Financial Stress and Economic Dynamics:  
the transmission of crises*

Kirstin Hubrich  
European Central Bank  
Frankfurt am Main, Germany  
kirstin.hubrich@ecb.int

Robert J. Tetlow  
Federal Reserve Board and IMF  
Washington, D.C.  
www.roberttetlow.com

First draft: September 2010  
This version: August 7, 2011  
PRELIMINARY VERSION – COMMENTS WELCOME

Abstract

The recent financial crisis and the associated decline in economic activity have raised some important questions about economic activity and its links to the financial sector. This paper introduces an index of financial stress—a measure developed in real time by the staff of the Federal Reserve Board to monitor the crisis—and shows how stress interacts with real activity, inflation, and monetary policy. We examine a variety of questions including the implications of financial stress for the real economy; the implications of shocks to the real economy for financial stress; the role of monetary policy and what constitutes a useful and credible measure of stress in this context. We address these questions using a richly parameterized multivariate Markov-switching VAR model estimated using Bayesian methods. We clearly reject the constant parameter model and find that the negative output effects of a financial stress shock are much more pronounced and long-lasting in times of high financial stress than in normal times. We also find that monetary policy has reacted differently in times of financial stress than otherwise.

JEL Classification: E44, C11, C32

Keywords: Markov switching, financial crises, monetary policy transmission

*We thank Tao Zha and Daniel Waggoner for help interpreting their code and Peter Chen, Trevor Davis and Jens Kruk for their capable research assistance. Thanks to Gert Bekaert, Larry Christiano, Martin Eichenbaum, Jordi Gali, Simon Gilchrist, Anil Kashyap, Sharon Kozicki, Thomas Laubach, Marco del Negro, Harald Uhlig and Egon Zakrajesk as well as participants of several conferences and seminar participants at Maastricht University and the Federal Reserve Board for helpful comments. All remaining errors are ours. The views expressed in this paper are solely the responsibility of the authors and should not be interpreted as reflecting the views of the European Central Bank, the Board of Governors of the Federal Reserve System or the International Monetary Fund (where Tetlow was visiting while part of this paper was written) or the views of any other person associated with any of these institutions.
1. Introduction

Financial factors have long been recognized as being important for understanding macroeconomic dynamics; see, e.g. Bernanke and Blinder (1988), Kashyap and Stein (1994) and Hubbard (1998). The recent financial and economic crisis in the U.S. and elsewhere has brought the relationship between financial market conditions and macroeconomic outcomes to the forefront of policy discussions. Not only did U.S. stock market wealth fall from its peak by 50 percent and real estate wealth by 15 percent, but risky spreads in capital markets widened by unprecedented amounts and major financial institutions collapsed.\(^1\) And yet, despite this recognition, prior to the crisis, relatively few models have been formulated that include meaningful linkages between the real and financial sectors.\(^2\) As Kashyap and Stein (1994) outline in their survey of the topic, one reason why this is so is that the quantification of the credit channel is difficult. First, there is the difficult issue of identifying shocks to, for example, loan supply as distinct from shocks to loan demand. Second, it is likely that the transmission of shocks and their damping by policy, could vary depending on financial conditions owing either to jumps in risk aversion or the zero lower bound on nominal interest rates. And third, there is reason to believe that there are either nonlinearities in dynamic propagation of shocks in financial markets, or non-normalities in the shocks themselves, or both.

This paper investigates the interactions between financial market conditions, volatility and macroeconomic outcomes in the United States. Our motivation is, not surprisingly, the financial crisis of 2007-08 and the critical role of finance in that episode. In particular, the power that financial factors can have on the real economy became abundantly clear: following the plunge in financial conditions in 2007 came the most severe recession in US postwar history. But just as interesting is the apparent relationship flowing in the other direction: in the absence of macroeconomic recovery, the stability of financial institutions and nonfinancial firms alike was in doubt raising the cost of finance and constricting the availability of credit. And the reluctance of households and firms to borrow exacerbated solvency issues for financial institutions.

An increase in financial stress—that is, a deterioration in financial conditions—affects the economy in three more-or-less distinct ways: first and most simply, it raises the cost of funds for firms and households seeking to purchase durable goods by raising risky spreads. Second, when financial stress is associated with asymmetric information and uncertainty, it can result in credit rationing

---

1 According to the US flow of funds accounts, stock market wealth fell from 2007:Q3 and 2009:Q1 by 50 percent, or about $11 trillion, before recovering somewhat thereafter. Real estate wealth fell from its local maximum in 2006:Q4 to 2009:Q1 by 15 percent or about $7 trillion. This amounts to more than a year’s worth of nominal GDP.

2 In particular, prior to the crisis, there are few structural macroeconomic models with meaningful financial sectors. Exceptions include Bernanke et al. (1999) and Iacoviello (2005).
as banks come to doubt the credit worthiness of borrowers. The result is a restriction of credit that might not be adequately captured in the price terms of capital markets or bank lending. And third, to the extent that financial stress is episodic, an increase in financial stress can increase the option value of waiting for would-be borrowers, raising the value of delaying purchase decisions that are costly to reverse until such time as the uncertainties associated with the stress are alleviated.3

The episodic nature of financial crises and the two-way causality between the financial and real sectors leads us to examine the issue in a nonlinear, multivariate framework. In particular, we build on the work of Sims and Zha (2006) and Sims, Waggoner and Zha (2008) by employing a multivariate Markov switching vectorautoregression (MS-VAR) model estimated using Bayesian methods. In acknowledgement of likely shifts in the variances of the shocks during these periods, and in economic and financial history more generally, we allow for switching in the variances of shocks to the model. In addition, to capture possible time variation in the relationship between financial and macroeconomic variables, and specifically with monetary policy, we allow for regime switching in the model’s structural parameters as well. The distinction will allow us to determine whether all the time variation in financial stress and in the real economy comes from switching in variances, or whether shifts in regime are also associated with different transmission of financial shocks to the real economy, and finally whether variations in the efficacy of monetary policy that depend on the regime also play a role.

