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Financial stress and economic dynamics: The transmission of crises

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ABSTRACT

A financial stress index for the United States is introduced—one used by the staff of the Federal Reserve Board during the financial crisis of 2008–2009—and its' interaction with real activity, inflation and monetary policy is investigated using a Markov-switching VAR model, estimated with Bayesian methods. A “stress event” is defined as a period of adverse latent Markov states. Results show that time variation is statistically important, that stress events line up well with historical events, and that shifts to stress events are highly detrimental for the economy. Conventional monetary policy is shown to be weak during such periods.

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1. Introduction

Financial factors have long been recognized as being important for understanding macroeconomic dynamics; see, e.g., Bernanke and Blinder (1988) and Kashyap et al. (1993). Yet the inclusion of financial frictions within dynamic stochastic general equilibrium (DSGE) models has been a notably recent phenomenon. One reason why modeling financial frictions was neglected is that it is empirically challenging. As the survey articles by Kashyap and Stein (1994) and Hubbard (1998) make clear, it has been remarkably difficult to uncover significant effects of financial frictions in macroeconomic time-series data. Indeed, with the noteworthy exceptions of Carlstrom and Fuerst (1997) and Bernanke et al. (1999), DSGE models with financial frictions have arisen after the experience of the recent financial crisis and subsequent recession.

In this paper, we argue that a reason why statistically significant and macroeconomically important linkages have been elusive is because the importance of financial factors tends to be *episodic* in nature. In “normal times,” firms make investment decisions on the basis of whether a project's expected rate of return exceeds the user cost of capital, and then having made that decision, seek the financing. In such times, the financing decision is, in some sense, subordinate to the real-side decisions of the firm; credit “does not matter.” In other times, when the financial system is not operating normally, financial frictions become important as lending terms and standards tighten, making the interest rate a much less reliable metric of the cost of funds, broadly defined. During such times, referred to here as *stress events*, credit can seem like it is the only thing that matters.

Our contention that there are stress events that are episodic in nature, together with the associated interdependency of the financial sector and the macroeconomy, leads to the examination of the issue in a nonlinear, multivariate framework.

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In particular, building on the work of Sims, Waggoner and Zha (SWZ 2008), a richly parameterized Markov switching vector autoregression (MS-VAR) model is formulated and estimated with Bayesian methods. The primary focus is on whether the economy behaves differently during periods where the latent Markov state is one of high stress, as the story sketched above suggests. Does the economy propagate shocks differently—transmit crises—during such periods? Accordingly, a major part of the investigation concerns whether the VAR coefficients shift over time, and whether these shifts coincide with established events in U.S. economic and financial history.

Mindful of the possibility that financial stress could arise from outsized shocks, we also explicitly allow for switching in the variances of shocks—or *variance switching*, for short. Besides being an issue in its own right, allowing for variance switching is important to avoid biasing results toward the erroneous finding of *coefficient switching*. As in the literature on the origins of the Great Moderation, variance switching and coefficient switching are rivals in explaining the data.

A second contribution of this research, is the public introduction and assessment of a financial stress index, one that covers a broad range of financial market phenomena, that was formulated and used by the Federal Reserve Board staff during the crisis—on the fly, as it were—to analyze financial conditions and their macroeconomic consequences.

This paper is not the first paper in this area, broadly defined. Since the onset of the crisis, a second generation of DSGE models with financial frictions have sprung up, including Curdia and Woodford (2009), Jermann and Quadrini (2012) and Gilchrist et al. (2014). These and other papers have added insight to thinking about financial frictions as a source of shock amplification, but in most instances, their depiction of model economies allows for a single time-invariant steady state; no role for instability, volatility dynamics or important nonlinear effects is considered. There are also Markov switching DSGE models, including Liu et al. (2011) and Bianchi (2013). However these papers focus on business cycle phenomena, rather than financial stress.

The noteworthy empirical models in the area have included Lown and Morgan (2006), who examine the interaction of real variables and the responses to the Fed's Senior Loan Officers' Opinion Survey in a quarterly time-invariant VAR. An MS-VAR is arguably preferable to model the abrupt, discrete changes in economic dynamics of the recent crisis. Among the very few Markov switching models that pay attention to financial stress that we are aware of is Davig and Hakkio (2010) who, like us, employ an index of financial stress; however, their model is much simpler than ours and omits any consideration of monetary policy or price determination.

To presage the results, taking as a benchmark the standard, time-invariant Gaussian VAR model, substantial evidence is uncovered of non-Gaussian shock processes and nonlinearities: the linkage between financial stress and the macroeconomy is not well described by the benchmark model. Second, variance switching alone is not sufficient to model the departures from the benchmark model; unlike the business cycle characterization of Sims and Zha (SZ 2006), or the depiction of the drivers of the most recent recession described by Stock and Watson (2012), both of which explain the phenomena under study as arising from unusual sequences of shocks, the finding here is that coefficient switching—and hence, nonlinear dynamics—is important. Third, the financial stress index used here (and that the Federal Reserve Board's staff used during the crisis) is shown to be a useful tool that can aid in capturing periods of financial stress in real time. Fourth, the results suggest that conventional monetary policy is not particularly effective in times of high financial stress; a much more powerful mechanism is to induce a switch from a high-stress state back to "normal times."

While linearized DSGE models may be useful for thinking about the role of financial factors in business cycle fluctuations, we argue that if one is interested in the type of dynamics that underscored the 2008–2009 financial crisis, linearized DSGE models will be of limited applicability. Rather, MS-DSGE models, such as Bianchi (2013), or fully articulated nonlinear models, solved with global methods, are better equipped for the job. Examples of the latter include Brunnermeier and Sannikov (2014), Mendoza (2010), He and Krishnamurthy (2012), J. Bianchi (2011) and Boissay et al. (2013).[2] On the empirical side, it also follows that inference regarding the relationship between financial stress and the macroeconomy that is gleaned from a constant-parameter model may be inappropriate.

The remainder of the paper proceeds as follows. Section 2 discusses the history of financial stress in the United States, introduces the data and the association of the data to historical events. The third section discusses the modeling framework and econometric strategy while the fourth presents the results. The fifth section explores the economic interpretation of the results, in part through an analysis of robustness, while the sixth demonstrates the macroeconomic properties of the base-case model. A seventh and final section sums up and concludes. Two appendixes provide details on data and computation as well as more results.

2. Measuring financial stress

This section begins with a bit of recent financial history for the U.S. before turning to a discussion of the Financial Stress Index.

[2] Taking Brunnermeier and Sannikov (2014) as an example, models of this class can allow for instabilities and periodic episodes of volatility, driven in part by occasionally binding financial constraints. Such models emphasize the highly non-linear amplification effects caused by leverage and feedback effects from asset prices. Risk is sometimes endogenous in such models so that financial innovations can lead to better sharing of exogenous risk, but higher endogenous systemic risk as agents optimally respond to the safer environment they find themselves in. Externalities can lead to socially inappropriate levels of leverage, excess volatility and higher correlations of asset prices.

Table 1
Selected financial events affecting the US Economy, 1986–2011.

