted as rC, which is the annuitized value of the policy cost C at the rate r; i.e., the savings from not incurring C at time T. The cost is the discounted value of the utility flow from enacting the policy minus its cost C, all expressed in probabilistic terms based on the hazard function. In notational form the cost is $([\theta\bar{u}+(1-\theta)\underline{u}]/r-C)h(t_w)$.[27] Thus, the first order condition for the optimal time to act, denoted as t_1^*, is

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

With respect to the second order condition, the intuition is that the policymaker

[27] 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 Section 3.3.

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 before acting. Notably, these are characteristics of the hazard function presented in Figure 3. With respect to comparative statics, the optimal time is increasing in both C and r (i.e., the policymaker defers longer when the policy cost is higher) as decreasing in θ (i.e., more effective policies lead to higher benefits and thus earlier implementation).

4.2 Calibration to the CCyB proposal

Among the various macroprudential policies available, we focus here on the countercyclical capital buffer (CCyB), which requires an increase in regulatory capital for affected financial institutions once the private, nonfinancial credit-to-GDP gap exceeds a certain threshold. In the U.S., the CCyB policy is the responsibility of the Federal Reserve and was first enacted in September 2016 with a CCyB rate set to zero.[28] However, these policies have been in place and in use in Europe for some time. For example, the Financial Policy Committee (FPC) of the Bank of England was established in June 2013. Translating the CCyB policy details for the U.S. into the KS framework requires a formulation of the event hazard function, which was developed in the prior section, and calibration of the various cost and benefit parameters described above.

The immediate cost of enacting the CCyB policy is incurred by the affected financial institutions in raising the needed capital.[29] Thus, as a lower bound, we calibrate C in terms of the firms' current capital base at time T; that is, we determine the dollar cost of the CCyB policy enactment as a capital raise for the affected firms. The current size threshold for affected firms is \$250 billion in total assets with certain exceptions. These firms would be required 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 the calibration exercise, we assume that the policymaker operates as if its cost is of equal magnitude; i.e., it internalizes the entire cost either by funding it directly or by assuming that the cost to the firms should be

[28]See the Federal Reserve press release at
http://www.federalreserve.gov/newsevents/pressreleases/bcreg20160908.htm

[29]In the Federal Reserve's CCyB framework, the affected firms are banking organizations subject to the advanced approaches capital rules, which generally apply to those 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). 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.

viewed as a social cost. This value represents the lower bound of C in our calibration as the policymaker may consider other costs, such as the potential macroeconomic effect of raising bank capital requirements. As a robustness check, we also examine calibrations using up to a multiple of 5 times the baseline value of C.

Another important concern for policymakers is the macroeconomic effect of raising bank capital requirements. For example, the FPC lowered its CCyB on banks' UK exposures from 0.5% to 0% in July 2016 based on the view that "[t]he availability of banks' capital resources, and their use to absorb shocks if risks materialize, increase against a tightening of bank credit conditions."[30] 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.[31] For these reasons, we capture the broader welfare costs of the CCyB within the utility flows of the KS framework, linking them to our Markov-switching model estimates for average GDP growth in each state of financial stability.

To calibrate the utility flows $\bar{u}$ and $\underline{u}$ to our model-generated GDP growth projections, we begin by defining μ_1 and μ_2 as the estimated average long-run GDP growth rates in the model's high and low states of financial stability; i.e., $\mu_1 = \alpha_1/(1-\beta_1)$ and $\mu_2 = \alpha_2/(1-\beta_2)$. The $\bar{u}$ parameter represents the present utility flow, which we define as $\mu_1 * GDP_T > 0$. If an event occurs that transitions the economy into the adverse state, then the utility flow is instead $\mu_2 * GDP_T < 0$.[32] However, if the policymaker takes an action to mitigate the possibility of transitioning into the adverse state, the utility flow changes to an intermediate value, which we denote as μ_{12}. The intuition here is that the policymaker lowers the utility flow from μ_1 in an attempt to avoid the consequences of the adverse state, i.e. μ_2. We calibrate μ_{12}, the policy-adjusted growth rate, as an intermediate rate based on our parameter estimates as $\mu_{12} = \alpha_1/(1-\beta_2)$; that is, the policy-adjusted, long-run growth rate exhibits the constant of the high stability state and the mean reversion of the low stability state. Accordingly, $\underline{u}$ is calibrated as $\mu_{12} * GDP_T > 0$.[33]

[30] BOE Financial Stability Report of 11/2016

[31] For the U.S., studies such as Edge & Meisenzahl (2011) have examined such costs associated with CCyB policies, such as declines in lending volume and increased lending rates. Similarly, Berrospide & Edge (2016) find in the post-crisis period that a one percentage point increase in equity capital increases one-year commercial loan growth between 10 to 15 percentage points. However, the effects are shown to vary across firms and over time. Carlson et al. (2013) find related results for a dataset of U.S. banks matched by geography and other business characteristics.