As noted, nonlinearities are at the center of the subject of interest here. That said, there are alternatives to the MS-VAR approach used here: one can introduce nonlinear dynamics into a model with a single regime. He and Krishnamurthy (2011) do this through the inclusion of capital constraints that can generate potentially destabilising asset price dynamics, while Brunnermeier and Sannikov emphasize the highly non-linear amplification effects caused by leverage and feedback effects of asset prices. And Markov switching can be used but in the context of a DSGE model. Liu, Wagonner and Zha (LWZ, 2010) add Markov switching to an otherwise much studied environment; they are interested in standard business cycle dynamics, not periods of financial stress as in this paper. Similarly, Fernández-Villaverde et al (2010) build a medium-scale dynamic stochastic general equilibrium (DSGE) model with both stochastic volatility and parameter drifting in the Taylor rule.4 The question that interests us, however, is different and novel. The myriad ways in which

---

3 The description of channels in the main text is a generic one and not meant to do justice to the complexities of the crisis of 2007-9. In the financial crisis itself, there were still more channels of importance including the refusal of banks to trade with one another (a run on wholesale markets, in other words), the associated fire sale of distressed assets, and the deleveraging of balance sheets as banks suffered losses of capital. See Gorton (2010) for an accessible summary.

4 Schorfheide (2005) and Bianchi (2011) use Markov switching in DSGE models to study monetary policy switch-
financial stress manifests itself—widened spreads of risky bonds over Treasury bond rates, jumps in volatility, substantial increases in liquidity premiums in bond markets, shifts in the equity premium—together with the multiplicity of channels through which stress can operate, leads us to avoid the restrictions implied by a DSGE model, at least until the literature identifies the most important channels of effect.

To investigate the implications of financial stress one needs data on financial stress. We employ a unique index of financial stress that was constructed and is used by the staff of the Federal Reserve Board to analyze the economy in real time during the financial crisis. The index, which spans the period from late 1988, is discussed in detail in the next section.

Ours is not the first paper to investigate quantitatively the link between financial markets in general, and episodes of financial stress in particular, and the business cycle, see Lown and Morgan (2006), Kaufmannn and Valderama (2007, 2008), Gilchrist, Yankov and Zakrajsek (2009), Misina and Tkacz (2009) and Davig and Hakkio (2010), among others.

To anticipate the results, we clearly reject a constant-parameter model in favor of more complex models that allow switching in at least some parts of the parameter space. This finding is in common with Sims and Zha (2006) among others, although the period of study and the context are quite different. Our preferred specification includes two Markov states in the variances of shocks; we also find evidence that the transmission of shocks during periods of high financial stress is different than otherwise. At the same time, our findings do not suggest that switching is restricted to stress alone, or even stress and monetary policy; rather the data suggest that all equations shift together. In particular, there is no evidence that the interest rate equation has constant parameters. It follows that monetary policy has reacted differently in times of financial stress than otherwise; this in turn implies that inference regarding the conduct of monetary policy that is gleaned from a constant parameter model may be inappropriate for periods when the policy is conditioned on movements in financial stress.

The remainder of the paper proceeds as follows. In section 2, we discuss the history of financial stress in the United States. We also introduce our data and link these events to the data. The third section discusses our modeling framework and econometric strategy while the fourth presents our results. A fifth and final section sums up and concludes.
2. Measuring financial stress

2.1. Some history

To casual observers, financial stress would seem like a recent phenomenon. But it has been more prevalent than one might think. Students of banking history know that there were banking crises in the U.S. in 1837, 1857, 1873, 1907 and 1933. It is only recently that crises have become rare. But the absence of full-blown crises does not mean that there has not been episodes of financial stress. Table 1 lays out some events over the last twenty years that have buffeted financial markets.

<table>
<thead>
<tr>
<th>Event description</th>
<th>Date(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>a Savings &amp; loan (S&amp;L) crisis</td>
<td>1986-1994</td>
</tr>
<tr>
<td>b Mexican peso crisis</td>
<td>Dec. 1994-1995</td>
</tr>
<tr>
<td>c Asia crisis</td>
<td>July 1997-1999</td>
</tr>
<tr>
<td>d Decline and fall of Long-Term Capital Management (LTCM)</td>
<td>May-Sept. 1998</td>
</tr>
<tr>
<td>e Russian debt default</td>
<td>August 1998</td>
</tr>
<tr>
<td>f Argentine financial crisis</td>
<td>Dec. 2001-2002</td>
</tr>
<tr>
<td>g Bear Stearns closes down three troubled hedge funds</td>
<td>July 31, 2007</td>
</tr>
<tr>
<td>h Fed announces Term Auction Facility (TAF)</td>
<td>Dec. 11, 2007</td>
</tr>
<tr>
<td>i AIG announces imminent bankruptcy, gets bailed out</td>
<td>Sept. 16, 2008</td>
</tr>
<tr>
<td>j Bear Stearns forced sale to JP Morgan Chase</td>
<td>March 2008</td>
</tr>
<tr>
<td>k Fannie Mae and Freddie Mac are bailed out</td>
<td>Sept. 7, 2008</td>
</tr>
<tr>
<td>l Lehmann Brothers declares bankruptcy</td>
<td>Sept. 14, 2008</td>
</tr>
<tr>
<td>m Congress passes Troubled Asset Relief Program (TARP)</td>
<td>Oct. 3, 2008</td>
</tr>
<tr>
<td>n Term Asset-backed Securities Loan Facility (TALF) announced</td>
<td>Nov. 25, 2008</td>
</tr>
<tr>
<td>o Treasury department announces stress tests</td>
<td>Feb. 10, 2009</td>
</tr>
<tr>
<td>p US bank stress test results announced</td>
<td>May 7, 2009</td>
</tr>
</tbody>
</table>

There were financial crises long before troubles at hedge funds owned by Bear Stearns showed up in the spring of 2007. Many of these originated from outside the country, but not the S&L crisis wherein more than a thousand mostly small, regional financial institutions collapsed in the late 1980s and early 1990s. The S&L crisis has been cited as both a cause and a propagation mechanism of the 1991 recession and the subsequent "jobless" recovery.

2.2. Indexes

To capture in real time some of the events described in the previous subsection, in 2008 the staff of the Federal Reserve Board constructed a Financial Stress Index (FSI). Built up from daily data,
the earliest versions were used simply for more-or-less instantaneous assessment of developments as they unfolded. Minor adjustments allowed for the creation of historical data and thus for empirical work used to gauge the effects of stress on the economy and, at a lower frequency, the effects of policy actions on stress. The index is deliberately focused on capital market measures of stress, as opposed to banking measures; there are costs and benefits associated with this focus. As we noted in the introduction, financial stress manifests itself through both price and non-price channels, and in both capital markets and in banking. The most common source of data for (something like) stress in banking is the Senior Loan Officer Opinion Survey (SLOOS), also a product of the Federal Reserve. While there is a great deal of merit to the SLOOS, the fact that it is a quarterly survey and only comes out a quarter after the survey is conducted represents a significant drawback for our purposes. The short sample of the SLOOS also represents an impediment. There are capital-markets based measures of banking stress, such as the well-known TED spread, but these too have their own problems.

