

# Financial Stress and Economic Dynamics the transmission of crises

## unpublished appendix

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### Abstract

Included here are two appendices. Appendix A has information on model priors, selected material on the data, and some details on computation. Appendix B contains an extended treatment of alternative measures of stress, and alternative measures of real activity, including how these measures compare to the base case model in terms of picking up the same state probabilities and, in some cases, qualitative discussions of how they forecast out of sample.

- **JEL Classification:** E44, C11, C32.
- **Keywords:** nonlinearity, Markov switching, financial crises, monetary policy. transmission

## Appendix A

This appendix is devoted to the base case estimates summarized in the main text. It contains information on model priors, the data used and aspects of computation. Appendix B follows, and includes a discussion of alternative results, robustness of our estimates, and related issues.

### A.1 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:

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

The priors that apply to switching are a little 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. The matrix  $A_+$  can be rewritten as

$$A_+(s_t) = D(s_t) + \hat{S} A_0(s_t) \text{ where } \hat{S} = [ I_n \quad 0_{(m-n) \times n} ] \quad (.1)$$

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 defining  $B$  in the main text, namely equation (5):  $B(s_t^c) = A_+(s_t^c)A_0^{-1}(s_t^c)$ , 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:

$$p(P) = \prod_{k \in H} \left[ \frac{\Gamma(\sum_{i \in H} \alpha_{ik})}{\prod_{i \in H} \Gamma(\alpha_{ik})} \right] \times \prod_{i \in H} p_{ik}^{\alpha_{ik}-1} \quad (.2)$$

where  $\Gamma(\cdot)$  is the gamma distribution. 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.

For our baseline specification, we use priors that are well-suited for a monthly model. In particular, we specify  $\mu_k$   $k = 1, 2, \dots, 6 = \{0.57, 0.13, 0.1, 1.2, 10, 10\}$  and Dirichlet priors of 5.6 for the two coefficient states and 11.33 for the three shock variance states. With the values of  $\mu_k$  we

begin with what Sims and Zha (2006) suggest for monthly data, except  $\mu_1$  where we use a lower number, and  $\mu_2$  which is slightly higher. The value for  $\mu_1$  reflects that we are interested less in shrinkage toward the random walk and more for allowing persistence. The Dirichlet priors we use are looser than what would be usually used for monthly data. They imply an 85 percent prior probability, for both shock variances and coefficients that the economy will, in the next period, continue in the same state as it is in the current period. This strikes us as a fairly low probability, consistent with the notion that shifts are associated with jumps in asset prices.<sup>1</sup>

## A.2 Robustness of priors selection

In broad terms, our preferred model is resilient to moderate changes in model priors. For example, if we alter the priors governing VAR coefficients that we used following SZ (2006) with alternatives, such as those that SZ (2006) recommend for a quarterly model, we get, once again, several 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.

## A.3 Data transformations

As noted in the main text, we use levels of the federal funds rate and the stress index and growth rates of real personal consumption expenditures (PCE), money and prices. Unit roots tests on the stationarity of these growth rates tend to be mixed, with many tests unable reject the null hypothesis of a unit root. The sole exception is money growth where the bulk of the tests reject the unit root. Similar criteria were used for data transformations of the alternative real variables that are summarized in Appendix B below.

## A.4 More on the data

In the main text, we noted without proof that the risky spreads were the components of the FSI that bore the highest correlation with the index itself, and more generally that the components of the FSI are correlated, sometimes strongly so. Table A.1 shows the correlation matrix. The final row of the table shows the correlation of the components with the index as a whole. Indeed, the risky spreads, *AA* and *BBB*, stand out as being highly correlated with the FSI as a whole, followed by the *VIX* and then several of the liquidity premiums.

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<sup>1</sup> There are a number of methods outlined in the literature for computing MDDs when the posterior distribution is likely to be far from Gaussian. The alternatives are all based on constructing weighting distributions as initial approximations from which the posterior distribution can be computed. The method of Waggoner and Zha (2011) that we used 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.

**Table A.1**  
**Correlation coefficients on components of Financial Stress Index\***

	risky spreads		term slope	implied volatilities		on-the-run premiums		equity prem.	
	<i>AA</i>	<i>BBB</i>	<i>ff - 2yr</i>	<i>Tbond</i>	<i>pbond</i>	<i>10 liq</i>	<i>2 liq</i>	<i>equity</i>	<i>VIX</i>
<i>AA spread</i>	1								
<i>BBB spread</i>	0.94	1							
<i>ff - 2yr slope</i>	0.27	0.15	1						
<i>Tbond volatility</i>	0.53	0.61	-0.20	1					
<i>pbond volatility</i>	0.67	0.73	-0.12	0.86	1				
<i>10 - yr liquidity</i>	0.69	0.75	-0.04	0.56	0.57	1			
<i>2 - y liquidity</i>	0.22	0.21	0.25	0.06	0.04	0.28	1		
<i>equity premium</i>	0.55	0.47	0.14	0.24	0.52	0.09	-0.30	1	
<i>VIX</i>	0.76	0.77	0.25	0.55	0.64	0.67	0.32	0.20	1
<b>FSI</b>	<b>0.92</b>	<b>0.93</b>	<b>0.28</b>	<b>0.69</b>	<b>0.81</b>	<b>0.75</b>	<b>0.33</b>	<b>0.49</b>	<b>0.85</b>

\* Variables appear in the same order as in Table 2 of the main text.