	Event description	Date(s)
a	Savings & loan (S&L) crisis and its aftermath	1986–1992
b	Iraqi invasion of Kuwait	August 2, 1990
c	Mexican peso crisis	December 1994–1995
d	Asia crisis	July 1997–1999
e	Collapse of Long-Term Capital Management (LTCM)	May–September 1998
f	Russian debt default	August 1998
g	Technology bubble bursts (NASDAQ descent)	March '00-0April '01
h	Enron scandal and bankruptcy	October–November 2001
i	Argentine financial crisis	December 2001–2002
j	Bear Stearns halts redemptions from two of its funds	July 17, 2007
k	Run on the repo market starts, according to Gorton (2010)	August 9, 2007
l	Fed announces Term Auction Facility (TAF)	December 12, 2007
m	TSLF and PDCF initiated; Bear Stearns sold	March 2008
n	AIG announces imminent bankrupty, gets bailed out	September 16, 2008
o	Lehmann Brothers declares bankruptcy	September 14, 2008
p	Congress passes Troubled Asset Relief Program (TARP)	October 3, 2008
q	Term Asset-backed Securities Facility (TALF) announced	November 25, 2008
r	Treasury department announces stress tests	February 10, 2009
s	US bank stress test results released	May 7, 2009
t	Greece admits deficit-to-GDP ratio of 12 percent	October 18, 2009
u	First Eurozone-IMF rescue plan completed	May 2, 2010
v	European FSB cleared to purchase sovereign bonds	July 2011

2.1. *Some history*

To casual observers, financial stress might 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. Nevertheless, the rarity 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.

As the table notes, there were financial incidents long before troubles at hedge funds owned by Bear Stearns showed up in the spring of 2007.

2.2. *A financial stress index*

As the financial crisis began to take hold in 2007, as a complement to existing models, and to capture the higher frequency dynamics that no quarterly model could absorb in real time, a Financial Stress Index (FSI) for the United States was constructed by the staff of the Federal Reserve Board. One contribution of this paper will be an assessment of the efficacy of the FSI as a useful real-time tool during this critical period.[3]

The index focusses on capital market measures of stress, as opposed to banking measures. There are costs and benefits associated with this focus. As was noted in the introduction, financial stress manifests itself through both price and non-price channels, and in both capital markets and in banking. A common source of data for (something like) stress in banking is the Senior Loan Officer Opinion Survey (SLOOS), however, its quarterly periodicity, time lag to release, and short sample are significant drawbacks. There are measures of banking stress that trade in capital markets, such as the well-known TED spread, but these too have their problems.[4] Finally, there are other indexes of financial stress that mostly use principal components analysis of fairly large numbers of series, including some series used in the FSI, as well as banking related data, and the levels of interest rates which we prefer to avoid.[5] These indexes have some similarities to the FSI, but typically do not go back as far in history.

[3] The FSI discussed in this section is based on an index described in Nelson and Perli (2005), modified to allow a longer historical series. Note that our goal is not to construct the best, ex post, measure of financial stress; an index that is data mined to “explain” historical financial events would likely turn out to be fragile.

[4] The TED spread is the difference between interbank lending rates and the rate on short-term US Treasury securities. In normal times, these should be very close substitutes, but when counterparty risk is an issue, the spread between the two can widen. The definition of the TED spread has changed over time. The LIBOR-OIS spread, which is arguably better than the TED spread for some purposes, only goes back to 2001. Both of these indexes measure only a subset of the phenomena captured by the FSI.

[5] The St. Louis Fed's STLFSI is the first principal component of a variety of variables, some of which that are also in the FSI, plus the levels of some interest rates. It starts in 1993. For details, see Kliesen and Smith (2010). The Cleveland Fed's CFSI uses daily data from credit, foreign exchange, equity and interbank markets and dates back to 1994. See also Oet et al. (2011). The Kansas City Fed's index (KCFSI) is constructed using principal components of 11 monthly financial market variables. See Hakkio and Keeton (2009) for details. The Chicago Fed produces an index (NFCI) that is a dynamic factor of an unbalanced panel of mixed frequency indicators of financial activity. See Brave and Butters (2012) for details.

Table 2
Components of the Federal Reserve Board staff's Financial Stress Index[a].

#	Description	Source	Stddev
1.	AA rate-Treasury spread, const. maturity	Merrill & Bloomberg	66.3
2.	BBB rate-Treasury spread, const. maturity	Merrill & Bloomberg	96.2
3.	Federal funds rate less 2-yr Treasury yield	FRB & Bloomberg	0.70
4.	10-year Treasury bond implied volatility	Bloomberg	1.40
5.	Private long-term bond implied volatility	Bloomberg	2.30
6.	10-year Treasury on-the-run premium	Bloomberg	9.43
7.	2-year Treasury on-the-run premium	Bloomberg	3.60
8.	S&P 500 earnings/price less 10-year Treasury	I/B/E/S & FRB	2.01
9.	S&P 100 implied volatility (VIX)	Bloomberg	8.53

[a] The FSI is a simple demeaned sum of the nine components shown, weighted as a function of the inverse of their sample standard deviations.

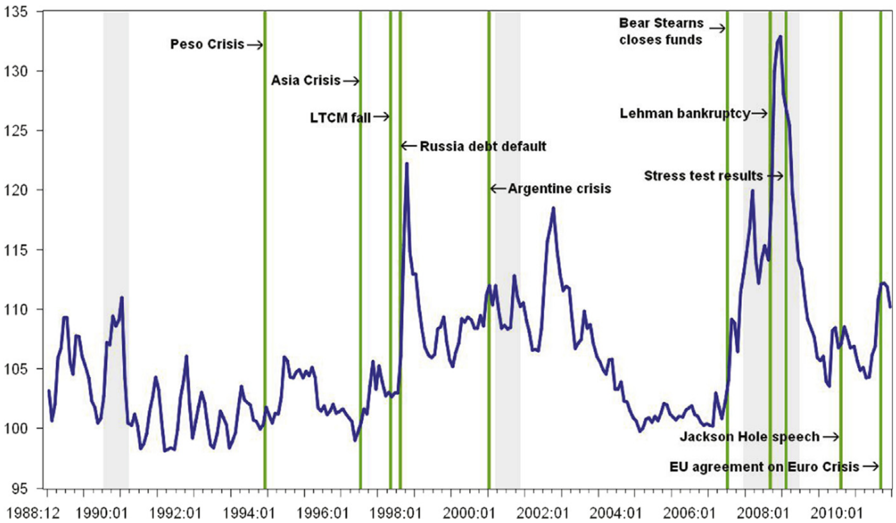

Fig. 1. The Federal Reserve Board staff's Financial Conditions Index (FCI), 1988:12–2011:12.

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),[6] 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 to 1988:12; the last observation we use is 2011:12, leaving 277 observations.

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. 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. Section 5 explores modifications of, and alternatives to, the FSI, with some elaborations offered in Appendix B.

Fig. 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 readings with modest fluctuations, together with shorter episodes of high levels and volatility. This impression is reinforced by the overlay of some of the key dates in U.S. 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, with the period beginning with the forced merger of Bear Stearns standing out as one of particularly high stress. That said, it is worth noting that not every recession—the NBER datings of which are marked in gray in the figure—is associated with financial stress, and not every period of high levels of the FSI is associated with a recession. And finally it is not the case that every headline generating event manifests itself in high stress: the Peso crisis in 1994–1995 generated much discussion, and a great deal of activity at the U.S. Treasury, and yet resulted in scarcely any movement in the FSI. The level of FSI is not a sufficient statistic for assessing economic outcomes; as shown below, it is the interaction of stress with the rest of the economy that is key to understanding the role of stress.

[6] 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.

3. Model specification, estimation and evaluation

The Markov-switching framework employed here is ideal for current purposes, for several reasons. First, and most obviously, it provides a formal framework to investigate the presence of nonlinearities. Moreover, it does so by allowing discrete shifts, which is more appropriate than, say, a time-varying-parameter framework since drifting parameters will be unable to pick up the flight-to-safety phenomena that often occurs in financial markets. Second, it can distinguish between variance switching and coefficient switching. Regime switching in coefficients would suggest either that agents change their behavior during episodes of high financial stress, or that the environment they face is materially different; taken at face value, variance switching suggests that financial crises are a matter of happenstance. And third, the MS-VAR framework allows the investigation of feedback and amplification effects between the real and the financial sector.

