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Financial Stress Regimes and the Macroeconomy*

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Abstract

We identify financial stress regimes using a model that explicitly links financial variables with the macroeconomy. The financial stress regimes are identified using a large unbalanced panel of financial variables with an embedded method for variable selection and, empirically, are strongly correlated with NBER recessions. The empirical results on the selection of financial variables support the use of credit spreads to identify asymmetries in the responses of economic activity and prices to financial shocks. We use a novel factor-augmented vector autoregressive model with smooth regime changes (FASTVAR). The unobserved financial factor is jointly estimated with the parameters of a logistic function that describes the probabilities of the financial stress regime over time.

Keywords: factor-augmented VAR models, Smooth Transition VAR models, Gibbs variable selection, financial crisis.

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1 Introduction

In the aftermath of the 2008-2009 worldwide downturn, the research effort in macroeconomics concentrated on models with financial frictions able to describe nonlinearities in how shocks to the financial sector affect the macroeconomy. These models typically characterize two regimes: In the high-stress regime—or high-systemic-risk regime—financial constraints are binding; thus, shocks to the financial sector have stronger negative effects on investment (He and Krishnamurthy, 2014). This literature is supported by empirical evidence on the predictive content of financial condition indexes for financial variables (Hatzius, Hooper, Mishkin, Schoenholtz and Watson, 2010). Hubrich and Tetlow (2011) and Hartmann, Hubrich, Kremer and Telow (2013) show how financial shocks have larger variance and stronger transmission to macroeconomic variables in periods of financial stress.1

A caveat of previous empirical exercises is that the measure of financial conditions is taken as given based on a financial condition index computed by central banks and economic institutions. Kliesen, Owyang and Vermann (2012) show that these indexes combine information from different sets of financial variables and they have different levels of correlation with future economic activity.

In this paper, we use a novel econometric approach to identify financial stress regimes using a large unbalanced panel of financial variables jointly with changes in macroeconomic dynamics. Our approach allows us to choose a subset of financial variables that better describes nonlinearities from the financial sector to the macroeconomy. Our main empirical result is that periods of financial stress are defined by (i) two measures of credit risk—such as the spread between Baa corporate bonds and 10-year Treasuries and high-yield spread, (ii) a measure of equity market returns (Wilshire 5000) and (iii) consumer survey data on conditions for buying large goods. Variables such as market volatility and the slope of the yield curve are less important. Our findings agree with those of He and Krishnamurthy (2014),

1 Additionally, Dahlhaus (2014) examines how changes in financial stress can alter the channels through which monetary policy acts.
who use credit risk spreads to characterize periods of high systemic risk, and the results of Del Negro, Hasegawa and Schorfheide (2013), who show that DSGE models that incorporate financial frictions and credit spreads forecast better than models with no financial frictions in periods of financial stress. Gilchrist and Zakrajsek (2012) explain that the information content of their credit spread index for economic activity is mainly related to changes in the excess bond premium.

Our modeling approach allows for dynamic responses to differ depending on the regime at the time of the shock. A one-standard-deviation shock to financial conditions that occurs during a high-financial-stress regime has a significant 0.2% negative impact on inflation at a horizon of one year. On the other hand, the dynamic effect on inflation of a shock to financial stress occurring during a low-stress regime is statistically zero at all horizons. This highly asymmetric response of inflation to financial conditions is one of the main empirical contributions of this paper and supports the development of macroeconomic models with nonlinearities from financial variables to aggregate prices.²

The response of the growth in industrial production is not as asymmetric as the response of inflation, but the negative response is faster if the shock occurs in the high-stress regime, with negative significant effects to a one-standard-deviation shock of 0.8% after only four months. This weak evidence of asymmetric responses of economic activity is supported by Ng and Wright (2013), who argue that it is hard to find nonlinearities in the dynamics of business cycles using aggregate data. We can clearly show that our identified periods of financial stress are strongly correlated with NBER recessions.

Throughout the paper we compare two specifications of our nonlinear VAR model: one that allows for dynamic feedback from macroeconomic variables to the financial conditions

²Gilchrist, Schoenle, Sim and Zakrajsek (2014) provide evidence that firms with "weak" balance sheets increased their price during the 2008 crisis, while firms with "strong" balance sheets decreased their prices as expected. Our results support the claim that after a negative financial shock (a type of negative demand shock), average prices go down significantly during periods of high financial stress but do not change during periods of low financial stress. Because we also find that financial shocks are larger in periods of high financial stress and we only look at aggregate prices, our results are agreeable with the attenuation in price dynamics caused by financial distortions of the model in Gilchrist et al. (2014).
factor (or index) and another that does not. The dynamic responses from a financial shock in the model without the feedback are more persistent because the effect of the shock on financial conditions themselves is more persistent. This supports the claim that it is better to estimate financial conditions indexes within a macroeconomic model since there are strong feedbacks in both directions: from financial conditions to the macroeconomy and from the macroeconomy to financial conditions. A disadvantage of the model with feedbacks in both directions is that the confidence bands for the weights of the financial stress regime are wider, implying additional regime identification uncertainty. In general, financial stress indexes published by central banks and economic institutions do not take into account feedback effects between the financial sector and the macroeconomy. Hatzius et al. (2010) filter the time series of financial variables to exclude the effect of macroeconomic conditions before building their financial condition index (Brave and Butters (2012) also follow a similar approach). This novelty in our approach may also explain why we cannot find large asymmetric responses from economic activity to financial shocks as in Hubrich and Tetlow (2011) and Hartmann et al. (2013).

We evaluate our econometric modeling approach to identify periods of high-stress regimes in pseudo real-time from September 2007 up to April 2010. Our results show that we could have signalized the high-stress regime with a probability higher than 80% from February 2008, while this probability is below a 50% threshold in January 2010. The pseudo real-time analysis also shows that the financial variable selection changes after January 2009. Before 2009, measures such as housing inflation, long-term interest rates and the growth in credit stock would have been selected more than 84% of the time based on the posterior distribution. After January 2009, the number of variables that are frequently selected shrinks and a larger weight is given to the Baa–10-year Treasury spread.