### A.5 On the estimated state probabilities

To provide further justification for our selection of the  $3v2c$  specification as the preferred one, consider Table A.2 which shows the estimated transition probabilities taken from the posterior mode of the distribution for selected model specifications. By comparing the first and third lines of the table, we see that the introduction of a second state in coefficients to what would otherwise be the  $3v1c$  model changes the probabilities of the variance states quite dramatically. This finding illustrates the fact that switching in shock variances and switching in coefficients are rivals in explaining the data; as SZ (2006) have emphasized, failing to account adequately for one will bias estimates of the other. The fact that the  $2v2c$  model and the  $3v2c$  model are economically similar is demonstrated by the fact that the state probabilities that the two models have in common does not change markedly with the introduction of the third state in variances. In both specifications, it is the case that the high-stress coefficient state is short-lived in duration, on average. The severity of the 2008-9 episode is therefore marked by two unusual phenomena by historical standards: the fact that the high-stress coefficient state lasted as long as it did, and the fact that it was also associated with a period of high-stress shock variances. Figure 4 in the main text showed our estimates of stress events defined in this way. That figure revealed that the early sample periods of high-stress coefficients were not terribly consequential in macroeconomic terms because they were not associated with shock-variance regimes that were conducive to widespread contagion.<sup>2</sup>

<sup>2</sup> Campbell *et al.* (2013) show that default spreads—which are a part of the FSI—have regime-switching like properties for asset returns in that modest levels of volatility are good for stockholders, because they are the residual claimants on firm assets, but once volatility gets large, the effect switches sign, because the viability of the firm comes into question. This characterization of conditional dynamics is very much in the spirit of the findings in this paper.

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**Table A.2**  
**Estimated transition matrix**  
(posterior mode)

model	variances			coefficients	
	$q_{hh}^v$	$q_{mm}^v$	$q_{ll}^v$	$q_{hh}^c$	$q_{ll}^c$
<i>3v1c</i>	0.80	0.89	0.89	-	-
<i>2v2c</i>	-	0.92	0.95	0.76	0.95
<i>3v2c</i>	0.83	0.93	0.97	0.73	0.95

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## A.6 Computation

In our MCMC computations, we use 100,000 proposal draws and 500,000 posterior draws, net, retaining every tenth posterior draw in order to minimize correlation across draws. A Markov-switching Bayesian VAR can have a very non-Gaussian likelihood surface, with multiple peaks and ridge lines. To ensure that our solutions are robust, we explored the parameter space by doing random global perturbations first with relatively larger perturbations, and then, once the neighborhood of the posterior mode is found, with smaller perturbations. When those perturbations direct the algorithm to a different region, the process is continued until convergence is achieved. This can be thought of as randomizing over the initial conditions from which the block-wise computation of the posterior mode is done. Computation of a specification’s posterior mode and the marginal data density took a minimum of 6 hours in clock time and can take as long as 8 days, depending on the specifics of the run. Adding lags, imposing restrictions on switching on variances and restricting switching in equation coefficients is costly in terms of computing times.

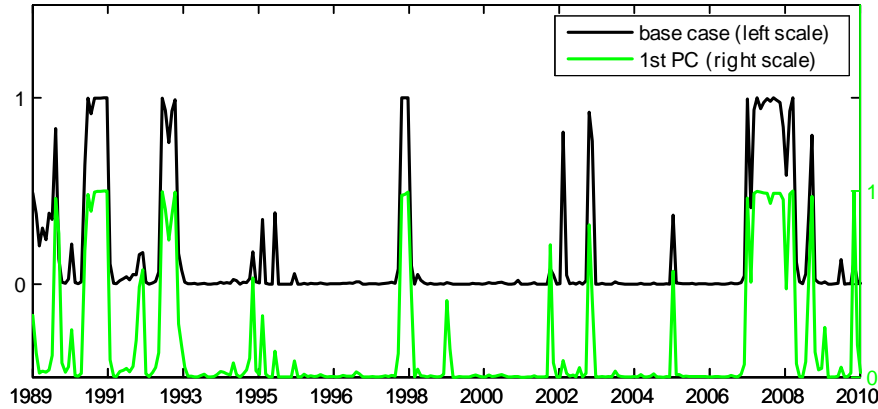
## Appendix B

This appendix contains more information on estimates of the high-stress coefficient state with alternative indices or constructions of financial stress. It also covers results using selected alternatives to aggregate real growth in personal consumption expenditures (PCE) that was used in the base case. In some instances, we merely repeat the material in the main text but add a chart that is referred to but not included; in other instances, new material is added. In what follows, we compare our alternative results to the base case from the main text, defined as the *3v2c* specification of the model using growth in real PCE as the real activity variable and the FSI as the measure of financial stress.

### B.1 Aggregation of the FSI

The main text of this article noted that the construction of the FSI, with its averaging of the nine components of the FSI, weighted as a function of the inverse of sample standard deviations, is not critical to our results. Figure B.1 below demonstrates this point. In this figure, like several that follow, we show the (smoothed) probability of the high-stress coefficient state—in our view, the most consequential part of our analysis—for the base case *3v2c* specification, in black. We compare this against, in this case, the state probabilities estimated from the same index constructed as the

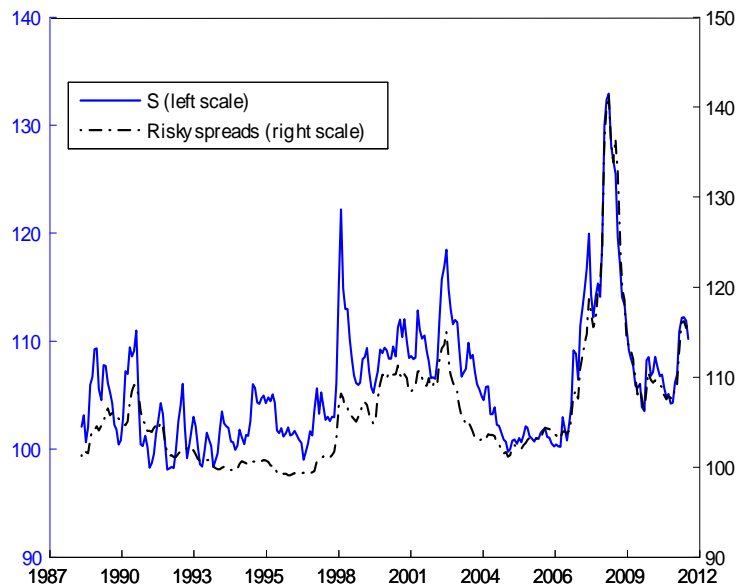
first principal component on the nine constituent pieces of the aggregate index, the lighter green line. The two lines are vertically offset, and double scaled, for ease of comparison of the dates at which probabilities climb or descend. As can be seen, the estimated switching dates of the 1st PC and the base case are very similar.