The combination of high dimensionality of the model, combined with the relatively short sample of the available data, presents a challenge from an econometric point of view. We address these challenges by employing state-of-the-art Bayesian econometric tools for MS-VAR models, as developed by SWZ (2008). This section lays out the basic model and discusses the methodological approach.

3.1. The model

Consider a (possibly) nonlinear vector stochastic process of the following form:

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

where y is an $n \times 1$ vector of endogenous variables; s^m, $m = \{v, c\}$ are unobservable (latent) state variables, 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—that is, 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:

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

Letting $A_+' = [A_1(k)', A_2(k)', \ldots A_p(k)', C(k)']$ and $x_t' = [y_{t-1}', \ldots y_{t-p}', z_t']$, the model can then be written as

$$y_t' A_0(s_t^c) = x_t' A_+(s_t^c) + \varepsilon_t' \Xi^{-1}(s_t^v), \quad t = 1, 2 \ldots T \tag{3}$$

where T is the sample size. Let us designate $Y^t = \{y_0, y_1, \ldots y_t\}$ as the vector y stacked in the time dimension. Assuming that the structural disturbances are normal, conditional on the state $p(\varepsilon_t | Y^{t-1}, s_t^m, A_0, A_+) \sim N(0_{n\times 1}, I_n)$, the reduced-form system is

$$y_t' = x_t' B(s_t^c) + u_t'(s_t^v, s_t^c), \quad t = 1, 2, \ldots T \tag{4}$$

with

$$B(s_t^c) = A_+(s_t^c) A_0^{-1}(s_t^c) \tag{5}$$

$$u_t'(s_t^v, s_t^c) = A_0'^{-1}(s_t^c) \varepsilon_t' \Xi^{-1}(s_t^v) \tag{6}$$

$$E(u_t(s_t) u_t(s_t)') = (A_0(s_t^c) \Xi^2(s_t^v) A_0'(s_t^c))^{-1}. \tag{7}$$

As can be seen in Eqs. (5)– (7), the reduced form contains structural parameters and shocks that make distinguishing regime switching impossible, whereas it is possible in the structural form, Eq. (3). More important for our application, notice that switching in the coefficients, s^c, imparts switching in the reduced-form residuals, Eq. (7), as does switching in the structural variance-covariance matrix, through s^v. To see the significance of this, consider a model in which only coefficient switching is permitted, so that s^v drops out of equations (6) and (7). There is still time variation in reduced-form shocks and coefficients, (5)–(7), but that variation is inextricably tied by a single Markov process. Now consider switching in structural shock variances only, so that s^c drops out of (5)–(7). In this instance, the reduced-form coefficients, (5), are fixed, but the shocks can vary in an unstructured way.

At one level of abstraction, fitting a Markov switching model is an exercise in giving interpretation and meaning to what, in the context of a single-regime model, would be considered outliers; allowing arbitrary non-normalities in shock processes is a highly flexible way of doing this, whereas coefficient switching is less so. It follows that empirical evidence of coefficient switching is likely to be harder to obtain than for variance switching.[7] It should be clear from Eqs. (4) to (7) that

[7] The importance of this issue is demonstrated by the debate between Cogley and Sargent (CS 2002) and SZ (2006) on the origins of the Great Moderation. CS (2002) argued that “good policy” as captured by drifting in the parameters of their VAR explained the Great Moderation; SZ (2006) showed that the omission of time variation in shock variances could bias results toward shifts in coefficients: “good luck” was responsible. CS (2005) revisited the issue allowing for stochastic volatility, and found “substantial variation” in all contributors, including coefficients. They also showed that tests of the time-invariance of coefficients of VARs in the presence of stochastic volatility have low power.

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 variance switching is not wrongly attributed to coefficient switching; it also follows that a finding of coefficient switching in a model that also allows for variance switching will be a noteworthy outcome.

In December 2008 the Federal Reserve lowered the federal funds rate to the zero lower bound (ZLB) where it remained for the remainder of the sample. The model handles the ZLB bound in two ways. First, and most straightforwardly, the ZLB can be thought of as simply another regime which the model can pick out, if warranted. Specifically, once the ZLB is obtained, the perception, if applicable, that the funds rate can fall no further would be captured by switching in coefficients that would rule out shocks from equations other than the federal funds rate equation resulting in negative values of the funds rate, plus switching in shock variances such that negative shocks to the funds rate do not obtain.[8] Second, there could be a change in the relationship between the federal funds rate and the stock of money either directly because of the ZLB, or because of nonstandard monetary policy measures that stand in for conventional monetary policy. Indeed, this is one reason why money growth is included as a variable in the model. Thus, the model can, in principle, pick out new states to capture the ZLB.

3.2. Estimation and evaluation

To estimate the model, a blockwise optimization algorithm is employed to find the posterior mode. As described in SWZ08, this methodology improves over, for example, the MCEM method proposed by Chib (1996), 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 be sure that the estimated posterior mode is a robust maximum, each (proposed) maximum point is perturbed with both large and small steps to generate new starting points from which the optimization process is recommenced. The posterior modes described in the paper are the peak values obtained from this process.

Two sets of priors are applicable for the model, one for the VAR parameters, the other for the state transition matrix. Following SWZ (2008) the standard Minnesota prior is used for the VAR parameters. However the priors employed for the VAR parameters are weaker than the ones suggested by SZ (2006) for monthly data. For the state transition matrix, the Dirichlet prior is used. The key prior here is the prior probability of remaining in the same state in the next period as in the current period. A prior that is reasonable for the problem under study, is one that does not promote, *a priori*, a finding of more switching in one part of the model over switching in another—in this context, switching in shock variances versus switching in coefficients. Appendix A provides some more remarks on priors.

To evaluate models in terms of goodness of fit, consistent with accepted practice, the marginal data densities (MDDs) of candidate specifications are compared. In this regard, a number of alternative methods have been promoted for computing MDDs, beginning with the standard, modified harmonic mean (MHM) calculation of Gelfand and Dey (1994). It has been established, however, that the MHM computation is not likely to work well with models whose posterior distributions may be far from Gaussian as is the case in the present application. At least three alternatives have been proposed that use weighting functions to approximate the unknown posterior distribution, including the bridge method of Meng and Wong (1996), a method suggested by Ulrich Müller of Princeton University in an unpublished paper, subsequently described in Liu et al. (2011, Section 5.1), and a method by Waggoner and Zha (2012, Appendix B). We found in experiments using artificial data that the method of SWZ (2008) was the most reliable for our purposes.[9]

4. Macro-financial linkages and financial stress

The focus in this paper is on five-variable MS-VARs identified using the well-known Choleski decomposition. In particular, let $y_t = [C\ \ P\ \ R\ \ M\ \ S]'$ where C is the monthly growth in personal consumption expenditures (PCE); P is CPI inflation, excluding food and energy prices (hereinafter, core inflation); R is the nominal federal funds rate; M is growth in the nominal M2 monetary aggregate; and S represents 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 2011:12.[10]

Three questions are of primary interest: first, whether there are periods of high financial stress, and if those periods are marked by different dynamics than more normal times; second, if there is evidence of regime switching, whether it is confined to variance switching, as SZ (2006) find in a different context, or whether differences in economic behavior, as captured by coefficient switching, better explain the data; and third, whether any regime switching is confined to specific

[8] Sveriges Riksbank, the central bank of Sweden, established that the nominal policy rate can be less than zero when it reduced the deposit rate to −0.25 percent in July 2009.

[9] The W-Z method is designed to reduce the sensitivity of the MDD computations to the construction of the weighting matrix by taking into account the overlap between the weighting function and the posterior distribution.

[10] The limiting factor in taking the data back further in history is the financial stress index. No meaningful extension of the index further back in time is possible without unduly narrowing the composition of the FSI.

Table 3
MS-VAR estimation results.