[32] Recall that we restricted μ_2 to be negative during estimation.

[33] Following KS, to assure that $\bar{u} = 0$ in the event that the adverse state is realized prior to action, we normalize the utility flows such that $\bar{u} = (\mu_1 - \mu_2) * GDP_T$ and $\underline{u} = (\mu_{12} - \mu_2) * GDP_T$. We acknowledge that this is not the only possible calibration based on our model estimated parameters, but we are certain on the basis of our numerical calculations that this one provides a reasonable representation of the policymaker's objectives.

The value of the rate r should be both a function of the horizon over which the policy decision is being made and of the overall riskiness of the policy action.[34] The horizon over which monetary policy is said to be focused on is two years, and it is thus reasonable to assume that such a horizon would be the case for the CCyB policy, especially since it has a built-in, one-year activation delay. Regarding the riskiness of the action, we will assume, as above, that policymakers internalize the cost themselves and, thus, use the risk-free discount rate. The only parameter remaining then is θ, the effectiveness of the chosen policy in lowering the probability of the adverse event occurring. Rather than estimate or calibrate this parameter, we instead examine a range of values to determine the overall sensitivity of our objective function $h(t_1^*)$ to obtain the implied range of solutions t_1^* given the maximum allowable size of the buffer under the CCyB proposal. [35]

At this point, it is important to note that the projections and calibrations used in the subsequent analysis are projections conditional on the data available at time T over the event horizon $T+\tau$. They are not structured to take account of the interactive adjustments in the economy subsequent to the policy actions regarding the CCyB. While this limitation is obvious, designing a complete response to policies is beyond the scope of this work and beyond the scope of most policy decisions based on calibrations. Instead, our approach provides conditional projections using available data in a real-time setting that should provide key operational insights to policymakers.

4.3 Calibration analysis

Table 2 presents the calibration values used for our KS analysis as of three separate year-end quarters: 2007.Q4, 2011.Q4, and 2015.Q4. The first quarter of analysis corresponds to the initial stages of the financial crisis, while the latter two correspond to periods that are relatively more stable, although with slightly different probabilities of entering the low financial stability state. 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.[36] As

[34]See Bazelon & Smetters (1999) for a discussion of the discount rates that should be applied for public policy projects.

[35]Please note that our choice to use the maximum percentage capital raise is relaxed in Section 4.4. See Bussier & Fratzscher (2002) for analysis of signal-related policy loss functions that address preferences and implementation timing. Edge & Meisenzahl (2011) examine several CCyB increments, although not the maximum value so as not to obtain extreme results.

[36]We used the variable BHCK A223 (total risk-weighted assets) from the consolidated Y-9C reporting forms. Note that the current 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 than the one 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.

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 2015.Q4, their total RWA was \$7.6 trillion dollars, which suggests a maximum CCyB need of \$189.7 billion (i.e., 2.5 percent of total RWA). Note that this capital amount must be raised within one calendar year of policy enactment.

The calibration of C for our 2007.Q4 and 2011.Q4 exercises is a bit more challenging as the firm size threshold in the CCyB proposal is quite high relative to bank RWA values as of these counterfactual dates. Accordingly, we assume that the *number* of affected firms would be the same for both dates. Thus, in 2007.Q4, we calibrate C as 2.5% of $\$5.8$ trillion, which is $\$145.2$ billion. The corresponding amounts for 2011.Q4 are $\$6.3$ trillion and $\$157.6$ billion, respectively. The incidence of this cost would most directly fall on the affected firms; i.e., they would need to issue the required dollar amount of equity. However, as this complicates the nature of the discount rate used in the exercise, we assume that the policymaker internalizes this cost, which allows us to set the rate at the two-year risk-free Treasury rate, as shown in the table. Finally, as noted above, we calibrate the utility flows $(\bar{u}, \underline{u})$ based on a weighted average of the estimated model coefficients, where the weights are the same as those applied to the hazard functions. The utility flows are in real dollar terms based on the real GDP year-end totals reported in the table. Therefore, we deflate the nominal dollar values for C in the table using the GDP deflator to preserve the KS calculations.