**Figure B.1** : Probability of high-stress coefficient state, 1st principal component of nine FSI constituent units (green, right scale) versus base case FSI construction (black, left scale)

## B.2 Risky spreads

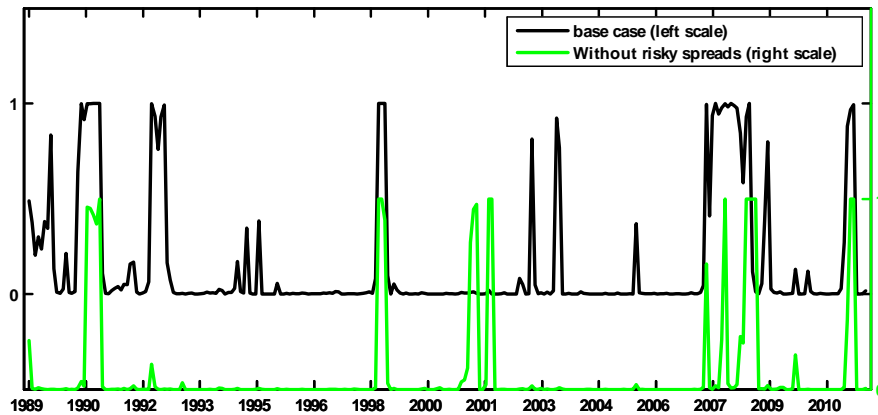
A combination of the spread of the AA rate and the BBB rate over the 10-year Treasury note rate. It makes no difference how these rates are combined. Figure B.2 below shows the data.



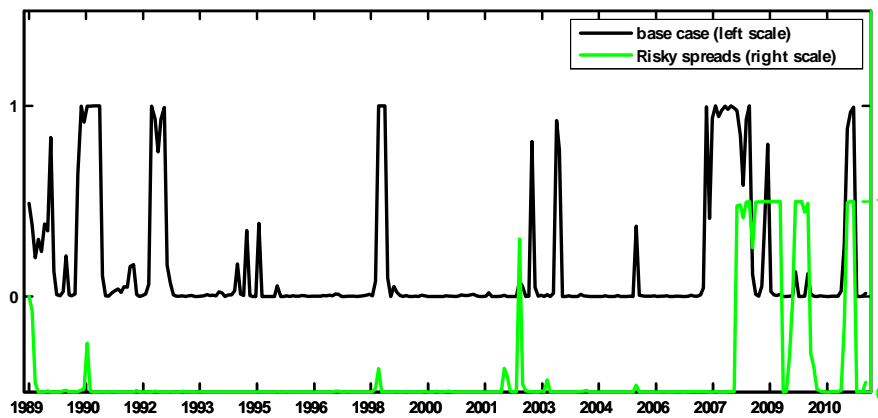
**Figure B.2** : Index of risky spreads (*sprd*), black dot-dashed line, right scale, and the FSI (*S*), blue solid line, left scale, 1988:12-2011:12

The performance of the FSI excluding the *sprd*, measured as always in terms of the high-state switching probabilities, compared with the base case, is shown in Figure B.3, while the case

where *sprd* substitutes for the financial stress index, is shown in Figure B.4. As can be seen, the omission of risky spreads harms the performance of the model in some ways, but it still picks up some critical episodes in financial and economic history, albeit tentatively in the case of the 2008-9 period. The replacement of the FSI by *sprd*, on the other hand, leads to a substantial deterioration in performance. Evidently, risky spreads are an important part of the story of financial stress and its transmission, but not a dominant part.



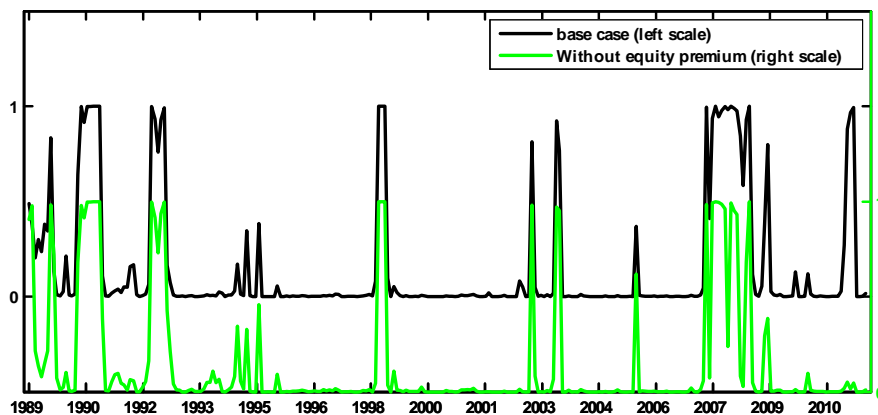
**Figure B.3 :** Probability of high-stress coefficient state, FSI excluding *sprd* (green, right scale), versus base case (black, left scale)



**Figure B.4 :** Probability of high-stress coefficient state, risky spread (*sprd*) as stress measure (green, right scale) versus base case (black, left scale).