In this paper, we develop a Metropolis-in-Gibbs approach to estimate a Factor-Augmented Smooth-Transition Vector Autoregressive Model (FASTVAR). The model has two regimes, allowing for dynamics changes depending on the financial condition factor. The proposed
model augments the smooth-transition VAR model (surveyed by Van Dijk, Terasvirta and Franses (2002)) with an unobserved factor as in Bernanke, Boivin and Eliasz (2005). Thus, the strength of the relation between financial conditions and economic activity depends explicitly on the unobserved financial conditions factor linked to a set of observed financial variables.

The unobserved factor is jointly estimated with the parameters of a smooth-transition function that describe the weights given to each regime over time. We also include a step in the estimation that allows for covariate selection to determine the composition of the data vector included in the financial conditions factor. A method to choose variables to enter factors was also performed by Kaufmann and Schumacher (2012) using sparse priors in the context of dynamic factor models and Koop and Korobilis (2013) using model averaging in FAVAR models.

Estimation of the model is conducted in a Bayesian environment using Metropolis-Hastings steps to draw the transition function parameters and a vector of indicator variables determining the financial series entering the factor. Because of the nonlinearity in the autoregressive parameters, the factor must be estimated using a nonlinear filter. We use the extended Kalman filter, implying that we use a first-order approximation of the state equation.

The balance of the paper proceeds as follows: Section 2 describes the general FASTVAR model with model indicators used for model selection. Section 3 outlines the Gibbs sampler used to estimate the model parameters, the factor, and the posterior distributions for the model inclusion indicators. Section 4 describes our dataset and presents and analyzes the results of our empirical exercise. Section 5 summarizes and offers some conclusions.
2 The Empirical Model

In this section, we propose a method to identify financial stress regimes. We begin by describing a VAR model that links an exogenously-defined financial condition index to economic activity. Then, we propose a FASTVAR model that allows for the joint estimation of a financial condition factor and the time-varying weights for the financial stress regime.

2.1 The Smooth-Transition VAR Model

Let $f_t$ represent the period–$t$ value of a financial conditions index. For now, assume that $f_t$ is scalar, observed and exogenously determined. Define $z_t$ as an $(N_z \times 1)$ vector of macroeconomic variables of interest—e.g., GDP growth, employment, inflation. Suppose that the effect of a shock to financial conditions on macroeconomic variables is linear but that financial conditions are also affected by macroeconomic variables—in particular, current economic activity. In this case, the dynamic response can be evaluated in a standard VAR framework. Define the $((N_z + 1) \times 1)$ vector $y_t = [z_t' , f_t]'$, where the ordering of $f_t$ last is intentional and provides the identifying restriction used to construct impulse responses. The VAR in question is then

$$ y_t = A(L) y_{t-1} + \varepsilon_t ,$$

where $A(L)$ is a matrix polynomial in the lag operator, $\varepsilon_t \sim N(0, \Omega)$, and we have suppressed any constants and trends. The matrixes $A(L)$ drive the transmission of financial shocks—shocks to $f_t$—to macroeconomic variables $z_t$. However the transmission in this specification cannot change over time or with the level of financial stress. Suppose that the transmission mechanism changes over time and depends on the size and sign of the financial conditions index; then, we can write

$$ y_t = [1 - \pi_t (f_{t-1}; \gamma, c)] A_1(L) y_{t-1} + \pi_t (f_{t-1}; \gamma, c) A_2(L) y_{t-1} + \varepsilon_t ,$$

where $\pi_t$ is the transition probability matrix.
where $A_1(L)$ and $A_2(L)$ are matrices of lag polynomials, $\varepsilon_t \sim N(0_{N_z+1}, \Omega_t)$, and $\Omega_t$ is the variance-covariance matrix. If $f_t$ is observed, the model described in (2) is a standard smooth-transition vector autoregression (STVAR) as in Van Dijk et al. (2002). In the parlance of the STAR models, $f_{t-1}$ is the transition variable and $\pi_t(f_{t-1})$ is the transition function, where $0 \leq \pi_t(f_{t-1}) \leq 1$. The transition function $\pi_t(f_{t-1})$ determines the time-varying weights of each set of autoregressive parameters $A_1(L)$ and $A_2(L)$ on the path of $y_t$.

The transition function can take a number of forms. One example is a first-order logistic transition function of the following form:

$$
\pi_t(f_{t-1}; \gamma, c) = \left[1 + \exp \left( -\gamma \left( f_{t-1} - c \right) \right) \right]^{-1},
$$

where $\gamma \geq 0$ is the speed of transition and $c$ is a fixed threshold. In (3), the regime process is determined by the sign and magnitude of the deviation of lagged financial conditions, $f_{t-1}$, from the threshold $c$. If $f_{t-1}$ is less than $c$, the transition function, $\pi_t(f_{t-1})$, gives more weight to the autoregressive parameters of the first regime, $A_1(L)$. The coefficient $\gamma$ determines the speed of adjustment: as $|\gamma| \to \infty$, the transition becomes sharper and the regime switches resemble a pure threshold model. At $\gamma = 0$, the model collapses to a linear model. Smooth-transition and threshold VARs have been employed to measure asymmetries in the dynamic effects of monetary shocks (Weise, 1999; Ravn and Sola, 2004) and in the effect of credit conditions on economic activity (Balke, 2000).

We allow for regime-dependent heteroskedasticity, so the variance-covariance matrix of the VAR equation is

$$
\Omega_t = \left[1 - \pi_t(f_{t-1}; \gamma, c)\right] \Omega_1 + \pi_t(f_{t-1}; \gamma, c) \Omega_2,
$$

where $\Omega_1$ and $\Omega_2$ are $((N_z + 1) \times (N_z + 1))$ symmetric matrices. A STVAR specification

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3This analysis implicitly assumes that the transition variable delay is equal to 1. Because typically financial condition factors are persistent time series, the assumption that the delay is equal to 1 is not very restrictive.
with regime-dependent heteroskedasticity as above but with \( c = 0 \) and a calibrated \( \gamma \) has been employed to measure asymmetries over business cycles of the impact of fiscal policy shocks by Auerback and Gorodnichenko (2012) and Bachmann and Sims (2012), and of uncertainty shocks by Caggiano, Castelnuovo and Groshenny (2014).

In the model composed of (2) and (3), a shock propagates differently depending on the (lagged) state of financial conditions. Shocks to macro variables have regime-dependent effects that can be determined conditional on ambient financial conditions. Shocks to financial conditions, on the other hand, have two effects. Conditional on the regime, the response to a financial conditions shock can be computed as a standard (state-dependent) impulse response. In addition, shocks to financial conditions can cause a change in future macroeconomic dynamics by driving the economy away from one regime toward the other.