Table 2 below describes the constituent parts of the FSI. As can be seen, the index includes two variables that measure risky spreads on bonds (#1 and 2), two that capture liquidity premiums on bonds (#6 and 7), three variables that capture market volatility as measured from options prices (#4, 5 and 9) in bond and equity markets, a variable measuring the slope of the term structure at the short end (#3) and finally a measure of the equity premium (#8). Data availability limits the start date of the (monthly version of the) index to 1988:M12; the last observation we use is 2009:M9.

---

5 The original index was created in the Monetary Affairs division of the Board of Governors. The version employed here was constructed and is maintained by the Macroeconomics and Quantitative Studies section of the Division of Research and Statistics. The source data are daily.

6 See, e.g. Lown and Morgan (2006) and Berrospide and Edge (2009). For details on the Senior Loan Officer Opinion Survey, see http://www.federalreserve.gov/boarddocs/snloansurvey/

7 The TED spread is the difference between interbank lending rates and the rate on short-term US Treasury securities. However, its definition has changed over time. The LIBOR-OIS spread, which is arguably better than the TED spread for some purposes, only goes back to 2001.

8 The on-the-run premium is the difference in yield between just-issued Treasury bonds and the identical bond from the previous auction, corrected for the difference in term to maturity. The on-the-run premium—or liquidity premium—reflects the fact that trading in older bonds is not particularly deep.
Table 2
Components of the Federal Reserve Board staff’s Financial Stress Index*

<table>
<thead>
<tr>
<th>#</th>
<th>Description</th>
<th>Source</th>
<th>Std.dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>AA bond rate-Treasury spread, const. maturity</td>
<td>Merrill L. &amp; Bloomberg</td>
<td>67.4</td>
</tr>
<tr>
<td>2</td>
<td>BBB bond rate-Treasury spread, const. maturity</td>
<td>Merrill L. &amp; Bloomberg</td>
<td>96.7</td>
</tr>
<tr>
<td>3</td>
<td>Federal funds rate less 2-yr Treasury yield</td>
<td>FRB &amp; Bloomberg</td>
<td>0.72</td>
</tr>
<tr>
<td>4</td>
<td>10-year Treasury bond implied volatility</td>
<td>Bloomberg</td>
<td>1.50</td>
</tr>
<tr>
<td>5</td>
<td>Private long-term bond implied volatility</td>
<td>Bloomberg</td>
<td>2.34</td>
</tr>
<tr>
<td>6</td>
<td>10-year Treasury on-the-run premium</td>
<td>Bloomberg</td>
<td>9.80</td>
</tr>
<tr>
<td>7</td>
<td>2-year Treasury on-the-run premium</td>
<td>Bloomberg</td>
<td>4.13</td>
</tr>
<tr>
<td>8</td>
<td>S&amp;P 500 earnings/price less 10-year Treasury</td>
<td>I/B/E/S &amp; FRB</td>
<td>1.61</td>
</tr>
<tr>
<td>9</td>
<td>S&amp;P 100 implied volatility (VIX)</td>
<td>Bloomberg</td>
<td>8.96</td>
</tr>
</tbody>
</table>

*Components are weighted as a function of the inverse of their sample standard deviations.

The components of the FSI capture different aspects of risk and uncertainty in capital markets. Risk premiums, for example, reflect default risk whereas liquidity premia capture unwillingness to trade. The two concepts are likely to be associated but are not the same. Table 2 shows the correlation matrix for the series. In general, the components are correlated, of course, and sometimes quite strongly, but not so much that one would argue that a series is redundant.

Table 3
Correlation coefficients on components of Financial Stress Index*

<table>
<thead>
<tr>
<th></th>
<th>AA</th>
<th>BBB</th>
<th>ff-2yr</th>
<th>Tbond</th>
<th>pbond</th>
<th>10 liq</th>
<th>2 liq</th>
<th>equity</th>
<th>VIX</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA spread</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>BBB spread</td>
<td>0.94</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ff-2yr</td>
<td>0.27</td>
<td>0.15</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Tbond vol</td>
<td>0.53</td>
<td>0.62</td>
<td>-0.20</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>pbond vol</td>
<td>0.64</td>
<td>0.73</td>
<td>-0.14</td>
<td>0.91</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10yr liq</td>
<td>0.76</td>
<td>0.79</td>
<td>-0.03</td>
<td>0.58</td>
<td>0.68</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2y liq</td>
<td>0.29</td>
<td>0.26</td>
<td>0.26</td>
<td>0.08</td>
<td>0.12</td>
<td>0.28</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>equity prem</td>
<td>0.53</td>
<td>0.50</td>
<td>0.17</td>
<td>0.29</td>
<td>0.43</td>
<td>0.24</td>
<td>-0.22</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>VIX</td>
<td>0.77</td>
<td>0.78</td>
<td>0.25</td>
<td>0.56</td>
<td>0.65</td>
<td>0.72</td>
<td>0.35</td>
<td>0.19</td>
<td>1</td>
</tr>
</tbody>
</table>

* Variables in this table appear in the same order as they are defined in table 2.

Figure 2.1 shows the FSI at a monthly frequency. The first thing to notice about the index itself is that it does not look like a stationary process with Gaussian disturbances; rather, the index appears to have lengthy periods of low stress with modest fluctuations, together with shorter episodes of high and volatile stress. This impression is reinforced by our overlay of some of the key dates in US financial history discussed in the previous subsection. Clearly, the periods of what the unaided eye sees as high stress are associated with well-known events in financial history. At the same time, however, it must be said that the period beginning with the forced merger of Bear
Stearns stands out as one of particularly high stress. Our index is not the only one available. The Federal Reserve Banks of St. Louis and Kansas City, to cite two examples, have also constructed measures of financial stress. Both use principal component analysis of a fairly large number of series including some we use here as well as banking related series and levels of interest rates. They share some similarities to the one we use. However, neither series goes back as far as ours and neither is available at business daily frequency.\(^9\)\(^10\) In a later subsection on robustness, we investigate perturbations to our measure of financial stress.