The bottom rows of table 2 show the calibrated hazard (or probability) values that optimize the KS first-order condition with various values of θ for our three sample periods. These calibrated KS values are the recommended policy implementation thresholds based on the total capital to be raised by the affected banks under a full 2.5% implementation of the CCyB policy. Notice that the threshold values vary only slightly with respect to θ given the small differences in our calibration of $(\bar{u}, \underline{u})$ in each sample period. Over all three sample periods, the calibrated probability values range from 1.08% to 1.42%, which is a relatively low threshold in each case. The policy intuition here is that the cost of the CCyB capital raise is quite low relative to the overall potential benefit of avoiding a substantial decline in real GDP. Based on these threshold values, we can identify calibrated policy implementation dates that incorporate both the policymaker's objective function and current financial stability projections. Table 3 summarizes the calibrated implementation quarters across our three projection points and eight model specifications as well as the Bayesian weighted-average outcome shown in Figure 3.

For the policymaker at 2007.Q4, the weighted-average hazard function suggests that the CCyB policy should be enacted immediately and likely should have been even earlier; i.e., all the threshold values depicted in the grey range at the very bottom of the graph are breached by the weighted-average hazard value of roughly 90% in PQ1. As shown in the first column of table 3, given the relatively low cost of the required capital raise, policymakers should consider implementing the policy within the coming year, especially given the projected financial stability conditions. The policymaker at 2011.Q4 and 2015.Q4 faces a contrasting set of conditions with a near zero hazard function for the first three projection quarters and then a steady increase to roughly 1.5%/2.0%, respectively, by PQ8. As shown in the second and third columns of table 3, the KS threshold values for seven of the eight models suggest policy implementation between PQ3 and PQ5 depending on the sample period. However, for the NFCI Nonfinancial Leverage subindex specification that dominates the Bayesian model averaging, the hazard function is quite low and does not exceed the KS thresholds at any horizon for both sample periods. Thus, for the weighted-average hazard function, the recommended implementation date is PQ7 and PQ6, respectively. This case illustrates how even a relatively low cost policy might not be reasonably implemented when facing a benign projection for financial stability.

The policy recommendations discussed above are based on whether or not to enact the CCyB policy using the maximum rate of 2.5% at the beginning of the 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 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 policy analysis fixes the policy enactment date and examines what the policy rate should be by solving for the magnitude of the CCyB rate that satisfies the KS first order condition at each date. This approach provides another perspective on the setting of the CCyB policy.

Figure 4 presents this alternative analysis for our three time periods. Please note that as the CCyB policy 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 2007, the clear policy recommendation from this figure based on the high probability of tipping into the adverse state is that the maximum CCyB rate should be put in place, regardless of which projection quarter is considered. Fortunately, the other two sample periods provide more nuanced answers. The results for 2011.Q4 show that if the policymaker wanted to enact a non-zero CCyB rate, it would be in effect in PQ4. However, given that this value is well below the 25 basis point threshold that has been used by the FPC, it would be reasonable to say that the policy recommendation would more appropriately be for inaction. In fact, under this rule-of-thumb, the policymaker would not need to act until PQ7 for the case of a completely ineffective policy outcome (i.e., $\theta = 0$) or PQ8 for the case of a fully effective outcome. Similarly, a policymaker at year-end 2015 would not need to act until PQ6 or PQ7, respectively. In both cases, the policymaker need not act immediately given the relatively low adverse event probabilities and, in fact, could even delay action for a few quarters in hoping for a clearer signal of potential financial instability.

5 Conclusion

The explicit introduction of macroprudential responsibilities and policies at central banks and financial regulatory agencies has created a need for new aggregate measures of national financial stability. While many have been proposed, these measures typically require further transformation or calibration for use by macroprudential policymakers; i.e., for introduction into decision-making processes and policy objective functions. We propose a transformation based on modeled transition probabilities between states of high and low financial stability as captured by common financial stability indicators. Probability estimates from these Markov regime-switching models can then be used directly within a decision-theoretic framework, as per Khan & Stinchcombe (2015), structured to address the implementation of countercyclical capital buffers.

Our calibrated examples using data as of 2007.Q4, 2011.Q4, and 2015.Q4 illustrate how this framework can be used to make macroprudential policy recommendations that incorporate both policymakers' objective functions and financial stability projections. For the 2007.Q4 projection date, we found that the high 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 maximum allowable capital buffer immediately (if not actually sooner). For the other two projection dates, the opposite pattern holds, with the suggested CCyB maximum buffer implementation dates being up to eight quarters ahead.

Our preliminary calibration exercises demonstrate how our proposed analytical framework could be used for macroprudential policymaking. By translating projected policy costs and benefits across reasonably estimated hazard functions of adverse events, this 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 policy of interest, the adverse event to be avoided, 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 methodology for approaching this problem with a closed-form solution, we hope to contribute to the effective design, ongoing implementation, and assessment of macroprudential policies.