### 2.2 The Factor-Augmented STVAR

The STVAR model in the preceding subsection relies on the fact that \( f_t \) is observed. This could be true if one used an observed proxy for financial stress or if one used a constant weight measure, as in the financial condition indexes surveyed by Hatzius et al. (2010). But how can we be sure we are properly modeling financial conditions such that we correctly identify financial stress periods? As a consequence, we estimate the financial conditions index as a factor within a FASTVAR based on a vector of financial variables, \( x_t \).

Let \( f_t \) be the factor that summarizes the comovements across \( N_x \) demeaned financial series, \( x_t \):

\[
x_t = \beta f_t + u_t,
\]

where \( \beta \) is the matrix of factor loadings and \( u_{it} \) are iid \( N(0, \sigma_i^2) \). Equations (2), (3) and (4) comprise the FASTVAR model. The factor is jointly determined by the cross-series movements in the financial variables and the behavior of the macroeconomic variables.
One of the central issues in the literature measuring financial stress is how to determine which financial series should comprise $x_t$. For example, Kliesen et al. (2012) surveyed 11 different indexes constructed from 4 to 100 indicators. While more series may provide a more complete view, increasing the cross-sectional dimension of $x_t$ may result in estimated factors that do not truly represent financial stress. We are interested in determining the set of financial variables that alters the underlying dynamics of the macroeconomy—that is, which financial variables switch the macroeconomic dynamics from $A_1 (L)$ to $A_2 (L)$ and vice versa.

To accomplish this, we augment (4) with a set of model inclusion dummies, $\Lambda = [\lambda_1, ..., \lambda_{N_x}]'$, $\lambda_i \in \{0, 1\}$. The inclusion dummies indicate whether a particular financial series should be included in the set of variables that make up the factor—that is, if $\lambda_i = 1$, $x_i$ is included in the set of variables that determine the factor. If $\lambda_i = 0$, $x_i$ is excluded of the estimation of the factor; the effect of $\lambda_i = 0$ is to set the factor loading associated with the $i$th element of $x_t$ to zero. We can then rewrite (4) as

$$x_t = (\Lambda \odot \beta) f_t + u_t.$$  

The vector of inclusion indicators, $\Lambda$, can be estimated along with the other parameters in the model.

**2.2.1 The State-Space Representation**

The state-space form of the model consisting of (2), (3), and (4) summarizes the assumptions behind the FASTVAR model that we have made thus far. For exposition, we assume that $p = 1$ and $N_z = 2$. The measurement equation is

$$\begin{bmatrix} z_t \\ x_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ 0 & (\Lambda \odot \beta) \end{bmatrix} \begin{bmatrix} z_t \\ f_t \end{bmatrix} + \begin{bmatrix} 0 \\ u_t \end{bmatrix}; u_t \sim iidN(0, \sigma^2_t).$$  

(6)
This differs from the FAVAR specification of Bernanke et al. (2005) by excluding the macroeconomic variables \( z_t \) as observable factors in the measurement equation of the financial variables \( x_t \).

The state equation is

\[
\begin{bmatrix}
  z_{1,t} \\
  z_{2,t} \\
  f_t
\end{bmatrix} = 
\begin{bmatrix}
  c_1 \\
  c_2 \\
  0
\end{bmatrix} + 
\begin{bmatrix}
  a_{11} & a_{12} & a_{13} \\
  a_{21} & a_{22} & a_{23} \\
  0 & 0 & a_{33}
\end{bmatrix}
\begin{bmatrix}
  z_{1,t-1} \\
  z_{2,t-1} \\
  f_{t-1}
\end{bmatrix} + 
\begin{bmatrix}
  \xi_{1t} \\
  \xi_{2t} \\
  \xi_{f_t}
\end{bmatrix}
\]

where \( \xi_t \sim N(0, \Omega) \), \( \pi_t(f_{t-1}; \gamma, c) = [1 + \exp(-\gamma(f_{t-1} - c))]^{-1} \) and \( d_{ij} = a_{2,ij} - a_{1,ij} \) measures the change in the autoregressive coefficients across regimes. In equation (7), we include additional restrictions in the factor dynamics, excluding the possibility of direct dynamic effects of macroeconomic variables on the financial factor. This is justified by the fact that the factor is estimated/filtered using both the measurement (6) and the state (7) equations, and we would like to relate the factor more strongly to financial variables in \( x_t \) than economic variables in \( z_t \). However, if there is a strong feedback from the macroeconomy to the financial sector, then these restrictions imply that we miss important dynamic effects when measuring the effect of exogenous financial shocks on the macroeconomic variables. As a consequence, we use both the restricted specification in (7) and an unrestricted specification that also estimates \( c_3, a_{31}, a_{32}, d_{31} \) and \( d_{32} \).

### 2.2.2 Impulse Response Functions

The FASTVAR allows for asymmetric transmission of financial shocks (i.e., to the \( f_t \) equation) to the macroeconomic variables. However, asymmetries will prevail only if estimates of \( d_{ij} \) do not collapse to zero or, alternatively, if the transmission of shocks differs even though
the size and sign of the shocks are invariant. We split the data on macroeconomic variables and a factor \( f_t \) (for \( t = 1, \ldots, T \)) draw into two subsets to verify whether the dynamic transmission changes with regimes. The first subset refers to the histories during the lower regime, \( \pi_t(f_{t-1}; \gamma, c) \leq 0.5 \), and the other subset refers to the upper regime, \( \pi_t(f_{t-1}; \gamma, c) > 0.5 \). Based on these two sets of histories, we compute generalized impulse responses conditional on the regime as suggested by Koop, Pesaran and Potter (1996) and applied by Galvao and Marcellino (2014). The responses measure the effect of a one-standard-deviation shock to financial conditions on the endogenous variables, assuming (i) a specific set of histories at the impact (either lower or upper regime) and (ii) that the regimes may change over horizon.