![U.S. Financial Stress Index (FSI)](figure.png)

Figure 2.1: U.S. Financial Stress Index (FSI)

---

\(^9\) Business daily frequency availability is of no particular relevance for the application considered in this paper but the advantage of being able to monitor developments in real time and at high frequency is obvious, particularly for central banks and financial market participants themselves. In this regard, it is also worth noting that one drawback of the use of principal components is that the index will necessarily be revised even if the underlying components are not.

\(^10\) The International Monetary Fund has also constructed a FCI with the restriction that it be applicable to 17 countries which limits the data that can be used. Nelson and Perli (2007) discuss selected indicators of financial stability. See also Beaton et al. (2009) and Hatzis et al. (2010).
3. Econometric Methodology

3.1. The model

Our investigation is concerned with uncovering nonlinear and possibly state-dependent relationships between financial stress—which appears, at least superficially, to have non-linear univariate dynamics—and key macroeconomic variables. The combination of high dimensionality of the model we have in mind combined with the relatively short sample of data with which we must work presents a challenge from a methodological point of view. Fortunately, recent advances in econometrics facilitate our investigation. In particular, we employ state-of-the-art Bayesian econometric tools for MS-VAR models, as developed by Sims, Waggoner and Zha (SWZ 2008). In this section, we lay out the basic model and discuss our methodology.

We consider (possibly) nonlinear vector stochastic processes of the following form:

\[ y_t' A_0(s_t^c) = \sum_{l=1}^{p} y_{t-l} A_l(s_t^c) + z_t' C(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \]  

(3.1)

where \( y \) is an \( n \times 1 \) vector of endogenous variables; \( s^m \), \( m = v, c \) are an unobservable (latent) states, one each for variances, \( v \), and intercepts and coefficients, \( c \); \( p \) is the VAR’s lag length; \( z \) is a matrix of exogenous variables which we are going to take as \( 1_n \), representing a column vector of constants. \( A_0 \) is an \( n \times n \) matrix of parameters describing contemporaneous relationships between the elements of \( y \), \( C(k) \) is an \( 1 \times n \) vector of parameters of the exogenous variables and \( A_l(k) \) is a \( n \times n \) matrix of parameters of the endogenous variables. The values of \( s_t^m \) are elements of \( \{1, 2, \ldots h^m\} \) and evolve according to a first-order Markov process:

\[ \Pr(s_t^m = i | s_{t-1}^m = k) = p_{ik}^m, \quad i, k = 1, 2, \ldots h^m. \]  

(3.2)

Let

\[ A'_+ = [A_1(k)', A_2(k)', \ldots A_p(k)', C(k)'] \quad \text{and} \quad x'_t = [y'_{t-1}, \ldots y'_{t-p}, z_t'], \]

then the model can be written as

\[ y_t' A_0(s_t^c) = x'_t A'_+(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \quad t = 1, 2, \ldots T \]  

(3.3)
where $T$ is the sample size. Let us designate $Y_t = \{y_0, y_1, ..., y_t\}$ as the vector $y$ stacked in the time dimension. We assume that the structural disturbances are conditionally normal:

$$
\epsilon'_t(s^c_t)|Y^{t-1} \sim N(0_{n \times 1}, I_n).
$$

The reduced form system is then:

$$
y'_t = x'_t B(s^c_t) + u'_t(s^v_t, s^c_t), \quad t = 1, 2, ..., T
$$

with

$$
B(s^c_t) = A_+ (s^c_t) A_0^{-1} (s^c_t)
$$

$$
u'_t(s^v_t, s^c_t) = A_0^{-1} (s^c_t) \epsilon'_t \Xi^{-1} (s^v_t)
$$

$$
E(u_t(s_t)u_t(s_t)') = (A_0(s^c_t) \Xi^{-1} (s^v_t) A_0(s^c_t))^{-1}.
$$

As can be seen in equations (3.5) through (3.7), the reduced-form equations contain structural parameters and shocks that make distinguishing regime switching in the reduced form impossible whereas it is possible in the structural form, equations (3.3). More important for our application, notice as well that switching in the coefficients, $s^c$, imparts switching in the reduced-form residuals, equations (3.7); and so does switching in the structural variance-covariance matrix, through $s^v$. Thus, our generalization of the model so that the number of regimes in variance switching differ from those in parameter switching sets an empirical horse race between the two sources of variation in reduced-form error variances. The issue is critical as demonstrated by the debate between Cogley and Sargent (CS 2001) on the one hand, and Sims and Zha (SZ 2006) on the other. CS (2001) argued that shifts in the structural parameters of their VAR model explained the great moderation in the U.S. post-war data. However, CS (2001) did not allow for time variation in structural shock variances, while CS (2005) did.\footnote{Cogley and Sargent (2005) revisited the issue this time allowing for stochastic volatility and finding "substantial variation" in all contributors, including coefficients. They also show that tests of the null hypothesis of time-invariance of coefficients of VARs have low power.} SZ (2006) showed that failing to do so can severely bias results towards the erroneous finding of shifts in coefficients. It should be clear from equations (3.4) to (3.7) that for a given dataset the more $s^v$ accounts for variability in the data, the smaller the role of $s^c$ to explain the variability in the data, and vice versa. Thus it will be important to ensure that switching in variances is not wrongly attributed to parameter switching; and, therefore, a finding of shifting in coefficients that allows for shifting in variances will be a noteworthy outcome.

Finally, we will be interested in comparing our preferred MS-VAR model with a constant-parameter, constant-variance version, which imposes the restriction $h^m = 1$.\footnote{Cogley and Sargent (2005) revisited the issue this time allowing for stochastic volatility and finding "substantial variation" in all contributors, including coefficients. They also show that tests of the null hypothesis of time-invariance of coefficients of VARs have low power.}
3.2. Priors

There are two sets of priors of relevance to our model, one on the reduced-form parameters of the VAR conditional on a state, \( s \), and the other on the transition matrix. The priors on the reduced-form VAR are simply the standard Minnesota prior of Litterman (1986) on the lag decay dampening the influence of long lags. In other words, this prior shrinks the model towards a random walk. Furthermore, it seems reasonable that the importance of a variance decreases with lag length; and that priors on exogenous and deterministic variables, \( z \), be relatively uninformative.