Model – >	[1] 1*v*1*c*	[2] 2*v*1*c*	[3] 3*v*1*c*	[4] 1*v*2*c*	[5] 2*v*2*c*	[6] 3*v*2*c*
(a) General models						
MDD	−2569.7	−2438.4	−2425.0	−2464.7	−2366.9	−2349.1
Diff. from best	*−220.6*	*−89.3*	*−75.9*	*−115.6*	*−17.8*	*0*
Posterior density	−2286.9	2213.8	−2113.6	−2169.2	−2076.2	−2047.6
Model – >	[7] 3vS2c	[8] 3vSC2c	[9] 3vSCP2c	[10] 3vSRM2c	[11] 3vRM2c	[12] 3vRMC2c
(b) Restricted models						
MDD	−2438.1	−2397.1	−2370.4	−2408.4	−2438.1	−2383.5
Diff. from best	*−89.0*	*−48.0*	*−21.3*	*−59.3*	*−89.0*	*−34.4*
Posterior density	−2115.8	−2102.5	−2055.1	−2098.5	−2067.2	−2078.0

Notes: Marginal data densities (MDDs) and posterior modes are in logarithms.

equations—such as the stress equation alone, or the monetary policy response to stress—as opposed to applying to all equations.

With regard to model selection, Bayesian econometrics lends itself to model assessment on the basis of comparing the marginal data density (marginal likelihoods) of alternative models. Comparisons of this nature are reported, but we emphasize broader criteria for model selection, placing 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.

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

At this point, it is useful to introduce a bit of notation in order to facilitate the presentation of results. Let us designate $\#v, \# = 1, 2, 3$ to indicate the number of independent Markov states governing *variance switching*, and $\#c$ to indicate the number of states governing *coefficient switching* (that is, slope and intercept parameters). Also, when shifts in structural parameters are constrained to a particular equation(s), the restriction is indicated by prefixing the letter of the variable, $l = \{\}, C, P, R, M, S$, with $\{\}$ representing a null entry. So, for example, an MS-VAR with two Markov states in the variances and two in coefficients with the latter restricted to the financial stress variable would be designated as $2vS2c$.

The results are summarized in Table 3. Focus, for the moment, on panel (a) which shows outcomes for "general models", in which switching is entertained in all equations but could be in either variance switching alone or in variances and coefficients. The first line of the panel shows the MDDs. The second line reports the difference in MDD for the applicable model from that of the best fitting model in the same table. The third line is essentially a reference item that shows the rankings of models by posterior mode thereby allowing the reader to see whether the method we employ for computing MDDs materially affects the ranking: it does not.

There are a number of interesting observations that can be taken from panel (a). First, a model with constant coefficients and constant shock variances, the $1v1c$ model, shown in column [1]–is not favored by the data: extensions of the model to add a second state in variances—column [2]—or in coefficients—column [4]—improve 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, or a non-Gaussian one, or both. Second, while Stock and Watson (2012) using a dynamic factor model, argue that the Great Recession arose from an unusual sequence of shocks, the results shown here suggest, with some assurance, that allowing for coefficient switching is beneficial, a result demonstrated below to be robust.[11] The comparison of the $2v1c$ model in column [2] with that of the $2v2c$ model in column [5] provides an example: the improvement in fit from adding switching in coefficients is of the order of 60 in terms of log MDDs, which is very large; by comparison, adding a third Markov state for variances, as in column [3], improves the fit only in relatively small ways. Thus, the transmission of crises is not merely a non-Gaussian phenomena, but a non-linear one as well. Third, of the models shown in panel (a), the best model, on goodness-of-fit criteria, is the $3v2c$ model, shown in column [6].[12]

4.2. *Whence switching: is it just in stress or everywhere?*

We now turn our attention to models with coefficient switching restricted to certain equations, and compare their goodness of fit to the $3v2c$ base case. Financial crises could be associated with different financial sector behavior, but with

[11] The Stock and Watson (2012) approach has the advantage of taking into account a wider range of information than we use, but does not formally account for nonlinearities as in our model.

[12] Based solely on MDD computations, an even more elaborate model, the $3v3c$ specification, is better still, albeit only slightly. However, the $3v3c$ model's economic dynamics are difficult to interpret. And, unlike the models shown in the table, the ranking of models based on the posterior densities does not accord with the rankings by MDDs for the $3v3c$ specification.

macro and policy responses unchanged; or it could be that changes in financial sector behavior induce changes in monetary policy, but the real side of the economy responds normally; or something else.

An assortment of restricted models was entertained, the most relevant of which are summarized in panel (b) of Table 3. The primary focus here is on restrictions of coefficient switching to the financial stress equation, either alone, *S*, or in combination with the real economy, *SC*; or in combination with monetary policy, *SRM*. 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 because consistency in policy is important, or does it switch to a policy that is germane to the conditions of the day? If the former is the case, switching will be observed in the *S* equation but not in the policy equations; otherwise both sets of equations will exhibit switching. Finally, cases were explored of switching in monetary policy either alone, *RM*, or in policy and the real economy, *RMC*.

Panel (b) shows that the data strongly favor switching in all equations, over the restricted specifications. This means that the dynamics of monetary policy have differed over recent monetary history, and these changes have coincided with changes in financial stress and other variables. 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, 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.

Omitted from formal presentation here are results for models that restrict shock variance switching to subsets of equations. These results consistently supported the conclusion that models embodying such restrictions were inferior, in terms of goodness of fit, to unrestricted alternatives. This outcome buttresses the argument, advanced in Section 3.1, that it might be the flexibility of (unrestricted) variance switching that allows it to "push out" coefficient switching as a source of time variation in the data. That coefficient switching turns out to be helpful in explaining the data even in the presence of unrestricted variance switching is thus all the more noteworthy.[13]

4.3. *The economic history of stress: state probabilities*

Fig. 2 below shows the (smoothed, or two-sided) estimated state probabilities for shock variances for the preferred 3*v*2*c* specification, which we treat as our base case. As can be seen, what could be called the *high-stress variance state*, shown in the bottom panel, is not a common one, although there are periods other than the crisis of 2008–2009 that are identified. The first cluster of high-stress variance states begins in December 2000 when the tech-stock boom was cresting and ends in September 2001; the second has a spike in February 2008, when Northern Rock was nationalized by the British government, and another in September 2008, the month that Lehman Brothers declared bankruptcy.

Of greater interest is the probability of being in a *high-stress coefficient state*, because to be in such a state suggests fundamental differences in economic behavior—differences in the transmission of crises—as opposed to just enhanced volatility. As shown in Fig. 3, there have been perhaps six periods of high stress in coefficients. The first is a cluster in the early part of the sample beginning in July 1990 with German reunification and ending in February 1991, at the end of the Persian Gulf war. The second begins in July 1992 and lasts until November 1992, around the time when Britain and Italy were forced by speculative attacks off of the European Exchange Rate Mechanism. The third period, in 1998, corresponds with the Russian debt default and the collapse of Long-Term Capital Management. The fourth period, two short-lived spikes in November 2002 and July 2003, matches up well with the aftermath of the Argentine debt default, or perhaps the bankruptcy of Worldcom, while the fifth, which begins in August 2007 and ends in April 2009, is the period of the 2008–9 financial crisis and associated recession. Of note is that former date, August 2007, matches exactly the beginning of the run on the repo market described by Gorton (2010), while the latter date corresponds with the leaking of the results of U.S. bank stress tests. Finally, there is a short-lived spike beginning in June 2011 which lines up with a variety of developments in the European sovereign debt crisis. Overall there are 4 periods in which a medium- or high-stress variance state prevailed *and then* the economy transitioned into the high-stress coefficient state: September 1998, July 2003, August 2007 and June 2011, all dates of prominence in U.S. financial history. There are no periods during which a high-stress coefficient state preceded a jump in the shock variance state to medium or high stress from a lower level.[14]