### B.3 The equity premium

The stock market is conventionally thought of as a bellwether for all manner of financial and economic activity. It seems relevant, therefore, to consider whether stock market pricing that is out of line with risk-free bond rates is a critical variable for measuring financial stress. Figure B.5 below shows the probability of the high-stress coefficient state when the equity premium is excluded from the measure of the FSI. The figure shows that the equity premium is not particularly important.

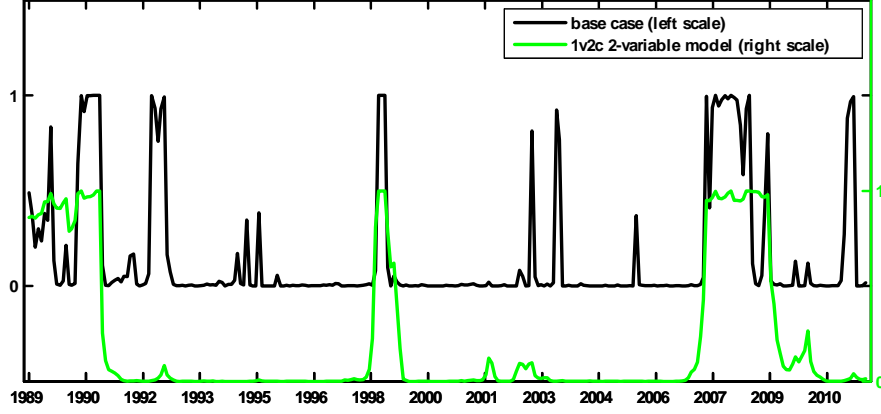


**Figure B.5 :** High-stress coefficient state probability, FSI excluding *eqprem* (in green, right scale), versus base case (in black, left scale)

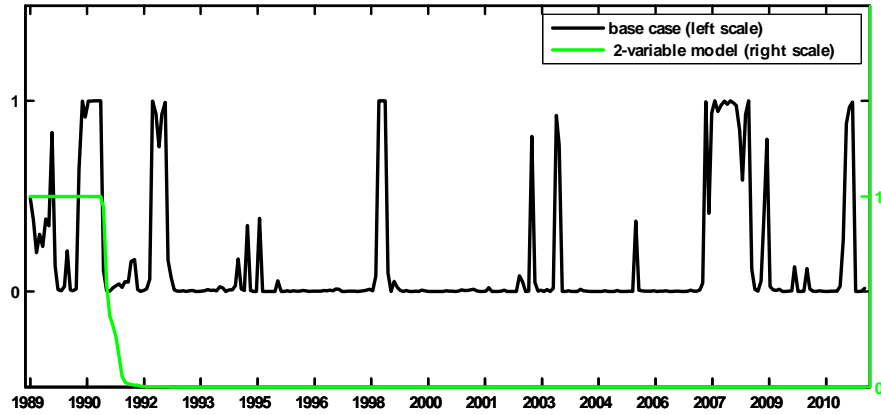
#### B.4 Analysis of the contribution of the FSI

To examine the contribution of the FSI to the results for the system as whole—whether it is the only thing that matters or whether it matters at all—we conduct reestimations of two classes of experiments. In one class, we remove variables from the system. Ideally, we would reduce the system to the FSI alone, however for technical reasons it is difficult to do this. As a very close substitute, we reduce the system to the FSI and the variable that we have concluded is the least consequential to the dynamics, namely price inflation. We show the estimated high-stress coefficient state probabilities for two cases with this specification. The first is for a model that allows switching in coefficients only—not in shock variances—that is, a *1v2c* specification. The main text established that in the full system, the data are well described by regime switching. Sims and Zha (2006) note that not allowing for switching in shock variances can lead to the erroneous conclusion of switching in coefficients; in other words, it can bias results in favor of coefficient switching. Figure B.6 shows that even after accepting this possible bias as a design feature of the experiment, the reduced dimension model misses many high-stress coefficient states that the base case model picks up. In particular, it misses the key 2010 high-stress episode during the European public debt crisis. Figure B.7 considers the same two-variable model but allowing for the same three states for shock variances and two for coefficients that we use for the base case model. As can be seen, when switching in shock variances is permitted in this way episodes of high-stress coefficients are almost obliterated.



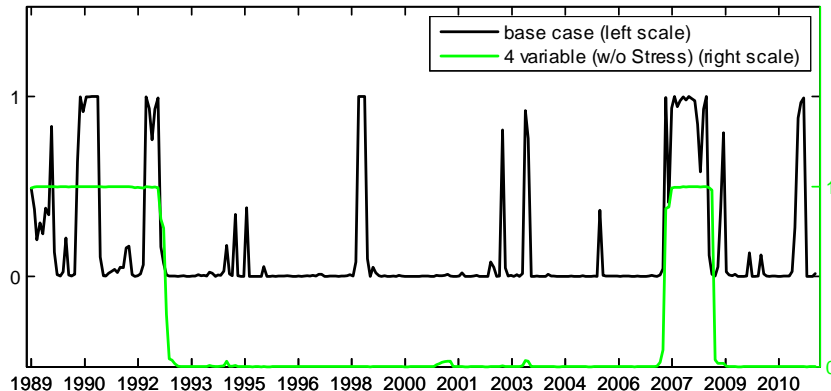


**Figure B.6 :** Probability of high-stress coefficient state,  $1v2c$  2-variable model with prices (green, right scale) versus base case (black, left scale)



**Figure B.7 :** Probability of high-stress coefficient state,  $3v2c$  2-variable model with prices (green, right scale) versus base case (black, left scale)

The second class of experiments exploring the role of the FSI to system dynamics is the complement to the case described immediately above: it preserves all the macro variables in the base-case MS-VAR except for the FSI which is removed. The results for this exercise are shown in Figure B.8. In this case, we see that the system without the FSI does pick the 2008-9 financial crisis, but that is about all it picks up. To us this merely suggests that the crisis was severe enough that the omitted variable is picked up by other variables in this circumstances. That this version of the model fails to pick up on other episodes of known importance but less gravity makes this model unsatisfactory, in our view.