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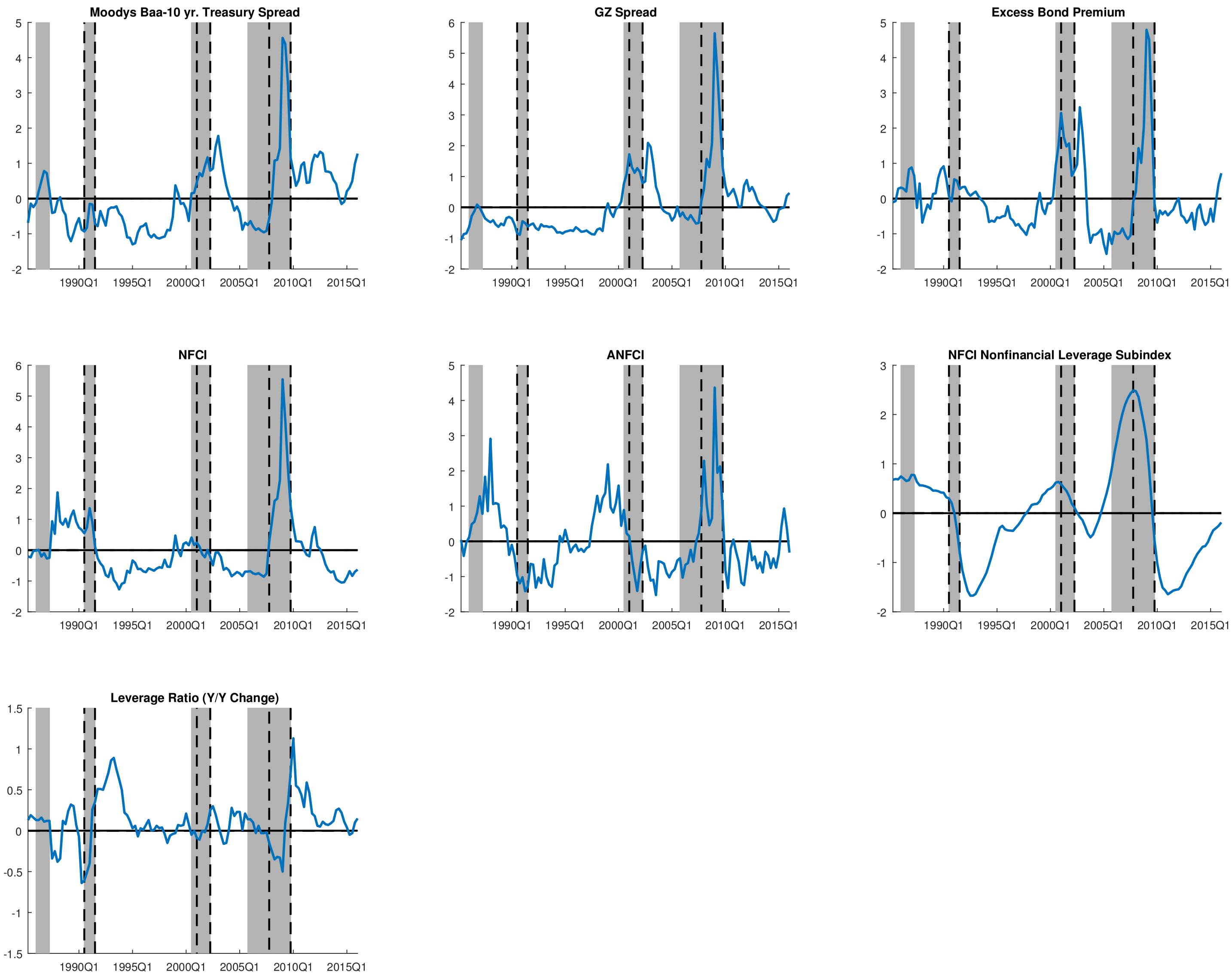

Figure 1. Financial Stability Indicators (FSIs), standard deviation units.
Shaded periods reflect quarters with weighted average smoothed probabilities of the low financial stability state > 0.5.
Dashed vertical lines within the shaded periods denote NBER recessions.