We simulate data to compute the conditional expectations of \( y_{t+h} \) with and without the shock to compute responses:

\[
IRF_{h,v,s} = \frac{1}{T_s} \sum_{t=1}^{T_s} \left\{ E[y_{t+h}|F_t^{(s)}, v_t = v] - E[y_{t+h}|F_t^{(s)}] \right\},
\]

where \( T_s \) is the number of histories in regime \( s \), \( F_t^{(s)} \) is a history from regime \( s \) (typically including \( z_t, \ldots, z_{t-p+1} \) and \( f_t, \ldots, f_{t-p+1} \)) and \( v_t = v \) is the shock vector. In the empirical application, we use 200 draws from the disturbances distribution to compute each conditional expectation using a given set of FASTVAR parameters. The \( IRF_{h,v,s} \) measures the responses of both macroeconomic variables and the factor at horizon \( h \) from shock \( v \) that hit the model in regime \( s \) (either the lower or the upper regime defined using the transition function as above). This approach for computing impulse responses takes the nonlinear dynamics of the FASTVAR fully into consideration.

In the computation in (8), we are implicitly assuming a fixed set of parameters of the FASTVAR \( (A_1(L), A_2(L), \gamma, c, \Omega_1, \Omega_2) \) and a specific estimate of \( f_t \). In our empirical implementation, we compute the impulse response function for many parameters and factor draws from the posterior distribution. We use a set of equally spaced draws from the posterior distribution, and we plot the posterior mean for \( IRF_{h,v,s} \) and 68% confidence intervals.
3 Estimation

We estimate the model using the Gibbs sampler with a Metropolis-in-Gibbs step. Let $\Theta$ collect all of the model parameters. We can partition the set of model parameters into blocks: (1) $\Psi = [A_1 (L), A_2 (L)]$, the VAR coefficients; (2) $\Omega_1$ and $\Omega_2$, which are the regime-specific VAR variance-covariance matrixes; (3) $\gamma$ and $c$, the transition speed and the threshold; (4) $\beta$, $\Lambda$ and $f_T = \{f_t\}_{t=1}^T$, the factor loadings, the inclusion indicators and the factor, respectively; and (5) $\{\sigma_{i,t}^2\}_{t=1}^{N_x}$, the variances of financial variables. The algorithm samples from each block conditional on the other blocks. After a suitable number of draws are discarded to achieve convergence, the set of conditional draws forms the joint distribution of the whole model.

3.1 Priors

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Prior Distribution</th>
<th>Hyperparameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>$vec(\Psi)$</td>
<td>$N (m_0, M_0)$</td>
<td>$m_0 = 0_N$ ; $M_0 = 10I_N$ ; $N = 2N_z (N_z + 1) P + 2N_z + 2P$</td>
</tr>
<tr>
<td>$\Omega_1^{-1}, \Omega_2^{-1}$</td>
<td>$W \left( \frac{\nu_0}{2}, \frac{D_0}{2} \right)$</td>
<td>$\nu_0 = 1000$ ; $D_0 = I_N$ ; $\Delta_{\Omega_1} = \Delta_{\Omega_2} = 150$</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>$\Gamma (g_0, G_0)$</td>
<td>$g_0 = 6$ ; $G_0 = 3$ ; $\Delta_\gamma = 0.01$</td>
</tr>
<tr>
<td>$c$</td>
<td>$Unif (c_L, c_H)$</td>
<td>$c_L = f_{0.10}$ ; $c_H = f_{0.90}$</td>
</tr>
<tr>
<td>$\sigma_{n}^{-2}$</td>
<td>$\Gamma (\omega_0, W_0)$</td>
<td>$\omega_0 = 1$ ; $W_0 = 1$ ; $\forall n$</td>
</tr>
<tr>
<td>$\beta_n$</td>
<td>$N (b_0, B_0)$</td>
<td>$b_0 = -100$ ; $B_0 = 0.01$ ; $\forall n$</td>
</tr>
<tr>
<td>$\lambda_n$</td>
<td>$\rho_0$</td>
<td>$\rho_0 = 0.01$ ; $\forall n$</td>
</tr>
</tbody>
</table>

We assume a proper normal-inverse-Wishart prior for the $VAR(P)$: Each regime-dependent coefficient matrix has a multivariate normal prior; the covariance matrix is inverse Wishart. The threshold in the transition function has a uniform prior bounded by the 10th and 90th quantiles of the distribution of the factors; the transition speed has a gamma prior. We also adopt a normal-inverse-gamma prior for the factor equation: Each of the factor loadings has a normal prior and each variance is inverse gamma. The prior for the inclusion indicator is
set such that more weight is assigned to excluding variables. This makes the factor estimated
over, ex ante, as parsimonious a vector of financial indicators as possible. Table A presents
the prior hyperparameters. We describe the tuning parameters $\Delta_\gamma$, $\Delta_{\Omega_1}$ and $\Delta_{\Omega_2}$ below.
The values of these tuning parameters in Table A are set such that the acceptance rate of
both Metropolis steps is around 10% after 10000 initial (discarded) draws.

3.2 Drawing $\Psi$ conditional on $\Theta_{-\Psi}, f_T, z_{d,T}$ and $x_T$

Conditional on $\pi_t (f_{t-1})$, a draw from the posterior distributions for the VAR parameters is
a straightforward application of Chib (1993) and Chib and Greenberg (1996). Rewrite the
VAR of $y_t = [z_t, f_t]'$ as follows:

$$y_t = \theta_t \tilde{\Psi} + \varepsilon_t,$$

where $\tilde{\Psi}$ is the $(2(N_z + 1)N_zP + 2N_z + 2P \times 1)$ stacked vector of parameters,

$$\theta_t = \begin{bmatrix} I_{N_z} \otimes \tilde{y}_{t-1} & 0_{2P} \\ 0 & \tilde{f}_{t-1} \end{bmatrix},$$

$$\tilde{y}_{t-1} = \left[ \pi_t (f_{t-1}) y^p_{t-1}, (1 - \pi_t (f_{t-1})) y^p_{t-1} \right],$$

$$y^p_{t-1} = [1, y'_{t-1}, \ldots, y'_{t-p}],$$

$$\tilde{f}_{t-1} = \left[ \pi_t (f_{t-1}) f^p_{t-1}, (1 - \pi_t (f_{t-1})) f^p_{t-1} \right],$$

and $f^p_{t-1} = [f'_{t-1}, \ldots, f'_{t-p}]'$. Then, given the prior $N (m_0, M_0)$, the (stacked) joint parameter
vector can be drawn from

$$\Psi \sim N (m, M),$$

where
\[ M = \left( M_0^{-1} + \sum_{t=1}^{T} \theta_t' \Omega_t^{-1} \theta_t \right)^{-1} \]

and

\[ m = M \left( M_0^{-1} m_0 + \sum_{t=1}^{T} \theta_t' \Omega_t^{-1} y_t \right). \]