**Figure B.8 :** High-stress coefficient state probability, 4-variable model, without  $S$  (in green, right scale) versus base case (in black, left scale)

### B.5 Investigating the real variable in the system

How financial stress affects the real economy might depend on which real variable one considers. To the extent that results differ depending on the real variable could reveal information on what channel is at work in the propagation mechanism. For example, if the effects of financial stress were stronger, in some sense, for industrial production than for base case using aggregate PCE, one might conjecture that this is because the role of working capital in facilitating production is important, as opposed to, say, something to do with consumer credit as a source of funds or as a means by which consumers can substitute intertemporally. Or if business fixed investment was more empirically persuasive as a measure of real activity in the model it might suggest something to do with the availability of credit to firms, or the costs and terms of credit, as an important channel.

In this subsection, we investigate alternative measures of our real variable focussing on two commonly articulated mechanisms by which financial shocks are sometimes thought to be transmitted. The first story builds around the observed volatility of expenditures on (or production of) durable goods to ask whether the complementarity of credit and durables is a major source of the propagation and magnification of shocks. The second is broader, and concerns what could be a lower frequency (and thus possibly less switch-like) mechanism, namely the transmission of shocks via labor markets. In this story, it is less financial disruption that is at work, and more either mismatch in labor market, as could be the case in the 2008-9 recession in the United States given the concentration of the shock in the construction and financial industries, or induced changes in savings behavior in the form of household "balance sheet restructuring" that somehow manifests in extended periods of unemployment.<sup>3</sup> To investigate, however imperfectly, these stories, we re-estimated the model substituting various measures of durable goods on the one hand, and labor market variables on the other, as our real variable. As before, to assess these alternative specifications, we compare the high-coefficient state probabilities—analogueous to Figure 3 in the main text—with those of our base case; however, given the subject matter of this investigation, as a compact demonstration of model properties, in a few cases we also show conditional forecasts of the model—analogueous to Figure 11. In the construction of conditional forecasts in this section,

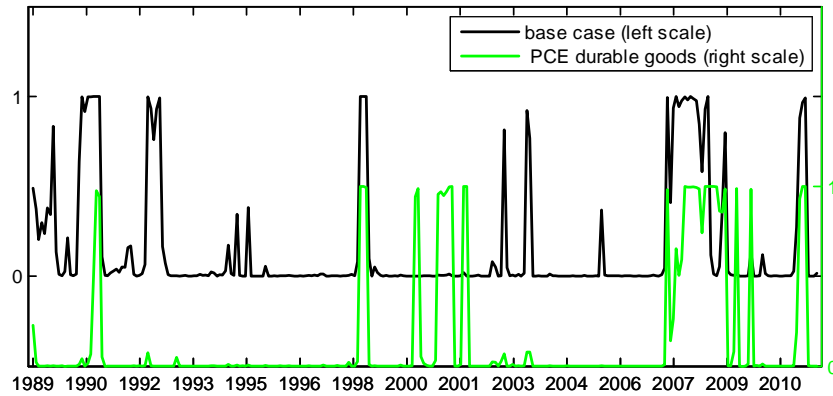
<sup>3</sup> The latter story is a bit tricky in that an autonomous increase in private savings need not cause the labor market to fail to clear. Completing the circle on that story requires something more, such as workers not recognizing that the market clearing wage has declined and thus electing to tolerate longer spells of unemployment than otherwise instead of bidding down the real wage.

as in the main text, we simply fix the latent Markov states as appropriate, and simulate out of sample, beginning in January of 2012, without shocks, holding all else constant.

### B.5.1 Durables goods

We looked at durables in three different aspects of the macroeconomy. First, we examined durables in consumption, by splitting our base-case real variable, real PCE, into PCE on durable goods, and PCE on services and nondurable goods including footwear.<sup>4</sup> Second, we examined durables in factor inputs, by using growth in investment in equipment and intangibles (hereinafter, simply investment).<sup>5</sup> And third we explored durables in production, in the form of growth in total industrial production. We consider these three cases in order.

Figure B.9 reprises part of the information contained in Figure 6 in the main text, showing that PCE durables produces many of the same coefficient switches as the base. In particular, it captures the 2008-9 crisis—albeit haltingly given that it retraces its climb for a time in 2008—and the 2011 euro area sovereign debt crisis. At the same time, the model with PCE durables misses some earlier episodes and misinterprets a period at the turn of the century as a period of high stress. Figure B.10 shows forecasts of the model conditional on the coefficient state—high stress or low. As can be seen, the forecasts are entirely conventional and quite similar to Figure 11 in the main text. Forecasts conditional on the high-stress coefficient latent Markov state render higher levels of stress itself, and markedly lower (negative) growth in PCE durables expenditures ( $\Delta PCE_{dur}$ ), despite substantially easier monetary policy ( $R$ ). The only outcome that is materially different from the base case is the inflation response ( $\Delta P$ ) which, in the base case showed uniformly higher inflation under the high-stress coefficient latent Markov state than under the low-stress state, whereas the pattern is less straightforward here. We noted in the main text that the inflation response shown in Figure 11 supported the interpretation that a switch to the high-stress state is akin to a negative productivity shock; the effect is more equivocal in the case of PCE durables.<sup>6</sup>