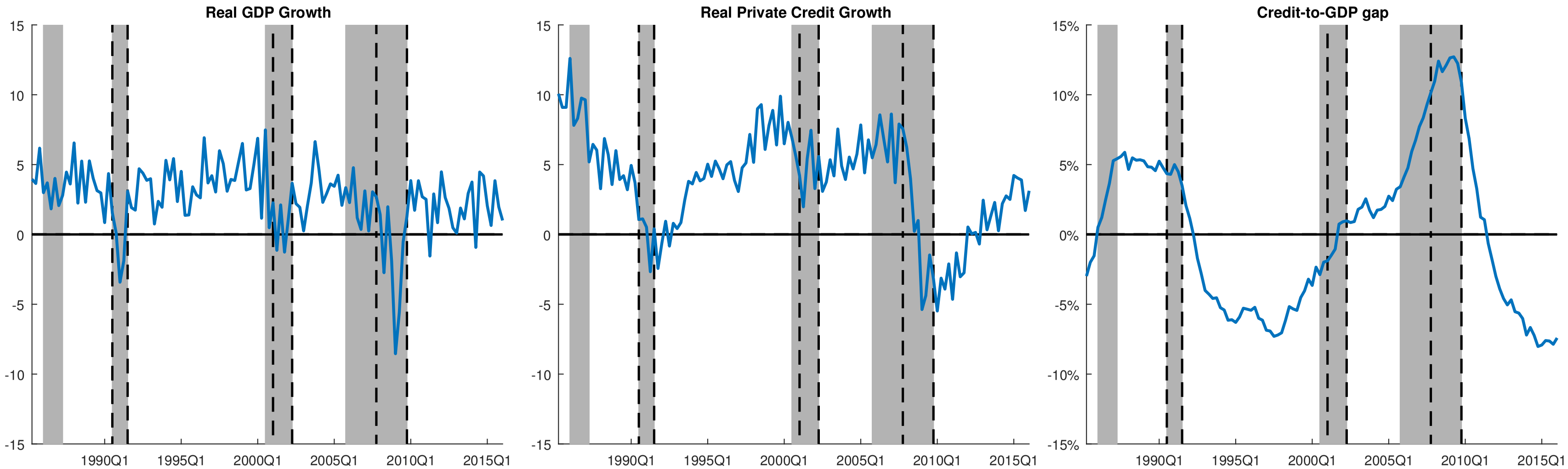

Figure 2. Real GDP and Private Credit Growth (percent annual rate) and Credit-to-GDP gap (percent deviation from trend)
Shaded periods reflect quarters with weighted average smoothed probabilities of the low financial stability state > 0.5.
Dashed vertical lines within the shaded periods denote NBER recessions.