Let the relative tightness on the prior on the own lags, non-own lags, and exogenous or deterministic variables be \( \mu_1 \) through \( \mu_3 \) respectively. The prior variances of the parameters are then specified as:

\[
\text{Var}(x_i) = \begin{cases} 
\mu_1/p & \text{for own lags} \\
\mu_2\sigma_i^2/p\sigma_j^2 & \text{for lags } i \neq j \\
\mu_3\sigma_i^2 & \text{variables } z.
\end{cases}
\]

The priors that apply to switching are less straightforward. Even without restrictions of some sort, \( A_0(s_t) \) and \( A_+(s_t) \) could, in principle, be estimated straightforwardly, using the method of Chib (1996) for example, but as \( n \) or \( h \) grows, the curse of dimensionality quickly sets in. The problem is particularly acute in situations where one (or more) of the unobserved states lasts for only a short proportion of the number of total observations, as may be the case for us. Following Sims and Zha (2006), \( A_+ \) can be rewritten as

\[
A_+(s_t) = D(s_t) + \hat{S} A_0(s_t) \quad \text{where} \quad \hat{S} = \begin{bmatrix} I_n & 0_{(m-n)\times n} \end{bmatrix}
\]

(3.8)

which means that a mean-zero prior can be placed on \( D \) which centers the prior on the usual reduced-form random-walk model that forms the baseline prior for most Bayesian VAR models; see e.g. Sims and Zha (1998) for details. The relationship contained in (3.5) means that a prior on \( D \) tightens or loosens the prior on a random walk for \( B \).

The fact that the latent state, \( s \), is discrete and that the transition probabilities of states must sum to unity lends itself toward the priors of the Dirichlet form. Dirichlet priors also have the advantageous property of being conjugate. Letting \( \alpha_{ij} \) be a hyperparameter indexing the expected duration of regime \( i \) before switching to regime \( k \neq i \), the prior on \( P \) can be written:

\[
p(P) = \prod_{k \in H} \left[ \frac{\Gamma(\sum_{i \in H} \alpha_{ik})}{\prod_{i \in H} \Gamma(\alpha_{ik})} \times \prod_{i \in H} p_{ik}^{\alpha_{ik}-1} \right]
\]

(3.9)

where \( \Gamma(.) \) is the gamma distribution. As SWZ (2008) emphasize, the Dirichlet prior enables a flexible framework for a variety of time variation including, for example, once-and-for-all shifts.
and, by letting \( h \) become arbitrarily large, diffusion processes. Our application will not consider absorbing states and will keep the number of states small. We will, however, allow for switching in shock variances originating from a separate process from the one controlling shifts in parameters. Indeed, parallel to the debate between Sims and Zha (2006) on the one hand, and Cogley and Sargent (2005), on the other, regarding whether post-war US macroeconomic dynamics can be attributed solely to stochastic shock volatility or whether shifts in model parameters also contribute, we will be interested in a similar question here.

For our baseline specification, we use priors that are well-suited for a monthly model. In particular, we specify \( \mu_k = 1, 2, \ldots, 6 = \{0.57, 0.13, 0.1, 1.2, 10, 10\} \) and Dirichlet priors of 5.6 for both variances and coefficients. With the values of \( \mu_k \) we follow what Sims and Zha (1998) and Sims, Waggoner and Zha (2008) suggest for monthly data. The Dirichlet priors we use are looser than what would be usually used for monthly data. They imply an 85 percent prior probability that the economy will, in the next period, continue in the same state as it is in the current period. This is a fairly low probability, consistent with the notion that shifts are associated with jumps in asset prices.

### 3.3. Model Estimation and Evaluation

We employ a blockwise optimization algorithm to estimate the posterior mode, as described in SWZ08 that improves over, for example, the MCEM method proposed by Chib (1996) which can be very time-consuming, particularly for large-dimensional systems. In a first step, parameters are divided into blocks and the resulting initial guesses for the parameters are used in a hill-climbing quasi-Newton optimization routine.

To evaluate our models, we use a number of criteria—not merely goodness of fit—as discussed below. Within the realm of fit, however, consistent with standard practice in the Bayesian literature, we compare the marginal data densities of our models. In doing this, we employ two different methods: the standard, modified harmonic mean (MHM) calculation of Gelfand and Dey (1994) and a method suggested by Ulrich Mueller of Princeton University in an unpublished manuscript. Both methods use weighting functions to approximate the unknown posterior distribution, but the method of Gelfand and Dey tends to be unreliable when posterior distributions are far from Gaussian as is likely the case here. The Mueller method is less susceptible to this possibility; see Liu, Waggoner and Zha (2010), section V, for details.
4. Macro-financial Linkages and Financial Stress

We focus on five-variable MS-VARs identified using the well-known Choleski decomposition. In particular, let \( y_t = [i \; \pi \; R \; m \; s]^\top \) where \( i \) is the index of (total) industrial production; \( \pi \) is CPI inflation, excluding food and energy prices (hereinafter, core inflation); \( R \) is the nominal federal funds rate; \( m \) is growth in the M2 monetary aggregate; and \( s \) is the financial stress index. All variables are monthly (or monthly averages of daily rates, where applicable), seasonally adjusted, and expressed at annual rates. The data run from 1988:12 to 2009:9.

In terms of the empirics, we are interested primarily in three questions: first, whether there exist Markov latent states; second, whether regime switching, if it exists at all, is confined to variance switching, as Sims and Zha (2006) find; and third, whether any regime switching is associated with specific equations or occurs across all equations. Behind these questions are the macro questions of whether periods of high financial stress, if they exist, are marked by different dynamics than more normal times, and the associated question of whether it can be said that a different monetary policy response might be called for as a result.

Before proceeding to our results, we discuss briefly our criteria for model selection. Bayesian econometrics lends itself to model assessment on the basis of comparing the marginal data density (marginal likelihood) of alternative models. While we carry out comparisons of this nature, we use broader criteria for model selection. Among these criteria, we place some weight on the plausibility of the model, as captured by the state probabilities and the economic interpretation of their timing and duration in the light of past events. We also place some weight on the coherence of impulse response functions: IRFs that do not render plausible descriptions of shocks are less preferred to those that do. Finally, we also make reference to the log likelihood of the model. Because the posterior mode of the model is proportional to the prior times the likelihood, if the ranking of log likelihoods is seriously out of line with rankings of the marginal data densities (MDDs), it suggests that the prior probabilities might be the dominant force behind the latter ranking.