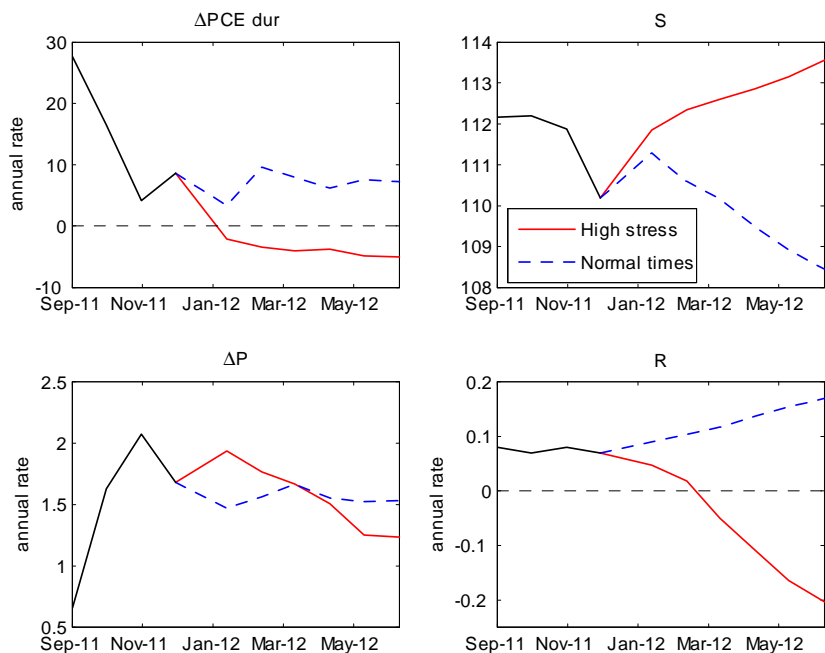


**Figure B.9 :** Probability of high-stress coefficient state, growth in expenditures on PCE durable goods ( $PCE_{dur}$ ) (green, right scale) versus base case (black, left scale)

<sup>4</sup> Created by chain-weighting the nominal series with the appropriate price indexes by the authors. Details are available on request.

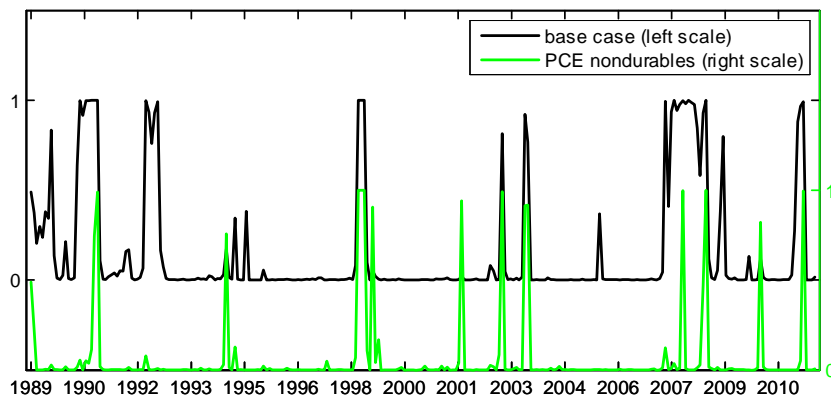
<sup>5</sup> In 2013, the BEA substituted equipment & intangibles for equipment & software as that part of business fixed investment that excludes investment in nonresidential structures.

<sup>6</sup> As in Figure 11 in the main text, for this figure and others we omit the response of  $\Delta M$  in order to keep the chart compact.

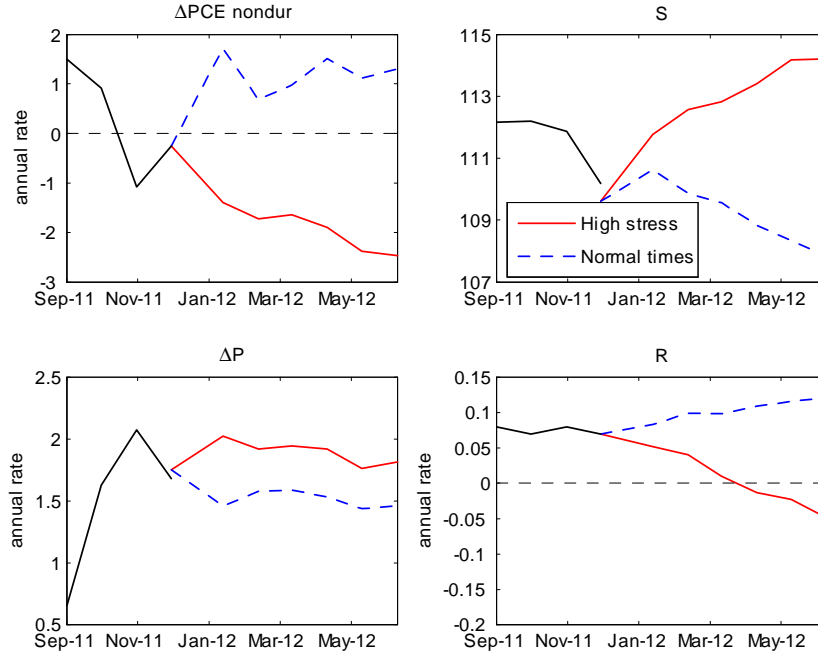


**Figure B.10 :** Model forecast, conditional on the state, consumer expenditures on durable goods (*pcedur*), from 2011:12. High-stress coefficient state (red solid lines) versus low-stress coefficient state (blue dashed lines)

Figure B.11 shows the high-stress coefficient state probabilities for PCE nondurables. Results here are much worse than for PCE durables, missing most of the financial crisis, among other problems. Figure B.12 shows the conditional forecast for this model. Despite very different switching dates in history, the out-of-sample forecasts for PCE nondurables are very similar to the base case. To summarize, consumer durables appear to be more important than nondurables for picking up switching behavior, but for a full characterization it appears that it is helpful to have both.