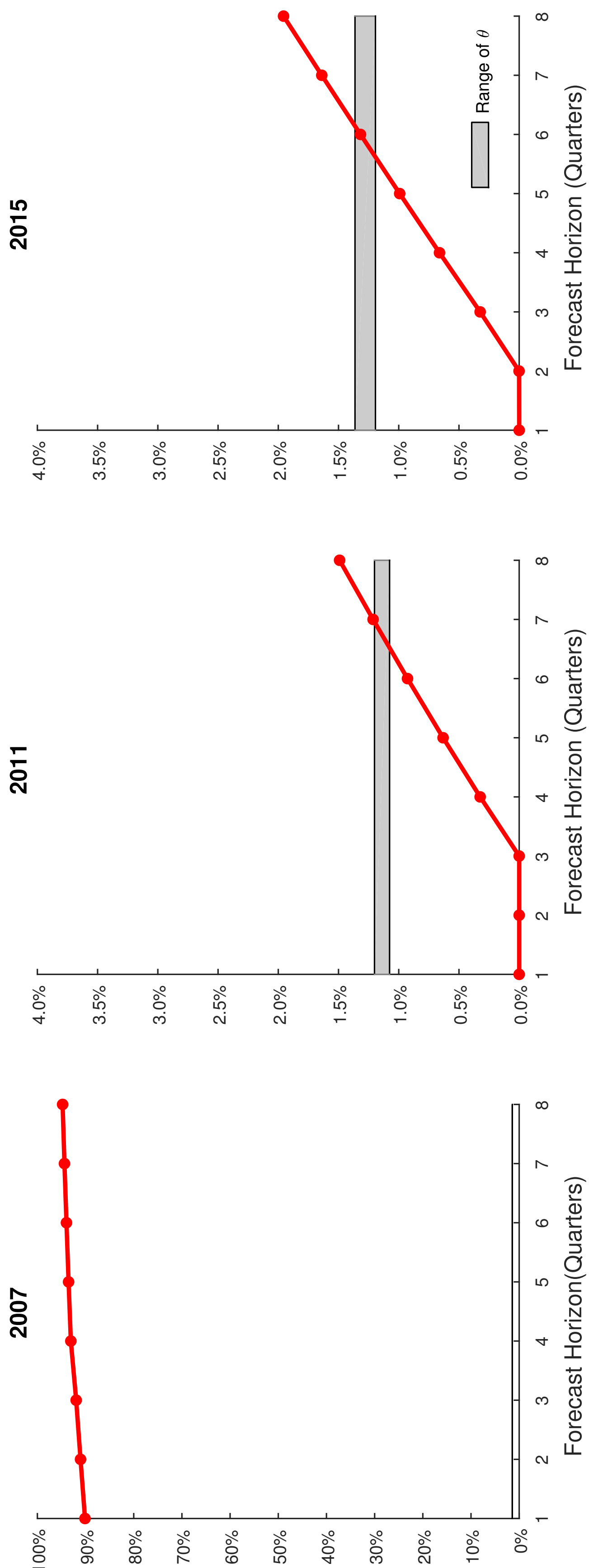

Figure 3. Model-Weighted Average Hazard Functions

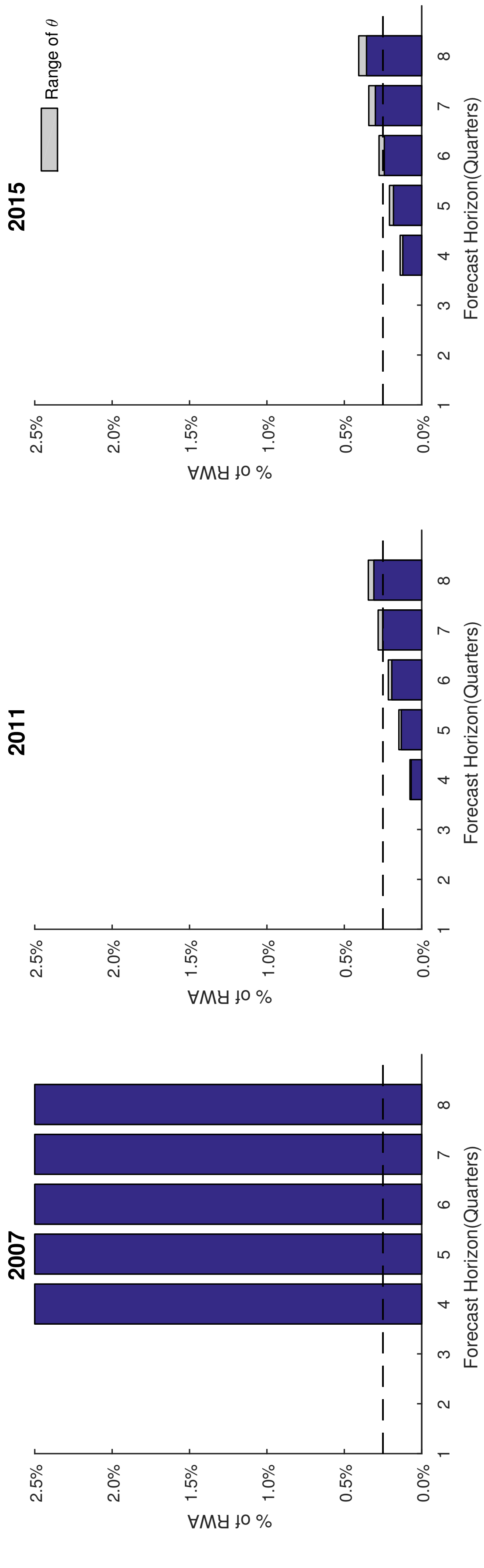

Figure 4. Model-Weighted Average Countercyclical Capital Buffers
Dashed line represents a 0.25% capital buffer.