### 3.3 Drawing \( \tilde{c}, \tilde{\gamma} \) conditional on \( \Theta_{-\{\tilde{c}, \tilde{\gamma}\}}, f_T, z_{d,T} \) and \( x_T \)

The prior on the hyperparameters of the transition equation is jointly Normal-Gamma. Given the prior, the posterior is not a standard form; \( \gamma \), however, can be drawn using a Metropolis-in-Gibbs step (Lopes and Salazar, 2005). To do this, we first draw the candidates, \( \gamma^* \) and \( c^* \), separately from random walk gamma and normal proposal densities, respectively:

\[ \gamma^* \sim G \left( \frac{(\gamma^{[i-1]})^2}{\Delta_\gamma}, \frac{\gamma^{[i-1]}}{\Delta_\gamma} \right) \]

and

\[ c^* \sim \text{Unif} (c_L, c_H), \]

where the superscript \([i-1]\) represents the values retained from the past Gibbs iteration and \( \Delta_\gamma \) is a tuning parameter and the bounds of the uniform distribution are chosen such that the proposed threshold always lies on the interior of the distribution of the factors for the current factor draw. The joint candidate vector is accepted with probability \( a = \min \{A, 1\} \), where
\[
A = \frac{\prod_t \phi(z_t | \pi_t (f_{t-1} | \gamma^*, c^*), \Psi, f_t)}{\prod_t \phi(z_t | \pi_t (f_{t-1} | \gamma^{[i-1]}, c^{[i-1]}), \Psi, f_t)} 
\times \frac{dUnif(c^* | c_L, c_H)}{dUnif(c^{[i-1]} | c_L, c_H)} \frac{dG(\gamma | (\gamma^{[i-1]})^2 / \Delta^2)}{dG(\gamma^{[i-1]} | (\gamma^{[i-1]})^2 / \Delta^2)} \],
\]

\(\gamma^{[i]}\) represents the last accepted value of \(\gamma\), \(dUnif(.)\) is the uniform pdf, and \(dG(.)\) is the gamma pdf.

### 3.4 Drawing \(\Omega_1\) conditional on \(\Theta - \Omega_1, f_T, z_{d,T} \) and \(x_T\)

Under the assumption of homoskedasticity, \(\Omega_t = \Omega\) is constant and can be drawn from a conjugate inverse Wishart distribution with scale and shape determined, in part, by the number of observations and the sum of squared errors.

Under the assumption of regime-dependent heteroskedasticity, the draws of \(\Omega_1\) and \(\Omega_2\) are no longer conjugate and each requires Metropolis-in-Gibbs steps. Here, we describe the draw for \(\Omega_1\); the draw for \(\Omega_2\) is similar and can be inferred. To obtain a draw for \(\Omega_1\) conditional on \(\Omega_2\) and the other parameters, we draw a candidate \(\hat{\Omega}_1\) from an inverse Wishart distribution. Rewrite (2) in terms of the residual as

\[
\varepsilon_t = y_t - [(1 - \pi_t(f_{t-1})) A_1(L) + \pi_t(f_{t-1}) A_2(L)] y_{t-1}.
\]

Then, given the prior \(W(\nu_0, D_0)\) for \(\Omega_1^{-1}\), the candidate is drawn from \(\Omega_1^{-1} \sim W\left(\frac{\nu}{2\Delta_{\Omega_1}}, \frac{D}{2\Delta_{\Omega_1}}\right)\), where

\[
\nu = \nu_0 + \sum_t (1 - \pi_t(f_{t-1})) ,
\]

\[
D = D_0 + \sum_t (1 - \pi_t(f_{t-1})) \varepsilon_t \varepsilon'_t,
\]

and \(\Delta_{\Omega_1}\) is a tuning parameter. The draw is then accepted or rejected similar to the step
3.5 Drawing $\beta$, and $\Lambda$ conditional on $\Theta_{-\beta,\Lambda}, z_{d,T}, f_t$ and $x_T$

In a standard FAVAR, the factors can be drawn by a number of methods including the Kalman filter and the factor loadings are conjugate normal. In our case, we have two issues that can complicate estimation. First, because the composition of the vector of data determining the factor is unknown, we must sample the inclusion indicators, loadings and factors jointly. This joint draw requires a Metropolis step. Second, because the factors also affect the regimes through the transition equation, the state-space representation is nonlinear and a standard Kalman filter cannot be used.

The joint draw proceeds as follows. Our plan is to draw $\Lambda$ via a reversible-jump Metropolis step; however, a new candidate $\Lambda^*$ invalidates the $\beta$ from the previous draw. Thus, it is more efficient to draw $\beta$ and $\Lambda$ jointly. Define the joint proposal density, $q (\beta^*, \Lambda^*)$, as

$$q (\beta^*, \Lambda^*) = q (\beta^*|\Lambda^*) q (\Lambda^*).$$

First, we draw a set of inclusion candidates, $\Lambda^*$, from $q (\Lambda^*)$. Then, conditional on these candidates, we draw a candidate factor loading, $\beta^*$, from $q (\beta^*|\Lambda^*)$. This allows us to simplify the acceptance probability of the joint candidate.

3.5.1 Drawing the Inclusion Indicator Candidate

The financial stress index may be sensitive to small shocks in the financial variables because of the nonlinearities in the transition function, making variable selection important. Let $\Lambda^{[i-1]} = [\lambda_1^{[i-1]}, ..., \lambda_{N_x}^{[i-1]}]$ represent the last iteration’s draw of the matrix of inclusion indicator with $\lambda^{[i-1]} \in \{0, 1\}$. We draw an index candidate, $n^*$, from a discrete uniform with support 1 to $N_x$. The candidate $\Lambda^*$ is then
\[ \Lambda^* = \left[ \lambda_{i-1}, \ldots, \lambda_{i-1}, 1 - \lambda_n, \lambda_{n+1}, \ldots, \lambda_{N_x} \right], \]

which essentially turns the \( n^* \) switch on and off.