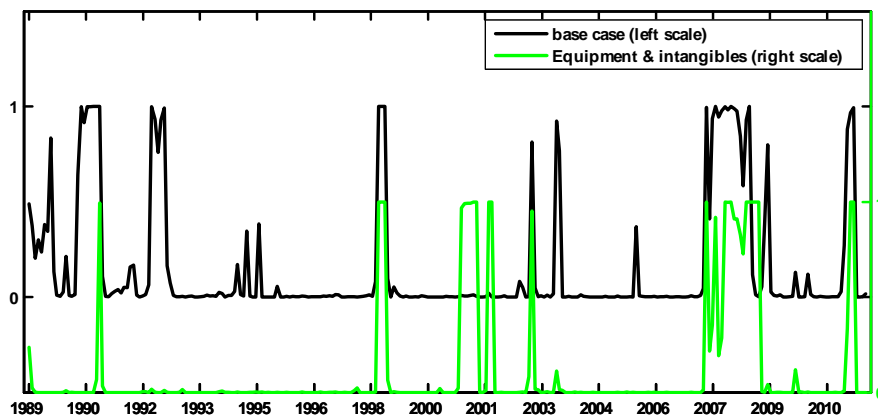


**Figure B.11 :** Probability of high-stress coefficient state, growth in expenditures on PCE nondurable goods including footwear plus services (*PCEnondur*) (green, right scale) versus base case (black, left scale)



**Figure B.12 :** Model forecast, conditional on the state, consumer expenditures on services and nondurable goods including footwear (*pce\_nondur*), from 2011:12. High-stress coefficient state (red solid lines) versus low-stress coefficient state (blue dashed lines)

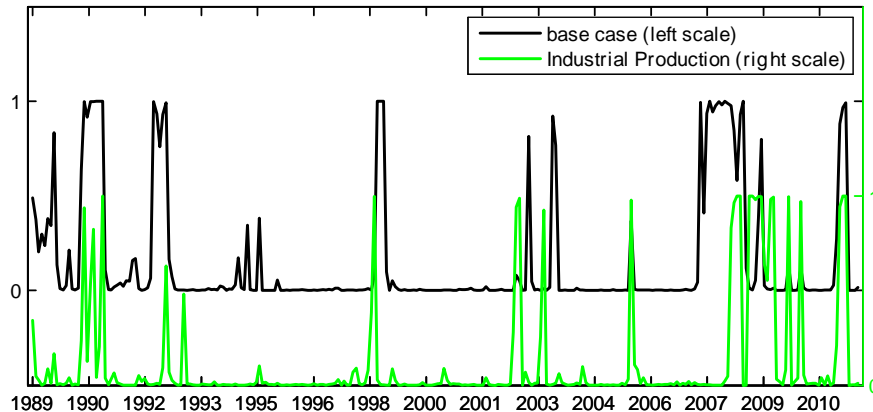
Next we turn to business investment.<sup>7</sup> Figure B.13 shows results for investment that are quite similar to those for PCE durables. Investment picks up the Great Recession, at least in part, the European sovereign debt crisis in 2010-11, as well as the 1998 Russian debt default and the 2002 Argentine sovereign debt crisis; like PCE durables it attributes a high-stress coefficient state to the bursting of the high-tech bubble in 2000-01, that the base case model does not see.



**Figure B.13 :** Probability of high-stress coefficient state, growth in investment in equipment & intangibles (*eandi*), (green, right scale) versus base case (black, left scale)

<sup>7</sup> The data for investment, or more specifically investment in equipment and intangibles, were taken from a recent vintage of the National Income and Produce Accounts and interpolated to monthly frequency using the Chow-Lin (1971) procedure using data for new orders of non-defense capital goods for identification. Details are available from the authors.

In the case of industrial production, Figure B.14 shows that *IP* does a reasonable job picking out many periods of high-financial stress particularly in the early part of the sample, but misses by a wide margin the onset of the financial crisis. The conditional forecast is much like the others shown in this section, except that it fails to produce much of a monetary policy response ( $R$ ), a reflection, perhaps, of the small share of the overall economy represented by industrial production as well as its nonrepresentativeness. We conclude that the nonlinearities captured by our base case model are not well represented by industrial production and therefore that the mechanisms that are germane to that sector, such as the availability of working capital do not seem to play an outsized role.



**Figure B.14 :** Probability of high-stress coefficient state, growth in industrial production (*ip*), (green, right scale) versus base case (black, left scale)

Taken together, these results for consumer durables, investment and industrial production suggest that a good part of the effects of financial stress likely operate through credit conditions or credit availability—nonprice terms, more generally—and their effects on expenditures on durable goods. For example, it is sometimes argued that disproportionate effects of shocks on durable goods occurs because of irreversibility of investment, irrespective of switching phenomena. However, while irreversibility could be expected to produce large movements in macroeconomic aggregates in response to negative shocks, there would, however, be no expectation that such shocks would produce Markov switching as an empirical phenomenon, unlike the case where credit availability is impinged. One mechanism that is consistent with our results through which credit conditions might operate is through collateral constraints where declines in the value of pledgeable assets would affect firms’ ability to finance new capital investment, or households’ ability to purchase big ticket durable goods. In this regard, our results are consistent with the empirical observations of Chaney *et al.* (2012) and the theoretical constructs of Liu *et al.* (2013), among other contributions.