Table 1A: Markov Regime-Switching Models – 2007.Q4

Model:	**Baseline**	**Baa Spread**	**GZ Spread**	**EBP**	**NFCI**	ANFCI	**NFCI-nfl**	**Lev. Ratio**
Weight	**0.33**	**0.01**	**0.03**	**0.02**	**0.02**	0.00	**0.57**	**0.02**
Parameters:								
Prob:								
δ_1	1.44	1.30	1.27	1.35	1.92	1.44	1.61	1.82
	(0.41)	(0.47)	(0.46)	(0.40)	(1.35)	(0.41)	(0.56)	(0.67)
δ_2	-1.11	-0.86	-0.76	-0.97	1.88	-1.09	-1.08	-0.97
	(0.46)	(0.47)	(0.47)	(0.53)	(2.12)	(0.50)	(0.50)	(0.58)
γ^{FSI}	-	-0.30	-0.50	-0.43	-2.22	0.12	-1.16	0.57
	-	(0.33)	(0.39)	(0.30)	(1.18)	(0.32)	(0.75)	(0.51)
Mean:								
α_1	3.44	3.46	3.50	3.53	2.49	3.44	3.38	3.26
	(0.63)	(0.62)	(0.61)	(0.64)	(0.63)	(0.64)	(0.58)	(0.62)
$\beta_1^{GDP_{t-1}}$	-0.19	-0.20	-0.20	-0.21	0.10	-0.19	-0.19	-0.10
	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.13)	(0.12)
$\beta_1^{C_t}$	-0.07	-0.07	-0.07	-0.08	0.09	-0.07	-0.07	-0.05
	(0.13)	(0.13)	(0.13)	(0.13)	(0.11)	(0.13)	(0.14)	(0.12)
$\beta_1^{C_{t-1}}$	0.29	0.30	0.28	0.30	-0.04	0.29	0.31	0.20
	(0.12)	(0.13)	(0.12)	(0.12)	(0.11)	(0.12)	(0.13)	(0.11)
α_2	-0.76	-0.77	-0.73	-0.63	-1.92	-0.76	-0.81	-0.96
	(0.74)	(0.78)	(0.87)	(0.65)	(1.08)	(0.69)	(0.81)	(0.92)
$\beta_2^{GDP_{t-1}}$	-0.13	-0.12	-0.11	-0.11	-0.10	-0.13	-0.14	-0.10
	(0.31)	(0.34)	(0.36)	(0.30)	(0.56)	(0.33)	(0.29)	(0.42)
$\beta_2^{C_t}$	0.41	0.42	0.42	0.38	0.39	0.41	0.40	0.44
	(0.19)	(0.19)	(0.19)	(0.17)	(0.33)	(0.18)	(0.18)	(0.26)
$\beta_2^{C_{t-1}}$	0.08	0.07	0.05	0.08	0.79	0.08	0.10	0.03
	(0.22)	(0.24)	(0.24)	(0.24)	(0.41)	(0.22)	(0.22)	(0.35)
σ_ϵ^2	2.07	2.03	2.04	2.04	2.52	2.07	2.07	2.24
	(0.52)	(0.53)	(0.54)	(0.48)	(0.39)	(0.54)	(0.50)	(0.54)

Table 1B: Markov Regime-Switching Models – 2011.Q4

Model:	**Baseline**	Baa Spread	GZ Spread	**EBP**	NFCI	ANFCI	**NFCI-nfl**	**Lev. Ratio**
Weight	**0.08**	0.00	0.00	**0.01**	0.00	0.00	**0.83**	**0.07**
Parameters:								
Prob:								
δ_1	1.68	1.63	1.48	1.46	1.64	1.68	1.81	2.09
	(0.36)	(0.39)	(0.40)	(0.39)	(0.38)	(0.40)	(0.55)	(0.65)
δ_2	-1.03	-0.95	-0.62	-0.74	-0.93	-1.03	-0.53	-0.96
	(0.36)	(0.44)	(0.43)	(0.43)	(0.39)	(0.36)	(0.64)	(0.72)
γ^{FSI}	-	-0.09	-0.45	-0.54	-0.15	0.03	-1.37	0.80
	-	(0.29)	(0.30)	(0.29)	(0.28)	(0.28)	(0.90)	(0.50)
Mean:								
α_1	2.89	2.97	3.10	3.18	2.92	2.88	2.92	2.92
	(0.39)	(0.41)	(0.43)	(0.44)	(0.42)	(0.39)	(0.41)	(0.42)
$\beta_1^{GDP_{t-1}}$	-0.05	-0.07	-0.11	-0.14	-0.06	-0.05	-0.07	-0.06
	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.12)	(0.12)	(0.12)
$\beta_1^{C_t}$	-0.05	-0.05	-0.03	-0.04	-0.05	-0.05	-0.06	-0.05
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.11)
$\beta_1^{C_{t-1}}$	0.22	0.22	0.21	0.23	0.22	0.22	0.25	0.21
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
α_2	-2.45	-2.37	-2.25	-2.17	-2.46	-2.46	-2.53	-2.50
	(0.95)	(0.92)	(0.89)	(0.87)	(1.00)	(0.97)	(0.98)	(0.87)
$\beta_2^{GDP_{t-1}}$	-0.26	-0.25	-0.22	-0.21	-0.27	-0.26	-0.29	-0.27
	(0.29)	(0.28)	(0.26)	(0.25)	(0.30)	(0.29)	(0.26)	(0.25)
$\beta_2^{C_t}$	0.68	0.68	0.69	0.65	0.69	0.68	0.66	0.68
	(0.12)	(0.11)	(0.11)	(0.10)	(0.12)	(0.12)	(0.11)	(0.12)
$\beta_2^{C_{t-1}}$	0.10	0.08	0.04	0.06	0.09	0.10	0.13	0.09
	(0.23)	(0.22)	(0.21)	(0.20)	(0.23)	(0.23)	(0.21)	(0.20)
σ_ϵ^2	2.56	2.55	2.49	2.47	2.55	2.56	2.51	2.56
	(0.48)	(0.48)	(0.49)	(0.48)	(0.48)	(0.48)	(0.48)	(0.46)