### 3.5.2 Drawing the Loading Candidate

Conditional on the factors and variances, the factor loadings can be drawn from a normal posterior given the normal prior, \( N(b_0, B_0) \). Moreover, because the \( x' \)'s are assumed to be orthogonal conditional on the factors, we can draw the candidate loadings one at a time:

\[ \beta_n^* \sim N(b_n, B_n), \]

where

\[
\begin{align*}
  b_n &= B_n^{-1} \left( B_0^{-1} b_0 + \sigma_n^{-2} f_T^T x_{nT} \right) \\
  B_n^{-1} &= B_0^{-1} + \sigma_n^{-2} f_T^T f_T.
\end{align*}
\]

### 3.5.3 Accepting the Draw

Once we have a set of proposals, we accept them with probability

\[
A_{n, \gamma} = \min \left\{ 1, \frac{|B^*|^{1/2} \exp \left( \frac{1}{2} b^* B^*-1 b^* \right)}{|B|^{1/2} \exp \left( \frac{1}{2} b B^{-1} b \right)} \frac{\pi(\Lambda^*)}{\pi(\Lambda^{i-1})} \frac{q(\Lambda^*)}{q(\Lambda^{i-1})} \right\},
\]

where \( b^* \) and \( B^* \) are defined and \( b_n \) and \( B_n \) are defined for \( \Lambda^{i-1} \).

### 3.6 Drawing the Factor

To implement the extended Kalman filter, we rewrite the model in its state-space representation. The state variable is \( \xi_t = y_t^p \) as defined above; let \( Y_t = [z_t', x_t']' \). Then,
\[
Y_t = H \xi_t + e_t,
\]
\[
\xi_t = G (\xi_{t-1}) + v_t,
\]
where
\[
H = \begin{bmatrix}
I_{N_x+1} & 0_{N_x \times 1} & 0_{N_x \times N_c} \\
0_{N_x \times N_z+1} & \Lambda \odot \beta & 0_{N_x \times N_c}
\end{bmatrix},
\]
\[
e_t = [0'_{N_x \times 1}, u_t']', \ v_t = [e_t', 0'_{(N_c+1) \times 1}]', \ N_c = (N_x + 1) (P - 1), \ E_t e_t' e_t = R \ and \ E_t v_t' v_t = Q.
\]

Note that, in general, both \( Q \) and \( R \) will be singular. The function \( G (.) \) is
\[
G (\xi_{t-1}) = [1 - \pi_t (f_{t-1})] A_1 (L) + (\pi_t (f_{t-1})) A_2 (L) y_{t-1},
\]
which is nonlinear in the state variable.

We can then draw \( \xi_T \sim p (\xi_{T|T}, P_{T|T}) \) which is obtained from the extended Kalman filter (EKF). The EKF utilizes a (first-order) approximation of the nonlinear model. The EKF, then, uses the familiar Kalman prediction and update steps to generate the posterior distributions for the state variable, \( \xi_t \sim p (\xi_{t|t}, P_{t|t}) \). The distribution \( \xi_{T-1} \sim p (\xi_{T-1|T}, P_{T-1|T}) \) is obtained via smoothing and preceding periods are drawn recursively.

### 3.7 Drawing \( \sigma^2 \) conditional on \( \Psi_{-\sigma^2}, Z_T \) and \( X_T \)

Given the inverse gamma prior, the measurement variances can be drawn from an inverse gamma posterior, \( \sigma_i^{-2} \sim \Gamma (\omega_i, W_i) \), where
\[
\omega_i = \frac{1}{2} (\omega_0 + T),
\]
\[ W_i = \frac{1}{2} (W_0 + u_{it} u'_{it}), \]

and

\[ u_{it} = x_{it} - \Lambda_i f_t. \]

4 Empirical Results

4.1 Data

To measure financial stress through its effects on the transition dynamics of macroeconomic variables, we require two sets of data. First, we need financial data with which we can search for common fluctuations. Second, we need a set of macroeconomic variables. For the former, we consider an unbalanced panel consisting of a vector of 23 financial series also used in Hatzius et al. (2010). These financial indicators include term spreads, credit spreads, Treasury rates, commercial paper rates and survey data. The data end in September 2012. All variables are monthly and described in Table 1. The selection of variables encompasses all subgroups described in Hatzius et al. (2010), Brave and Butters (2012) and Kliesen et al. (2012). These variables were all demeaned before estimation.

Because the financial data are monthly, we use the year-on-year growth rate in industrial production as our main economic indicator. We also include a monthly inflation measure, the year-on-year rate of change of headline CPI. Both series are seasonally adjusted.

4.2 Financial Conditions Factor and Regime Changes.

Figure 1 presents the estimates of the unobserved financial factor over two FASTVAR specifications: the one described in (7) that does not allow for dynamic feedback from the macro variables to the factor and the unrestricted version. In both cases, we present the posterior
mean and 68% confidence bands. We also show the results of applying principal components
to a balanced version of our dataset of 23 monthly financial variables.

Two clear results emerge. First, both the restricted and unrestricted specifications gen-
erate very similar factor estimates. Second, if large positive values of the factor are normally
associated with financial stress periods, the periods identified by the principal-component
approach may differ from those using the FASTVAR approach. This provides some initial
evidence that estimating the factor jointly with the VAR for macro data may matter for
identifying periods of financial stress.

Table 2 presents the posterior means of the inclusion dummies ($\lambda_i$) for each financial
variable for both the restricted and unrestricted specifications. The posterior means for
both specifications are very similar, in agreement with Figure 1. The variables selected over
more than 84% of the posterior distribution are (i) two credit spreads (baa10ysp and high-
yieldspread), (ii) a measure of equity returns (wilrate) and (iii) a consumer survey measure
(migoodsurv). Other credit conditions variables also have a high probability of being se-
lected. However, variables such as term spreads are not very important to define financial
stress regimes.

Figure 2 presents the posterior mean of the transition function (equation 3) for both
FASTVAR specifications. As opposed to the Markov-switching VAR model, in the FAST-
VAR model, the economy can reside in the transition state between the two extreme regimes.
The values of the transition function over time represent the weights given to the high stress
regime at each date. Values near zero imply that the economy is in the lower stress regime;
NBER recessions are shaded in gray. Two results are clear: (i) as before, both specifications
identify similar regime-switching history and (ii) the weights on the second regime’s coeffi-
cients are higher than 80% during most of the NBER recessions. Based on this, we classify
the second regime as the financial stress regime. We can also interpret the estimates in Fig-
ure 2 as a time series of the posterior probability of the financial stress regime. We have at
least one month of financial stress regime (probability/weights higher than 50%) within each
one of the four recession episodes covered. Since we estimate both the unobserved factor and the transition function within the FASTVAR model, this is a remarkable model to detect financial stress regimes correlated with recessions.