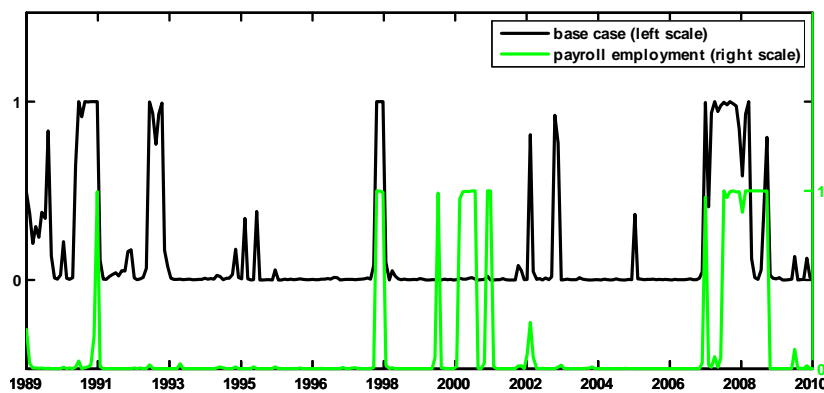
### B.5.2 Labor markets

Finally, we also re-estimated the model using three labor market variables as the real variable in our system, the unemployment rate, initial claims for unemployment insurance on state programs, and growth in private nonfarm payroll employment.<sup>8</sup> The results were uniformly inferior to the

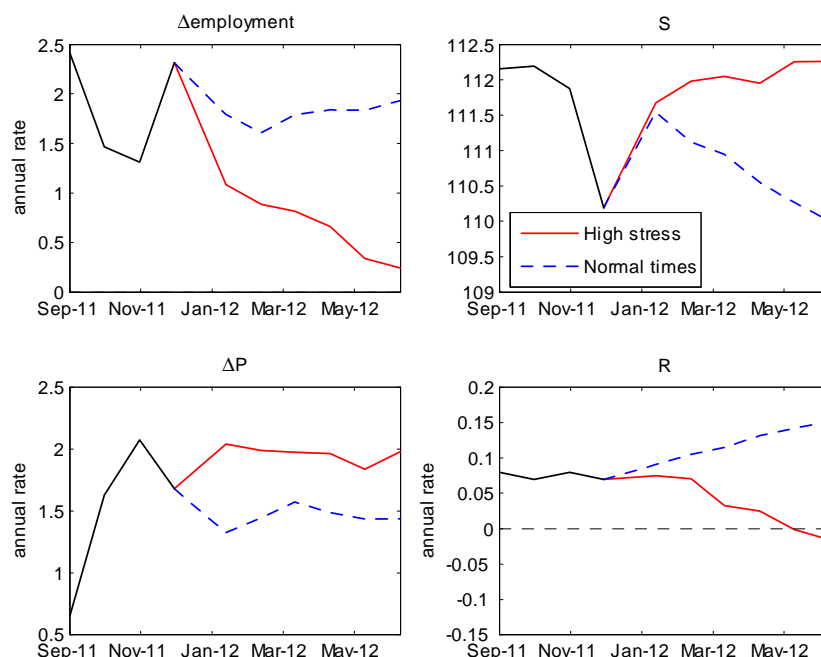
<sup>8</sup> The unemployment rate and nonfarm payroll employment are both monthly. Initial claims on state unemployment insurance programs is highly scrutinized by financial market participants because they provide a reasonably good real-time indication of the state of the labor market and are available weekly. We collapsed the weekly series to monthly by averaging.

expenditure-based real variables discussed above. Figure B.15 presents coefficient state probabilities for payroll employment, arguably the best of the three models. As can be seen, results for payroll employment are broadly similar to those for investment. At the same time, the conditional forecasts, shown in Figure B.16, are conventional.

At one level, the results for labor market variables are not surprising; there are fewer of the high-frequency discretely-shifting mechanisms in play for labor markets than there are for durable goods. Nevertheless, the fact that labor market variables perform relatively poorly compared to, say, PCE durables in our model does not mean that labor markets are immaterial to the transmission of crises. Rather, it suggests to us (but does not prove) that labor markets are not likely to be an independent source of the switching phenomena studied here, at least at the monthly frequency we use. Taking the 2008-9 Great Recession as our example, it is certainly possible—indeed plausible—that the fragility of household financial conditions—a condition that built up over many years in the U.S. economy owing in part to "jobless recoveries" from the 1991 and 2000 recessions and the large share of residential real estate on both sides of the typical household balance sheet—set the stage for severity of the recession by obligating a period of household deleveraging following the collapse of the housing market. It would certainly be a worthwhile endeavour to construct the datasets that are long enough and detailed enough to investigate the role of these lower frequency, cumulative processes.



**Figure B.15 :** Probability of high-stress coefficient state, growth in payroll employment (*pemp*), (green, right scale) versus base case (black, left scale)



**Figure B.16 :** Model forecast, conditional on the state, payroll employment ( $pemp$ ), from 2011:12. High-stress coefficient state (red solid lines) versus low-stress coefficient state (blue dashed lines)

## References

- Campbell, J.Y.; Giglio, S., Polk, C. and Turley, R. 2013. An intertemporal CAPM with stochastic volatility. unpublished manuscript, Department of Economics, Harvard University.
- Chaney, T., Sraer, D., Thesmar, D., 2012. The collateral channel: How real estate shocks affect corporate investment. *American Economic Review* 102, 2381-2409.
- Chib, S., 1996. Calculating posterior distributions and model estimates in Markov mixture models. *Journal of Econometrics* 75, 79-97.
- Chow, G.C., Lin, A. 1971. Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *Review of Economics and Statistics* 53, 372-375.
- Liu, Z., Wang, P., Zha, T., 2013. Land-price dynamics and macroeconomic fluctuations. *Econometrica* 81, 1147-1184.
- Sims, C., Waggoner, D.F., Zha, T., 2008. Methods for inference in large multi-equation Markov-switching models. *Journal of Econometrics* 146, 255-274.
- Sims, C., Zha, T., 1998. Bayesian methods for dynamic multivariate models. *International Economic Review* 39, 949-968.
- Sims, C., Zha, T., 2006. Were there regimes shifts in U.S. monetary policy? *American Economic Review* 96, 54-81.



Waggoner, D.F., Zha, T., 2012. Confronting misspecification in macroeconomics. *Journal of Econometrics* 171, 167-184.