Taking Figs. 2 and 3 together helps us understand the Great Recession. Fig. 2 portrays the period from 2004 to 2006 as a lengthy stretch of the low-stress variance state (the upper panel of the figure); Fig. 3 shows that this was also a period in which the coefficient state was low stress as well. Fig. 1 says that this was also the period in which the FSI itself was at a very low level—and showed little variation over time. In addition, the level of interest rates was very low and stable. It is commonly alleged that financial firms began "chasing yield" in response to this state of affairs, increasing leverage in order to magnify returns; see, e.g., Geanakoplos (2010). Back on Fig. 2, the economy then transitions in late 2006—about the time that prices of existing homes at the national level crested—to the medium-stress variance state (the middle panel). The crisis

[13] Also of interest is the fact that models that restrict variance switching to the monetary variables are not favored by the data, as was the case for switching in the coefficients for those equations. This suggests that the Fed's nonstandard policy measures—large-scale asset purchase programs, interest on required reserves, and maturity extension and reinvestment policies—do an adequate job of standing in for conventional policy. Or it could simply mean that the period of the ZLB is too short to be picked out of the data.

[14] A comparison of Figs. 1 and 3 reveal that it is *not* the case that one need only observe a high level of the FSI to conclude that one is in a high-stress coefficient state, or vice versa. It is the joint behavior of the system that determines the Markov state.

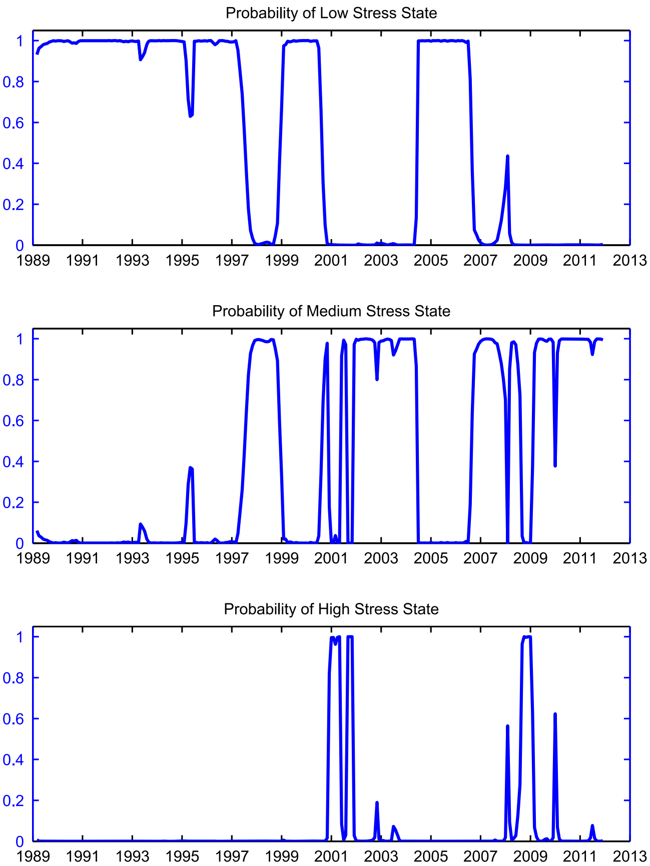

Fig. 2. Probabilities of shock variance states, smoothed estimates, 3*v*2*c* model specification.

begins in earnest when the economy transitions in August 2007 to the high-stress coefficient state and finally reaches full bore in September 2008 when the variance state also jumps to high stress (the lower panel of Fig. 2). All this leads to a proposed definition of a *stress event*: when the shock variance state is *either* medium or high, *and* the coefficient state is high. As can be seen in Fig. 4 below, this definition eliminates the periods of high-stress coefficients in the early 1990s at which time there was apparently insufficient turbulence to create severe difficulties for the real economy (although there was a mild recession). Also omitted from this status is the September 11, 2001 attacks and the associated extraordinary provision of liquidity by the Federal Reserve that followed those attacks.

4.4. *Real-time properties*

As we noted, the FSI was constructed and used by the Fed staff in real time during the financial crisis. Fig. 5 looks at the real-time efficacy of the index, showing with the lighter, cyan-colored lines, the real-time estimates of the state probabilities for the high-stress coefficient state; that is, the probability measured at each point in time based on information up to the current period.[15] Two noteworthy conclusions may be drawn from this figure. First, the switches in coefficients indicated in ex post data, the black line, were revealed in the real-time estimates, the colored lines; that is, false negatives are negligible. Second, while there are hints of false positives—for example in 1996 and 2002—at no time did the real-time data adamantly call for a switch that was rescinded, ex post.[16] All in all, we would argue that the model does remarkably well in real time.

[15] These are *quasi*-real-time estimates. There is no complete set of real-time data that would allow a full real-time assessment. That said, the FSI and the core CPI are not subject to revision. The money and real PCE data are subject to revision however.

[16] Charts of the real-time performance of the variance states are broadly similar.

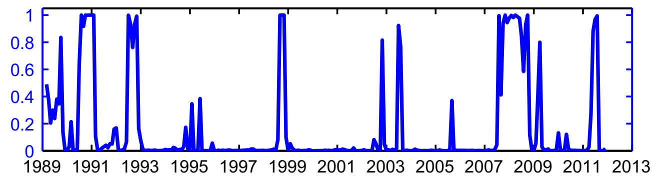

Fig. 3. Probability of high-stress coefficient state, smoothed estimates, 3*v*2*c* model specification.

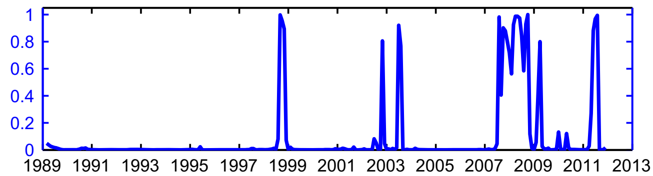

Fig. 4. "Stress events" in recent U.S. economic history, defined as high-stress coefficient states coincident with high- or medium-stress shock variance states.

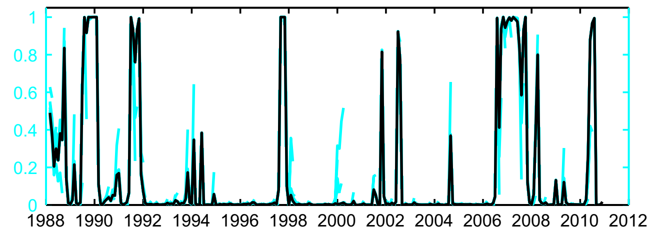

Fig. 5. Probability of high-stress coefficient state, quasi-real-time estimates (lighter tone), and ex post (black).

5. Some interpretation of results and their robustness

The objective in this section is three-fold: first, to provide some interpretation of the structural mechanisms that are likely behind the results just discussed, mostly through an investigation of the real macro variable that was used; second, to report on experiments that show the value-added of the FSI; and third, to discuss experiments that demonstrate the robustness of our results to alternative measures of stress. The economic properties of the base case model are discussed in Section 6. In order to conserve on space, the discussion here will be brief; most of the results are relegated to Appendix B.

5.1. The real variable: investment, durable goods and labor market variables

A common narrative in discussions of the Great Recession is the connection between financial stress, credit availability and expenditures, particularly expenditures on goods for which credit is seen as a strong complement, such as consumer durables, housing and business fixed investment. Sometimes the story is told in terms of the amplification and propagation of shocks because of costly state verification and associated leverage constraints, as in Bernanke et al. (1999). In other frameworks, it is collateral constraints that matter. For example, Chaney et al. (2012), and Liu et al. (2013), describe empirically and model structurally, respectively, how the value of real estate played a role in the decline of business fixed investment during the Great Recession.