Table 1C: Markov Regime-Switching Models – 2015.Q4

	Baseline	Baa Spread	GZ Spread	EBP	NFCI	ANFCI	**NFCI-nfl**	**Lev. Ratio**
Weight	**0.06**	0.00	0.00	0.00	0.00	0.00	**0.87**	**0.06**
Parameters:								
Prob:								
δ_1	1.78	1.81	1.64	1.57	1.74	1.79	1.98	2.18
	(0.35)	(0.39)	(0.37)	(0.40)	(0.37)	(0.39)	(0.56)	(0.65)
δ_2	-1.00	-1.06	-0.66	-0.62	-0.88	-1.01	-0.30	-0.92
	(0.37)	(0.44)	(0.45)	(0.42)	(0.41)	(0.37)	(0.67)	(0.78)
γ^{FSI}	-	0.06	-0.32	-0.51	-0.16	0.03	-1.36	0.79
	-	(0.27)	(0.26)	(0.26)	(0.25)	(0.27)	(0.86)	(0.47)
Mean:								
α_1	2.47	2.44	2.61	2.69	2.50	2.47	2.50	2.54
	(0.34)	(0.35)	(0.36)	(0.37)	(0.36)	(0.35)	(0.35)	(0.36)
$\beta_1^{GDP_{t-1}}$	-0.00	0.01	-0.04	-0.07	-0.01	-0.00	-0.02	-0.03
	(0.10)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
$\beta_1^{C_t}$	-0.06	-0.06	-0.05	-0.05	-0.06	-0.06	-0.07	-0.06
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.10)
$\beta_1^{C_{t-1}}$	0.25	0.25	0.25	0.26	0.25	0.26	0.28	0.25
	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.10)	(0.09)
α_2	-2.67	-2.74	-2.42	-2.25	-2.65	-2.67	-2.69	-2.60
	(1.09)	(1.09)	(1.09)	(1.01)	(1.14)	(1.09)	(1.01)	(0.96)
$\beta_2^{GDP_{t-1}}$	-0.29	-0.30	-0.25	-0.22	-0.29	-0.29	-0.31	-0.28
	(0.34)	(0.34)	(0.33)	(0.30)	(0.35)	(0.34)	(0.27)	(0.27)
$\beta_2^{C_t}$	0.69	0.69	0.70	0.67	0.69	0.69	0.66	0.68
	(0.13)	(0.13)	(0.12)	(0.11)	(0.13)	(0.13)	(0.12)	(0.13)
$\beta_2^{C_{t-1}}$	0.13	0.15	0.06	0.05	0.12	0.13	0.15	0.10
	(0.26)	(0.26)	(0.26)	(0.23)	(0.27)	(0.26)	(0.22)	(0.22)
σ_ϵ^2	2.60	2.61	2.57	2.56	2.60	2.60	2.56	2.60
	(0.46)	(0.46)	(0.48)	(0.48)	(0.45)	(0.46)	(0.45)	(0.44)

Table 2: Parameters for KS Policy Projections

	2007.Q4	2011.Q4	2015.Q4
KS Parameters			
BHC RWA for top 12 firms	\$6,075	\$6,162	\$6,955
CCyB cost	\$152	\$154	\$174
2-year Treasury rate (%)	3.05	0.25	1.06
GDP at year-end	\$14,992	\$15,190	\$16,491
$\bar{u}$	\$1,125	\$1,432	\$1,487
μ_g (%)	3.03	2.78	2.48
μ_b (%)	-0.71	-1.93	-2.03
$\underline{u}$	\$1,125	\$1,283	\$1,303
μ_{gb} (%)	3.03	2.29	1.93
μ_b (%)	-0.71	-1.93	-2.03
KS Values			
$\theta = 0.00$	1.42%	1.20%	1.36%
$\theta = 0.25$	1.42%	1.17%	1.32%
$\theta = 0.50$	1.42%	1.14%	1.27%
$\theta = 0.75$	1.42%	1.11%	1.23%
$\theta = 1.00$	1.42%	1.08%	1.19%

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

Table 3: KS Implementation Dates by Model Specification

	2007	**2011**	**2015**
Forecast Horizons			
Weighted-average	1	7	6
Baseline	1	4	3
Baa Spread	1	4	3
GZ Spread	1	4	3
GZ Excess Bond Premium	1	4	3
NFCI	3	4	3
ANFCI	1	4	3
NFCI: Nonfin. Leverage	1	-	-
Leverage Ratio	1	5	5