4.1. Financial stress regimes: Is it just the shocks or do agents change behavior?

As noted above, we consult a number of metrics for goodness of fit, including posterior probabilities and likelihood values. Consistent with the literature, however, our primary source of information

\[12\] In future work we will be working with more complicated identification schemes.

\[13\] The limiting factor in taking the data back further in history is the financial stress index. The availability of the series that comprise the index is such that there can be no meaningful extension back in time of the data through a modest narrowing the breadth of the index.
on fit comes from comparing marginal data densities. There are a number of methods outlined in
the literature for computing MDDs. Our reading of the literature leads us to rely mostly on an
unpublished method developed by Ulrich Müller at Princeton University, with some reference to
modified harmonic means (MHM) method of Gelfand and Dey (1994).

At this point, it is useful to introduce a bit of notation in order to facilitate the interpretation of
the tables that follow. We designate $\#v, \#c = \{ \}, 2, 3$ with $\{ \}$ representing a null entry, to indicate
the number of independent Markov states governing variance switching, and $\#c$ to indicate the
number of states governing shifts in structural coefficients (that is, slope and intercept param-
eters). Finally, when shifts in structural parameters are constrained to a particular equation(s), the
restriction is indicated by adding the letter of the variable, $l = \{ \}, i, \pi, R, m, s$. So, for example, an
MS-VAR with two Markov states in the variances and two in coefficients restricted to the financial
stress variable would be designated as $2v52c$.

Our presentation of results begins with Table 4 which focusses on models where switching is
entertained in all equations but could be in either variance switching alone or in variances and
to.\textsuperscript{15} The first line of the table shows MDDs for the MHM method with the second line
showing the difference in the MDD for the applicable model and the highest MDD for all models
shown. The third and fourth rows repeat this same exercise for the Mueller method.

The first thing to note from the table is that the constant coefficient (and variance) model—that
is, the $1v$ model—is strongly rejected by the data. Any extension of the model improves the fit, and
substantially so. It follows from this that the transmission of stress in the US economy is properly
thought of as a nonlinear phenomenon.

Taken at face value, the MDD computations suggest that relatively elaborate models outper-
form more parsimonious models, with at least three states in variance and perhaps switching in
coefficients.\textsuperscript{15} The first line of the table shows MDDs for the MHM method with the second line
showing the difference in the MDD for the applicable model and the highest MDD for all models
shown. The third and fourth rows repeat this same exercise for the Mueller method.

\textsuperscript{14} We also experimented with another method, one championed by Waggoner and Zha, that is designed to reduce
the sensitivity of MDD calculations to the construction of the weighting matrix by measuring and taking into account
the overlap between the weighting function and the posterior distribution. However, in our work we found that the
WZ method did not always converge. Accordingly, we restrict our attention to the Mueller and standard methods.
That said, in those instances where the SWZ method did converge, it tended to rank models similar to the Mueller
method. Work using a fourth method, the so-called bridge method of Meng and Wong (1996) is in progress.

\textsuperscript{15} Sims and Zha (2006) suggest that it is easy to draw erroneous conclusions regarding shifting in coefficients if
shifting in variances is not considered simultaneously.

13
these two models are scarcely differently economically from the 2v2c and 2v models, respectively. Moreover, although we do not show them here, the IRFs of the 3v2c model are nearly identical to simpler models, in particular the 2v2c model. The last line of the table shows log likelihood calculated at the posterior mode of the candidate models. Because the posterior mode is proportional to the prior times the likelihood, a contradiction in model rankings based on the log likelihood would suggest a reliance on prior values in the posterior mode results that some researchers might find disquieting. The 3v model shows a particularly low likelihood, not in keeping with its preferred status measured solely by the Mueller MDD. By contrast, the 2v2c model, which places second or third in MDD computations shows a markedly superior likelihood. As it happens, it also displays relatively attractive IRFs for the shocks that interest us, as we shall soon demonstrate. For these reasons, the 2v2c is our preferred model, at least among these so-called general models. Thus, in answer to our second empirical question, we would argue that, taken together, the economic and statistical evidence favors switching in coefficients as well as in shock variances.

Table 4

<table>
<thead>
<tr>
<th></th>
<th>1v</th>
<th>2v</th>
<th>2v2c</th>
<th>3v</th>
<th>3v2c</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(mdd)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MHM</td>
<td>-2369.10</td>
<td>-2239.25</td>
<td>-2196.52</td>
<td>-2230.95</td>
<td>-2185.98</td>
</tr>
<tr>
<td>difference</td>
<td>183.12</td>
<td>53.27</td>
<td>10.54</td>
<td>44.97</td>
<td>0</td>
</tr>
<tr>
<td>Mueller</td>
<td>-2369.10</td>
<td>-2236.48</td>
<td>-2242.81</td>
<td>-2230.92</td>
<td>-2289.00</td>
</tr>
<tr>
<td>difference</td>
<td>138.18</td>
<td>5.56</td>
<td>11.89</td>
<td>0</td>
<td>58.08</td>
</tr>
<tr>
<td>log(L)</td>
<td>-2231.66</td>
<td>-2049.45</td>
<td>-1976.68</td>
<td>-2038.08</td>
<td>-1989.75</td>
</tr>
</tbody>
</table>

4.2. Diagnosing switching: is it just in stress or in all economic relationships?

Table 5 compares the 2v2c model against models of similar size but with restricting coefficient switching to certain equations. We consider three restrictions: constraining coefficient restrictions to the stress equation, S, to the policy equations, Rm, and to policy and stress together, RmS. The motivation for these selections is as follows. From the perspective of the monetary authority, a shift to a period of high financial stress is an exogenous event that puts the authority in a quandary: does it stick to its policy rule on the grounds that consistent monetary behavior is a necessary condition for rational expectations equilibrium to obtain, or does it switch to a policy that is germane to the special conditions of the day? If the former is the case, switching will be observed in the FSI equation but not in the policy equations; otherwise both sets of equations will exhibit switching. There is also the possibility that policy could switch seemingly on its own, perhaps owing to "taking
out insurance” against financial or other shocks that do not occur but are thought possible. Indeed it is conceivable that high financial stress is caused, in some sense, by switching in monetary policy.

Table 5 shows that the data favor switching in all equations, over the restricted specifications. Of the alternative specifications, only the $2vS2c$ specification comes even close to the $2v2c$ case, and even then, not all that close. Moreover, the log likelihood calculations shown in the last row of the table strongly confirm this conclusion. This means that the dynamics of monetary policy have differed in parts of recent monetary history, and that these changes have coincided with changes in the behavior of other variables, most notably financial stress. Indeed, although this causality cannot be formally tested, it seems reasonable to assume that changes in the behavior of financial stress induced concomitant changes in the operation of monetary policy. At the same time, however, the limits to what monetary policy can do are indicated by the fact that shifts in monetary policy induced by shifts in financial stress were insufficient to leave the behavior of the real economy and inflation unchanged.