One way to cast light on this mechanism is to study how well the model works for real variables other than PCE, in particular, for classes of durable goods. For this and a number of other exercises described in this section, it is necessary to specify the basis for comparison of the results with those of the base case. For us, the fact that the estimated dates of coefficient switching coincide with known events in U.S. economic and financial history is compelling and so we rely on comparisons of smoothed coefficient state probabilities of selected alternatives, compared with the base-case results, shown in Fig. 3. To begin, growth PCE is split into growth in durables and growth in nondurable goods and services plus footware. Fig. 6 shows the smoothed high-stress coefficient state probabilities for these two series, alongside our aggregate PCE base case. Note that the figure uses offset vertical scales so that the precise dates of climbs and falls of probabilities can be distinguished.

As the figure shows, PCE durables picks up many of the same key switching dates as does the base case, while nondurables performs less well. Section B.5.1 of Appendix B demonstrates that this is not unique: broadly similar results obtain for a monthly interpolated version of investment in equipment and intangibles. Taken together, these results suggest

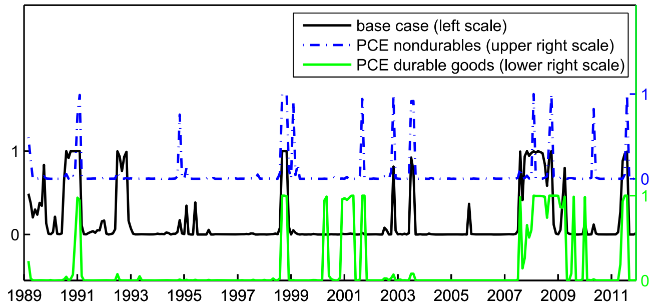

Fig. 6. Probability of high-stress coefficient state, with real variable PCE nondurables, services and footware (dot-dashed blue line, upper-right scale), PCE durable goods (lighter green solid line, lower-right scale) and the base case total PCE (black solid line, left scale). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

to us that the role of nonprice rationing of credit, defined to include collateral constraints, and its role in durable goods expenditures, is central in propagating financial crises.

Another conventional story of the Great Recession is that extraordinary dynamics in labor markets were in play, either through mismatch in employment, perhaps connected with the sharp decline in construction and finance industries, or more generally in the outsized drop in employment, relative to output, and an associated rise in precautionary saving. To examine this proposition, the model was re-estimated substituting each of the unemployment rate, growth in payroll employment and unemployment insurance claims as the model's real variable.[17] Results for all three cases, by our metric, were universally inferior to the base case.

5.2. The stress index: composition and construction

In an attempt to identify which aspects of the FSI are critical to the base-case results, and thereby cast some light on the stories conventionally offered to explain the transmission of crises, two broad classes of investigation were carried out, one regarding the weighting of the components of the FSI, the other regarding its composition. On the logic that financial stress is only important when it is systemic, one might argue that instead of weighting the components in the *ad hoc* way that the FSI does, a method that chooses weights to explain the maximum amount of variation of the nine components collectively would be efficacious. To test this, the index was reconstructed using the first principal component of the constituent parts of the FSI. The results from substituting this measure were very similar to those of the base case. All told, this tells us, first, that the FSI's ability to capture the phenomena of interest is not an artifact of the construction of the index, and second, that the *ad hoc* weighting of the FSI turns out to have been a good one.

For the second class of experiments, financial stress indexes were explored that excluded one of five blocks of components of the FSI. These five blocks were risky bond rate spreads (rows 1 and 2 of Table 2), the term spread (row 3), implied bond rate volatilities (rows 4 and 5), on-the-run premiums (rows 6 and 7), and equity market factors (rows 8 and 9). The results of the base case were largely unaffected by exclusion of the term spread, implied bond-rate volatilities, and on-the-run premiums, and that there were some modest differences from excluding the equity premium. The more interesting differences, for a variety of reasons, were obtained from exclusion of the risky spreads.

Of the variables that comprise the FSI, risky spreads exhibit the highest correlation with the aggregate FSI; thus, it would not be surprising if these variables turned out to be critical for our findings. There are, moreover, results showing that default premiums on bonds are predictors of financial distress, with a nascent literature on the proper measurement of these premiums; see, e.g., Gilchrist and Zakrajšek (2012). To address this issue, two additional models were estimated focussing on an index of risky spreads (hereinafter, *sprd*), created from the first two components of the FSI shown in Table 2, one in which *sprd* was *excluded* from the FSI, and the other where *sprd* was *substituted* for the FSI. The results, which appear in Appendix B, show that omitting *sprd* from the index results is a fairly substantial deterioration in estimated probabilities of high-stress coefficient state, missing some key events in history, underestimating the duration of the 2008–2009 event and posting a false positive at the turn of the century. Thus, the inclusion of *sprd* is necessary for the base-case results. The model with *sprd* alone suggests substantially fewer period of high-stress coefficients and, more importantly, misses the onset of the 2008–2009 financial crisis by several months. We conclude that risky spreads alone are insufficient to pick up the information contained within the FSI.

Finally, the proposition of whether the FSI is even necessary to obtain results similar to our base case, or whether the FSI alone is sufficient, was investigated. To summarize, in the case of systems that included macroeconomic variables, but omitted stress, the model tended to pick up switching somewhere during the 2008–9 episode, but not much of anything

[17] The Great Recession was marked by a more substantial decline in labor markets than in GDP. It seems plausible—if beyond the scope of this paper—that relatively low frequency movements in labor market conditions exacerbated the duration of the switch to the high-stress coefficient state in 2008.

else. In the complementary case of stress alone, a substantial deterioration of model performance was uncovered: macroeconomic variables are important for the results. These cases are described Section B.4 of Appendix B.

6. The transmission of financial stress

To illustrate some properties of the model and provide some historical perspective, two classes of simulations of the model are considered. The first are counterfactual simulations, some of which are designed to illustrate the unique features of the model in a compact and intuitive fashion, others are set around the 2008–2009 financial crisis, for historical reference. The second class of simulations are conditional forecasts initiated from the end of the sample period. These exercises provide much of the same information as do impulse responses except more compactly, and in a more intuitive and historically appealing context.

Markov switching aside, the unique aspect of the model is the financial stress index. To illustrate how financial stress affects the economy, two counterfactual simulations involving alternative paths for stress (S in the figures), are carried out, one during a period when the latent state is one of low stress, the other from more strained conditions.

Fig. 7 shows the effects of an autonomous increase in stress during a low-stress period in July 1989. The noteworthy aspects are two-fold: first, the monetary response is slight, with the federal funds rate (R) falling only marginally, relative to the historical data. The implications for real activity, measured here by growth in personal consumption expenditures (ΔC) in the upper-left panel are relatively small and short lived. Thus, this exercise ratifies our assertion that financial stress has been underappreciated through much of economic history as an important factor in the transmission of business cycles because in normal times—that is, through the bulk of history—stress has not been a major driver of events.

Fig. 8 carries out a broadly similar exercise, this time from August 1998, during the Russian debt default and associated collapse of LTCM. In the data, S climbed rapidly and substantially with the onset of the crisis; the counterfactual imagines that stress had instead remained low. Unlike in Fig. 7, in this instance there is a substantial monetary policy response, offsetting the expansionary implications of the lower level of stress. The implications for real activity end up being quite modest. What this says is that monetary policy, *when it has the capacity to do so*, is well disposed to respond to increases in stress, holding constant the stress regime, *when those increases are moderate and temporary*, as was the case in 1998. Arguably, actions by the Federal Reserve to elicit an orderly reorganization of LTCM ensured that this stress event was brief, and monetary policy defined in terms of setting the federal funds rate was in a position to ease. The contrast with the 2008–2009 financial crisis is fairly stark. The shock in the latter instance was larger, as shown in Fig. 3, the stress event lasted longer, and conventional monetary policy was limited in its ability to respond.