Figure 3 represents the posterior mean of the transition function for both FASTVAR specifications but now includes the 68% confidence bands. The confidence intervals on the regime weights are generally narrower using the restricted model. The unrestricted model allows for 3 extra parameters to change over regime, creating additional estimation uncertainty. The fact that regime definition is not as clear-cut in the unrestricted FASTVAR specification will have implications for the performance of the model in real time, as will be discussed later.

Figure 4 presents the square root of the posterior mean of the diagonal of $\Omega_t$, which is the regime-dependent variance-covariance matrix of the disturbances, for both FASTVAR specifications. The sizes of the volatility changes are generally larger for the restricted model than for the unrestricted specification. If we compare the relative size of the standard deviations in each regime, we can say that differences are very small for industrial production innovations. However, for inflation and financial factor innovations, the volatility of innovations in the high-stress regime are roughly 15% larger than in the low-stress regime. Because of the VAR ordering, this implies that financial shocks have higher volatility during financial stress periods, with a sizable increase of around 15%.

### 4.3 Impulse Responses

Figure 5 presents the 48-month dynamic responses from a one-standard-deviation financial shock with an assumed zero impact effect on industrial production growth and inflation. These are generalized responses—that is, they allow for regime switching over horizons and are computed conditional on the regime histories as described in Section 2.2.2. We use the average variance-covariance matrix over time to set the size of the shock ($\nu$ in equation (8)) such that the size of the shock is the same for both regimes, so asymmetries in the responses
are caused only by nonlinearities in the VAR dynamics and not by the changes in the regime-conditional variances reported in Figure 4. The plots present the mean response over 150 equally spaced draws from the parameter posterior distributions (based on 15000 draws) for the FASTVAR parameters and the factor time series, including 68% confidence bands. As before, we compute responses for both restricted and unrestricted specifications. Regime 2 is the financial stress regime.

The dynamic responses computed using the restricted FASTVAR parameters show a more persistent response to the financial shock than the unrestricted model. In both specifications, a negative financial shock (equivalent to an increase in the financial factor) has a large significant negative effect on economic activity with a peak effect of -0.8%. However, the response is zero after 3 years (68% confidence bands include zero) using unrestricted model estimates, but it is still sizable with the restricted model. The lack of feedback effects from macro variables to the financial factor explains this excessive persistence, which is not compatible with the average duration of recessions of around 1 year during the period. Similar excessive persistence is also detected for inflation.

Both specifications agree, however, that there is little asymmetry between regimes in the IP growth responses but substantial asymmetries on the inflation responses. During financial stress regimes, an exogenous increase in stress significantly decreases inflation by 0.2% nine months after the shock. A similar shock occurring in the low-stress regime has no effect on inflation. The posterior mean response of IP growth during the financial stress regime is -0.84% at a 4-month horizon and -0.74% when not initially in the financial stress regime. The cumulative effect after four years is -11% for IP growth and -4% for inflation in the financial stress regime. These results based on the unrestricted model are, in general, compatible with typical recession characteristics.

In summary, these results indicate that exogenous changes in the financial factor have significant negative effects on economic activity even if they do not initially occur in the financial stress regime. If in the high-stress regime, we find significant negative responses of
inflation to the financial shocks, while the results in Section 4.2 suggest we should expect larger financial shocks.

4.4 Identifying financial stress regimes during 2007-2010

One of the possible uses of the empirical model proposed in this paper is to provide an early warning mechanism for financial stress periods. If the economy is in financial stress, the likelihood of large financial shocks increases and inflation is more responsive to exogenous variation in the financial variables—in particular, to credit spread measures. Thus, it is important for policymakers to identify the onset of these regimes.

We evaluate the FASTVAR’s ability to detect financial stress periods from September 2007 up to April 2010. Figure 6 shows the posterior means of the regime weights for both the restricted and unrestricted models estimated with final data for this subperiod. The figure also presents pseudo real-time estimates computed by re-estimating the models over increasing windows of data starting from 1981M9 and ending at each month from 2007M9 to 2010M4. For each window, we re-estimate the model (20000 draws with the initial 5000 draws discarded) and save the posterior mean of the transition function for the last observation—that is, we compute real-time probabilities of being in the financial stress regime.

As in our previous results, the unrestricted model exhibits more uncertainty in identifying the financial stress regime than the restricted model.\textsuperscript{4} Using the restricted model, we are able to initially detect a probability of financial stress higher than 80% in February 2008, even though using data up to 2012M9, the estimated probability is only 32%. Both real-time and final measures drop to values below 50% in January 2010.

We also look at the selection of the financial variables into the financial factor during the period. Figure 7 presents the posterior mean of the $\lambda_i$s for each window of data finishing at the indicated date, computed using the restricted specification (results are similar for the

\textsuperscript{4}For some windows of data, the estimates of the factor loadings are, in general, negative instead of positive, as in the case of the full sample. This means that the factor and regimes flip. If this was the case, we flip the obtained estimates such that transition function values near $1$ are associated with the financial stress regime.
unrestricted one). For data windows up to January 2009, many variables are selected more than 80% of the time. The figure shows the selection by categories. When looking at interest rates and term spread, only the long-term interest rate is frequently selected before 2009. Both housing and equity prices changes are also selected, while the oil price is not. We consider many different measures of credit spreads and almost all of them are highly selected in the earlier period. Consumer survey measures and measures of growth of credit stock are also selected. After January 2009, with stronger evidence of a financial-related recession, the only variable that is selected more than 80% of the time is the Baa–10-year Treasury spread. Recall that when looking at the full sample, we find also three additional variables that are typically selected. These results support the development of macroeconomic models able to explain why credit spreads vary over time and how large credit spreads amplify the transmission of shocks, particularly to inflation.

In summary, the restricted FASTVAR model is adequate to detect financial stress regimes in real time. The flexibility from selecting the financial variables into the financial factor for a specific window of data is one of the key elements in this good performance.