<table>
<thead>
<tr>
<th>Table 5</th>
<th>MS-VAR model results: restricted models</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$2v2c$</td>
</tr>
<tr>
<td>log(mdd) MHM</td>
<td>-2196.52</td>
</tr>
<tr>
<td>difference</td>
<td>0</td>
</tr>
<tr>
<td>Mueller</td>
<td>-2242.81</td>
</tr>
<tr>
<td>difference</td>
<td>0</td>
</tr>
<tr>
<td>log(L)</td>
<td>-1976.68</td>
</tr>
</tbody>
</table>

4.3. The economic history of stress: state probabilities

Table 6 shows the estimated transition probabilities taken from the posterior mode of the distribution. As can be seen, in general, parameter coefficients, when they shift at all, shift relatively rarely while variance states tend to be more fleeting. This coincides with the interpretation of Sims and Zha (2006) that variance switching is better thought of as capturing non-Gaussian distributions for shocks than capturing shifts in distributions per se. Shifts in parameters, on the other hand, are well conceived as changes in regime. For the $2v2c$ model, for example, the table shows that when the economy is in state 2 (the low, or normal state) for coefficients, it is highly likely to remain in state 2 ($q_{22} = 0.98$), whereas in high-stress states the probability of remaining in high stress is substantially lower ($q_{11} = 0.90$). Figure 4.1 below, which shows the (two-sided) estimated state probabilities (or smoothed probabilities), confirms this impression. As shown in the bottom panel, there have been, according to the $2v2c$ model, three periods of high stress in coefficients, one in 1998, corresponding to the Russian debt default and the Asia crisis, a second period in about 2001.
that matches up well with the bursting of the hi-tech bubble, and a third, lengthier period during
the 2008-9 financial crisis and associated recession. The top panel shows the probability of being
in a state of high shock variance. Many of the high variance states also correspond with events in
US financial history including the savings and loan crisis in the early 1990s. Evidently, the model
has a tendency to characterize noteworthy periods in U.S. financial and economic history as coming
more (or first) from increases in the variances of shocks than from shifts in model coefficients.

![Shock Variances](image)

![Coefficients and Intercept Terms](image)

Figure 4.1: Smoothed estimates of state probabilities

During the crisis of 2007-9, it is of some interest in this regard, in that shock variances jumped
to the high state before coefficients did, and that period that is conventionally thought of as the
worst of all, the fourth quarter of 2008, is when both shock variances were high and coefficients
were at high-stress-state levels. The stock market reached its nadir in March of 2009, just as shock
variances switched back to low-stress levels. But while the stock market subsequently rallied for
several months, the real economy showed little tendency to rebound, at least prior to the end of
our sample. More generally, the periods during which the $1\nu$ model would most likely describe
as outliers are likely to be described by our model as involving both shifts in shock variances and model parameters.\textsuperscript{16}

<table>
<thead>
<tr>
<th>model</th>
<th>variances</th>
<th>parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$q_{11}$</td>
<td>$q_{22}$</td>
</tr>
<tr>
<td>$2v$</td>
<td>0.57</td>
<td>0.94</td>
</tr>
<tr>
<td>$2v2c$</td>
<td>0.82</td>
<td>0.91</td>
</tr>
<tr>
<td>$2vRm2c$</td>
<td>0.54</td>
<td>0.97</td>
</tr>
<tr>
<td>$2vS2c$</td>
<td>0.67</td>
<td>0.98</td>
</tr>
<tr>
<td>$2vRmS2c$</td>
<td>0.59</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Figure 4.2 shows the (quasi-) real-time estimates of state probabilities from the same model; that is, the probability of being in a given state at each point in time based on information up to the current period. Three noteworthy conclusions may be drawn from this figure. First, the switches in coefficients indicated in real time were confirmed in the \textit{ex post} estimates; that is, the three periods of high stress shown in the smoothed probability in Figure 4.1 are also in Figure 4.2. Second, while there are hints of false positives—for example in 2004 and one in the other direction in 2009—at no time did the real-time data adamantly call for a switch that was rescinded \textit{ex post}. Third, the record in real time on variance switching is also fairly impressive, particularly given how much switching the model calls for even in the \textit{ex post} estimates. Given our observation above that shifts in parameters are preceded by shifts in variances this is a comforting finding. All in all, we would argue that the model does remarkably well in real time.

4.4. The transmission of financial stress

As a device to trace through the effects of the shocks of interest for questions entertained in this paper, in this subsection we discuss impulse response functions (IRFs) of the model. A moderately large model, with switching in both the variances of shocks and model coefficients produces a large number of IRFs, of which only a subset is interesting in the context of this paper. Our interest is in the propagation of financial stress (FS) over time on the one hand, and the feedback relationship between financial stress and real activity on the other.

\textsuperscript{16} Note that there are no periods where coefficients are in the high-stress state and shock variances are not. The converse is not true. This observation provides an intriguing hint as to where structural modeling of switching phenomena might look for guidance.
To understand this focus, consider the recent crisis. Once financial stress reached high levels in 2008, the fears of market participants and policy makers were of three forms. First, there was the fear of contagion of financial disruption to the real side of the economy: would troubles in financial markets lead to the denial of credit to consumers and, especially, businesses inducing firms to horde cash and more generally make decisions uncharacteristic of those that would be normal for standard business cycle shocks? Second, there was the fear of contagion of financial distress as illiquidity in some markets led to fears of insolvency, counterparty risk, and refusals to trade in other markets, spreading stress across markets and then over time. Third, there was the fear of a vicious cycle as the struggle to conserve liquid assets and contain losses on the part of nonfinancial firms exacerbated problems for financial firms and vice versa.

With this in mind, the figures below show impulse response functions (IRFs) for selected shocks to our preferred $2v2c$ specification of the model. Both figures show responses conditional on high or low stress state. For comparative purposes, we also show the standard benchmark model, a
VAR with constant coefficients and constant variance—that is, the $1v$ model.