Let us now turn to the recent financial crisis and consider counterfactual changes in regime. Model estimates show, and Fig. 9 confirms, that a stress event began in the second half of 2007. The economy had already switched to the medium-stress variance state late in 2006—by itself not a big deal but sometimes a precursor to worse things—followed by a persistent switch to high-stress coefficients in October 2007; then, in September 2008, the state switched to high-stress variances together with the already high-stress coefficients. Fig. 9 poses the question, what would have happened, according to the model, if the state had remained in the low-stress coefficient state?

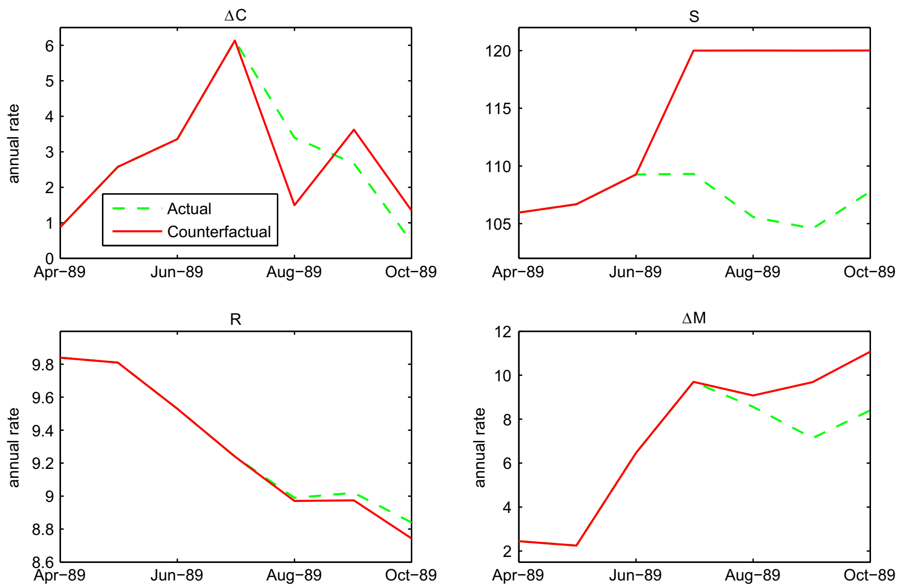

Fig. 7. Counterfactual experiment where financial stress, (S), rises to 120 in July 1989, a normal-times period, base-case $3v2c$ specification.

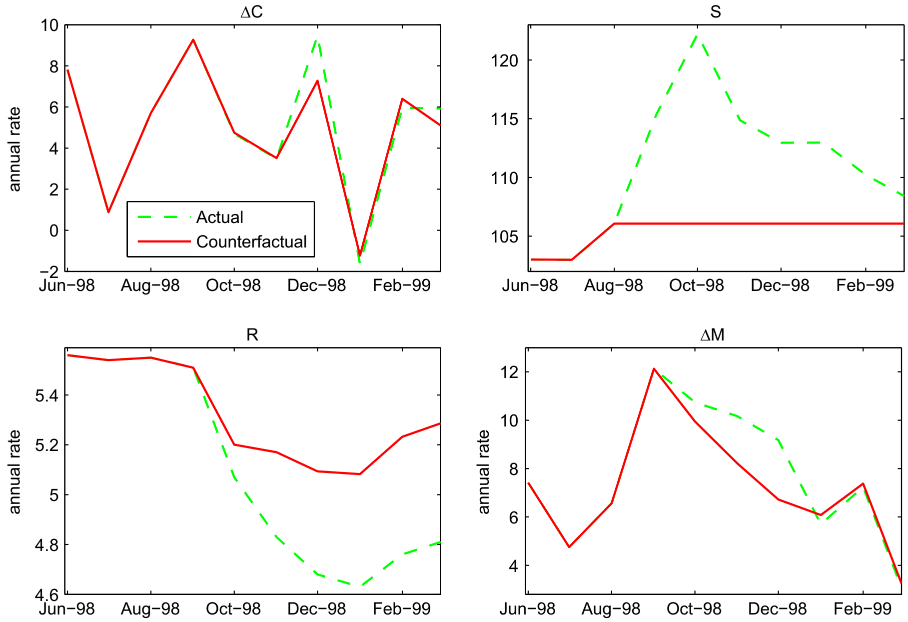

Fig. 8. Counterfactual experiment where financial stress, (S), is held at its August 1998 level, high-stress coefficient state, base case 3v2c specification.

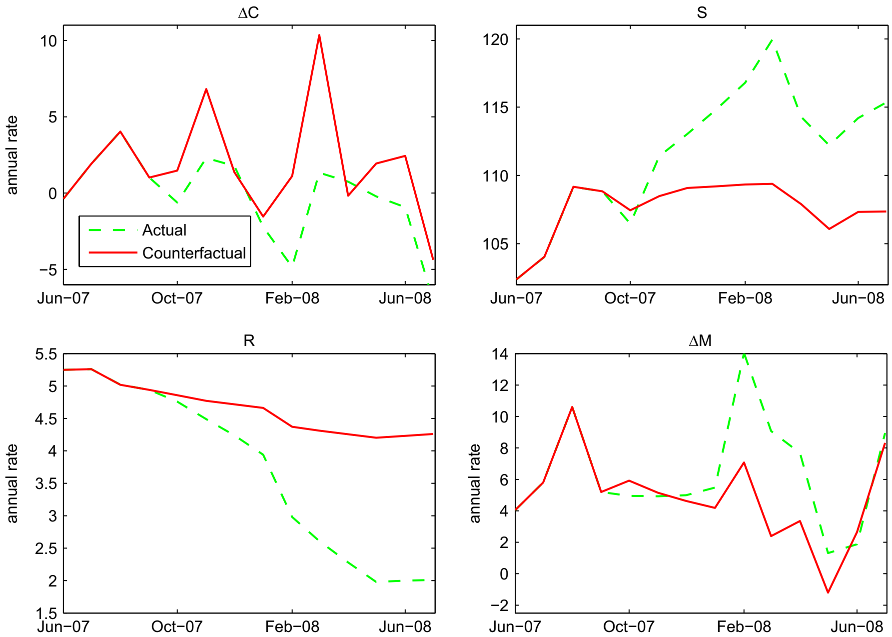

Fig. 9. Counterfactual experiment where the latent state returns to the low-stress coefficient state in October 2007, base case 3v2c specification.

We allow all the shocks borne by the economy to remain in play; the only thing that is counterfactual here is the set of coefficients through which those shocks play out. The figure shows that financial stress itself (S), would have been much lower than otherwise; this, in turn, would have obviated the need for very easy monetary policy, so that the federal funds rate (R) ends up about 2-1/2 percentage points higher than in history by mid-2008, and money growth would have been lower.[18] Tighter monetary policy notwithstanding, real growth would have been notably stronger than the historical experience. Clearly, the implications for the economy of a persistent, adverse switch in Markov states—that is, a stress event—are substantial.

[18] Inflation, not shown here, would have been higher in this scenario. We omit that panel of this and other charts, to keep the figure compact.