Figure 4.3: Model responses to an identified FS shock (conditional on the state)

Figure 4.3 shows model responses to an identified financial stress (FS) shock. Three lines are shown, one, the dashed line, for the $2v2c$ model in the low-stress state; the second, the dot-dashed line is the $1v$ model response; and finally the red solid line shows the response for the $2v2c$ model in the high-stress state. A number of points are worthy of note. First, on the simple dynamics of the model, the responses in all three cases are "sensible" in that regardless of the model or state, a positive perturbation to FS induces a drop in industrial production, a negative response to inflation and an easing in monetary policy (as measured either by the reduction in the federal funds rate or and increase in M2), just as conventional theory would suggest. Second, the
FS shock conditional on being in the high-stress state is very large—it dwarfs the shock conditional on the low-stress state, as shown in the bottom-left panel. The fact that IP spikes negatively on impact of the FS shock—the upper-left panel—suggests that financial stress acts like a constraint on activity, the imposition of which allows real activity to jump as opposed to responding sluggishly as we will show a mere shock to activity itself produces.

Third, our model casts some interesting reinterpretations of dynamics in the benchmark $1 \nu$ model. The middle-left panel shows that policy responses to an FS shock, as measured by the federal funds rate, are relatively small but drawn out over an extensive period of time. By contrast, the response of the $2\nu2c$ model conditional on low stress is much less persistent. Taken together, these responses suggest that the persistence of monetary policy responses in the constant parameter model is a manifestation of misspecification of the underlying model. If agents knew, $a$ priori, that the economy was in a low stress state and would stay in that low stress state notwithstanding the shock to stress itself, the response of policy would be front-loaded but short lived, as shown by the dashed line in Figure 4.3 and 4.4. It is because agents do not know this, that the policy response is as drawn out as it is.

Figure 4.4 shows responses to a shock to industrial production (IP). As with the FS shock, the differences among the cases are more of magnitude than direction: at this level of abstraction, activity shocks operating through financial stress produce dynamics that differ more in severity than qualitative behavior.

That said, the severity of the differences is remarkable. The original impulse to IP, given high stress—one standard deviation of the state-contingent standard deviation of the identified IP shock—is more than twice the magnitude of the shock in the low-stress state—and it persists far longer. Abstracting from the magnitude and persistence of the shock, a high-stress shock produces a great deal of inflation and a quantitatively similar response from the policy interest rate (and money). This is consistent with the decline in U.S. inflation in 2009 and moreover in the fall in long-term inflation expectations during the same period.

Of some interest is the response of financial stress. Recalling that FS is, by definition, at a high level in the high-stress state, an innovation to IP produces a noteworthy reduction in financial stress. This suggests that a significant part of the transmission mechanism of real shocks in an economy under financial stress is the effect of the shock on stress itself. Taken at face value, this might constitute an argument for the efficacy of fiscal policy innovations in conditions of high stress.
Third, by contrast the responses of the $1v$ model are very similar to the $2v2c$ model, conditional on being in the low-stress state. This points to an interpretation of macro dynamics that is highly conditional on stress, with stress being forgettable in "normal" times but being of critical importance for dynamics on those occasions when stress is high.

4.5. Robustness

In this section we consider a range of robustness checks, devoted mostly to the measure of stress used. In one set of cases, we examine how narrowing our stress index by excluding classes of variables affects the results. In the second set, we employ two completely different measures of
stress. We note that because in all cases we are using alternative data, likelihood based calculations are not comparable across models.

4.5.1. Exclusions of components of the index

Table 2 showed the composition of the FSI. As a test of robustness and an exploration of what channels one might wish to investigate in a structural model, we exclude, in the context of our preferred 2v2c specification, each of six classes of components of the FSI. These are risky bond rate spreads (rows 1 and 2 of Table 2), the yield spread (row 3), implied bond rate volatilities (lines 4 and 5), on-the-run premiums (line 6 and 7), equity premium (line 8) and the VIX, that is, the implied volatility of the S&P 500 price index (line 9).

None of these subsets of the broader index produced results that were preferred to our base case. In several instances, however, the results were very similar. In particular, omitting the on-the-run premiums or the implied volatilities of bonds made only slight differences in either switching probabilities or impulse responsibilities. This suggests that either these variables are not important or are encompassed by other variables. By contrast, omitting the VIX or especially the risky spreads does make a material difference to the results. We conclude that explorations of financial market switching using structural models might be profitably focused on phenomena that produce fluctuations in these variables.

4.5.2. Different priors

In broad terms, our preferred model is quite resilient to moderate changes in model priors. For example, if we substitute the priors over VAR coefficients that we used following Sims and Zha (2006) with priors for a quarterly model, we get, once again, three periods of high-stress coefficients and many periods of switching in variances. Altering the Dirichlet prior such that higher persistence of regimes is somewhat favored returns what looks like the same results as we showed for our preferred model.

5. Conclusions

This paper considers the implications of financial stress for the macroeconomy in the United States using a richly specified Markov-switching vector autoregression (MS-VAR) model, estimated with state-of-the-art Bayesian methods, and exploiting a unique series for financial stress constructed
and monitored by the staff of the Federal Reserve Board. Our objective is to uncover whether the transmission of financial stress differs in some states of the world than others. We also examine whether monetary policy in the high-stress state differs from what it is in low stress states.

Our analysis shows substantial evidence that a single-regime model of the macroeconomy and financial stress is inadequate to capture the dynamics of the economy. Moreover, the data show that there have been periodic shifts in both the dynamics of the economy and the variances of stochastic shocks. We further find that these shifts are best described as having occurred in all of the model equations instead of being restricted to subsets of equations. In particular, there is no evidence that the interest rate equation has constant parameters. It follows that monetary policy has reacted differently in times of financial stress than otherwise; this in turn implies that inference regarding the conduct of monetary policy that is gleaned from a constant parameter model may be inappropriate for periods when the policy is conditioned on movements in financial stress.

Quantitatively, we find that output reacts differently to financial shocks in times of high financial stress than in normal times, falling more and for a longer period in response to an increase in financial stress in high financial stress times. This implies that macroeconomic dynamics are highly conditional on financial stress, with stress being negligible in "normal" times but being of critical importance for dynamics when stress is high.

In future work, we anticipate investigating the role of monetary policy in endogenously eliciting a switch in state. One relevant framework in the context of DSGE models can be found in Davig and Leeper (2006). A second, similarly ambitious step would be to consider Markov-switching DSGE characterizations of the issues considered here. Last, and perhaps most important, we expect to carry out a related analysis using euro area data, taking into account the different structure of financial markets in the euro area in comparison with the US.
References