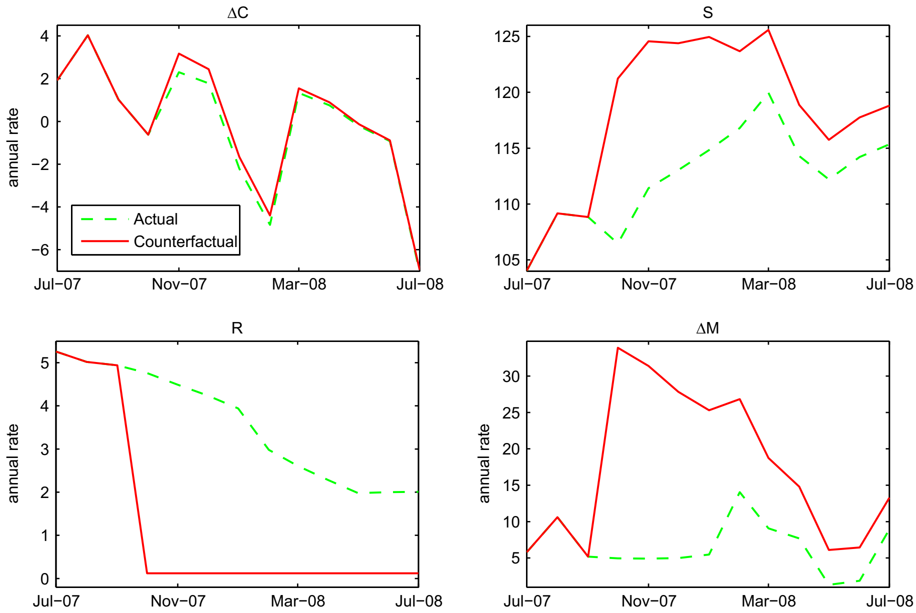

Fig. 10. Counterfactual experiment where the federal funds rate, (R), falls to 0.12 percent in October 2007, base case 3v2c specification.

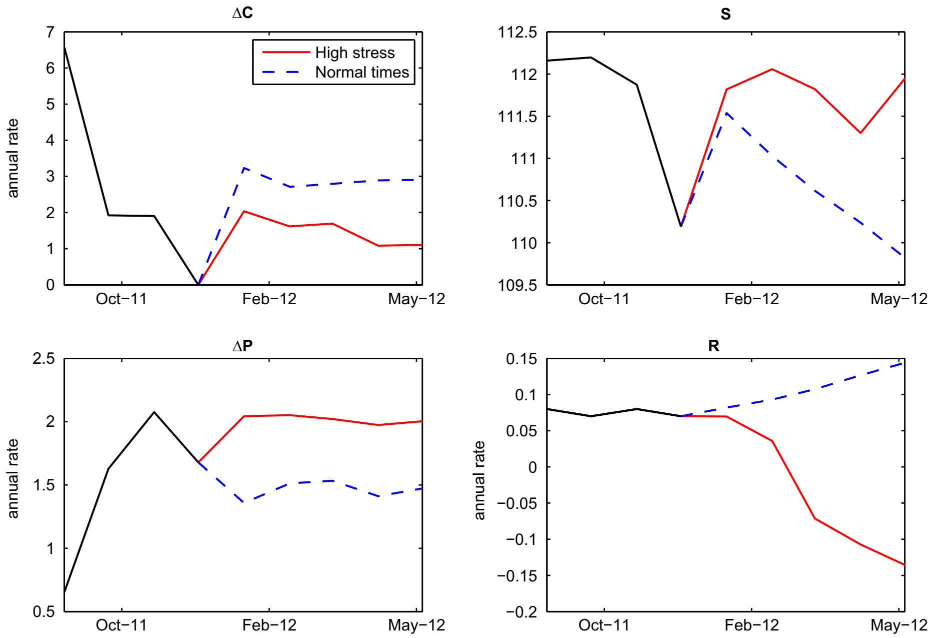

Fig. 11. Model forecast, conditional on the state, from 2011:12, base case 3v2c specification. High-stress coefficient state (red solid lines) versus low-stress coefficient state (blue dashed lines). (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

Fig. 10 considers a different counterfactual carried out over the same period beginning in October 2007. The experiment is to suppose that the Federal Reserve could have foreseen the grave conditions that were to come and thus immediately reduced the federal funds rate to the de facto zero lower bound of 0.12 percent.

As can be seen from the bottom-left panel, this is a large intervention, which induces a very large increase in money growth, the bottom-right panel. The effect on real activity is relatively small, however. The upper-right panel gives an indication of why this is so: financial stress *rises* measurably and persistently with the policy intervention. Evidently, in high-stress situations, agents regard conventional policy actions that would normally be beneficial as confirmation of incipient financial difficulties. The resulting higher levels of stress choke off the salutary effects of easy monetary policy. This observation may help explain why the recessions caused by financial crises tend to be long lasting; see, e.g., Reinhart and

Rogoff (2009). It is important to recognize that this result is germane to stress events: in normal times, a surprise reduction in the federal funds rate reduces financial stress, as one might expect. These results suggest that conventional monetary policy interventions, in the absence of actions to alleviate the fundamental causes of the stress event, or actions to arrest increases in financial stress, will only be modestly helpful for economic performance. At one level, this should not be surprising: it is received wisdom in economics that would-be policy cures should be tailored to the ultimate causes of the problem as opposed to the symptoms that those causes engender.

Finally, we turn to our second class of experiments, conditional forecasts that illustrates the importance of latent state for economic outcomes. These conditional forecasts are carried out, as were the counterfactuals described above, using the base-case model; however Section 5 (and Appendix B) show that similar results obtain when durables are used as the real variable. Fig. 11 shows two forecast paths beginning immediately at the end of our sample in 2011:12, one (the red solid line) conditional of a high-stress regime in both coefficients and variances, the other (the blue dashed line) on a low-stress regime in both coefficients and variances. All else is held constant, and unlike in the counterfactuals, there are no shocks in the simulation period.

As can be seen, PCE growth is much weaker in the high-stress world and this low growth is accompanied by elevated levels of financial stress, particularly in comparison with the low-stress world. Of significance is that the high-stress state is associated with *higher* price inflation than in the low-stress state, a finding that is consistent with the identification of a stress event as a negative supply shock that reduces real output and puts upward pressure on prices, all else equal, an interpretation that is in line with that of Jermann and Quadrini (2012) and de Fiore and Tristani (2013). All else is not equal here: monetary policy, as measured by the federal funds rate (or the growth rate of M2, not shown) is easier in the high-stress world than otherwise; but consistent with the interpretation of reduced potential output, this easy monetary policy is seen as something of a palliative that reduces the pain only modestly.

7. Conclusions

This paper has considered the implications of financial stress for the macroeconomy using a richly specified Markov-switching vector autoregression model, estimated with state-of-the-art Bayesian methods, and exploiting a unique series for financial stress constructed and used in real time by the staff of the Federal Reserve Board.

Our analysis showed substantial evidence that a single-regime model of the macroeconomy and financial stress is inadequate to capture the dynamics of the economy. The results demonstrated that there have been periodic shifts not just in the stochastic shocks that have buffeted the economy, but also in the dynamic propagation of shocks, with all equations of the model showing evidence of switching. It follows that inference regarding the conduct of monetary policy that is gleaned from a constant-parameter Gaussian model may be inappropriate for periods when the policy is conditioned on movements in financial stress.

Quantitatively, we found that output reacts differently to financial shocks in times of financial stress than in normal times: stress is of negligible importance in ”normal” times, but of critical importance when the economy is in the high-stress coefficient state. Our findings also show that an important precursor to particularly adverse economic events is a switch to what we call a stress event: a period in which the latent state for shock variances is relatively high and the latent Markov state for coefficients is also at a high-stress level. It was also shown that the Federal Reserve Board staff's use of the financial stress index described in this paper appears to have been an efficacious choice.

Lastly, in digging deeper into the results, we uncovered an interpretation emphasizing risky spreads as a key component of financial stress on the one hand, and durable goods as a real variable, on the other. This suggests to us that structural models aimed at explaining the phenomena studied in this paper would be well advised to assign a prominent role to perceptions of default risk, their role in eliciting occasionally binding constraints on lending, and contagion across markets and over time.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at http://dx.doi.org/10.1016/j.jmoneco.2014.09.005.

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