4.5 Robustness Exercises

The financial variables in Table 1 might be strongly related to monetary policy. One way to be sure that our dynamic responses are computed for financial shocks that are not caused by unexpected changes in monetary policy is to add a measure of monetary policy in the VAR vector $z_t$ in equation (2). An issue with this approach is that while it is easy to assume that the fed funds rate is a measure of monetary policy for the period before 2008, this is harder for the later period. This explains why we decide against including the fed funds rate in our baseline specification, differing from the specification of Bernanke et al. (2005) and Hubrich and Tetlow (2011). As a robustness check, we estimate an unrestricted FASTVAR model with the fed funds rate in addition to growth in industrial production and CPI inflation in the vector $z_t$. 

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Figure 8 presents the posterior mean of the transition function in the upper-left panel and responses from exogenous changes in financial stress computed as in Section 4.3. The identification of the financial stress regime does not change qualitatively with the inclusion of the monetary policy measure. Responses of IP growth and inflation are also qualitatively similar. The response of the fed funds rate is negative and persistent. The monetary policy reaction is weaker during the financial stress regime. This relative shallowness might explain why the response of inflation is stronger if the shock hits in the financial stress regime. However, it may also be related to zero lower bound constraints in the latter part of the sample.

5 Conclusions

The financial crisis emphasized the importance of identifying periods of high financial stress as these periods can have important and detrimental effects on the macroeconomy. In this paper, we construct a measure of the probability of a financial stress regime which—by design—includes only financial variables that alter the economic dynamics between financial conditions and macroeconomic variables such as industrial production and inflation. We find evidence that credit spread measures help to detect nonlinear dynamics from the financial sector to the macroeconomy. We also find that exogenous increases in financial stress have not only large negative effects on economic activity, but also amplification effects on inflation responses and the variance of financial shocks.

These empirical results based on our novel modeling approach support the development of models that describe amplifying effects from financial shocks to the macroeconomy during periods of large credit spreads, negative stock returns and low consumer confidence. The amplifying effect is relevant particularly when looking at aggregate inflation.
References


Figure 1: Financial Factor Estimates.
The figure shows estimates using the unrestricted FASTVAR model (solid dark line), the restricted FASTVAR model (dashed dark line) and principal components (dotted line). The principal components factor is estimated with a balanced panel, leading to a shorter sample. The 68-percent error bands for the unrestricted FASTVAR are shaded in gray.
Figure 2: Transition Function over time and NBER recessions.
The figure shows the values of the transition function for the unrestricted FASTVAR (grey solid line) and the restricted FASTVAR (dashed line). The NBER recessions are shaded in gray.
Figure 3: Posterior Values of the Financial Stress Regime Weights.
The two panels show the mean value of the posterior distributions of the transition function for the unrestricted FASTVAR (panel A) and the restricted FASTVAR (panel B). The 68-percent error bands are shown shaded in grey.
Figure 4: Time-varying Volatilities.
The figure shows the square root of the diagonal elements of the posterior mean of the variance-covariance matrix for the FASTVAR (std) and the restricted FASTVAR (std_rest) specifications. The first panel shows the value for the IP growth equation, the second panel shows the value for the CPI inflation equation, and third is for the factor equation.
Figure 5: Generalized responses of IP growth and inflation to a financial factor shock.
The response to a shock that occurs in regime 2 (\(_2\); financial stress regime) is denoted in light grey with dark grey shaded error bands and the response to a shock that occurs in regime 1 (\(_1\); low stress regime) is denoted in black with light grey error bands. The top panel shows the responses of industrial production (IP) growth and inflation (P) in the unrestricted FASTVAR model. The bottom panel shows the responses of both variables in the restricted FASTVAR model. The generalized impulse responses are computed with 200 draws from the historical shock distribution for each draw from the Gibbs sampler. We thin the sampling distribution using only every tenth Gibbs draw.
Figure 6: Probabilities of Financial Stress Regime during 2007-2010. The figure shows in-sample (F) and pseudo-out-of-sample (RT) estimates of the weights/probabilities of the financial stress regime for the Great Recession period starting September 2007 and ending April 2010. The solid lines are the in-sample estimates of the weights for the restricted (black line) and the unrestricted (grey line) models. The dashed lines are the pseudo-out-of-sample estimates of the weights for the restricted (black dashed) and the unrestricted (grey dashed) models. In the pseudo-out-of-sample estimates, the line reports the value of the weights for period $t$ estimated with all data prior to period $t$. 
Figure 7: Posterior Inclusion Probabilities for Covariates during 2007-2010.
The figure shows the posterior inclusion probabilities for various variables for the Great Recession period starting in September 2007 and ending in April 2010. The posterior inclusion probability is the mean of the estimate of the inclusion dummy across Gibbs iterations computed using data up to $t$. 

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Figure 8: Results for the FASTVAR model with the Fed rate.
Panel A shows the posterior means of the transition function for the model with the fed fund rates (grey line) and the benchmark (black line) with the NBER recessions shaded in grey. Panels B-D show the generalized impulse responses of IP growth (panel B), CPI inflation (panel C), and the fed funds rate (panel D) to a shock to the factor. For these graphs, the response to a shock that occurs in regime 1 is denoted in grey with light grey shaded error bands and the response to a shock that occurs in regime 2 (financial stress regime) is denoted in black with dark grey error bands.
Table 1 – Financial Variables included in the FASTVAR estimation.

<table>
<thead>
<tr>
<th>Description</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>10y</td>
<td>annual growth rate of the 10 year treasury rate 1981M9-2012M9</td>
</tr>
<tr>
<td>FFR3msp</td>
<td>fed fund rates - 3month bill rates 1981M9-2012M9</td>
</tr>
<tr>
<td>2y3msp</td>
<td>2-year treasury rates – 3-month bill rates 1981M9-2012M9</td>
</tr>
<tr>
<td>10y3msp</td>
<td>10-year treasury rates – 3-month bill rates 1981M9-2012M9</td>
</tr>
<tr>
<td>tedsp</td>
<td>TED spread 1981M9-2012M9</td>
</tr>
<tr>
<td>creditsp</td>
<td>Citibank corporate credit spread 1981M9-2012M9</td>
</tr>
<tr>
<td>exchrate</td>
<td>annual growth rate of the exchange rate 1981M9-2012M9</td>
</tr>
<tr>
<td>wilrate</td>
<td>annual growth rate of the Wishire 5000 1981M9-2012M9</td>
</tr>
<tr>
<td>houseinf</td>
<td>annual growth rate of the national house index 1981M9-2012M9</td>
</tr>
<tr>
<td>creditrate</td>
<td>annual growth rate of bank credit of commercial banks 1981M9-2012M9</td>
</tr>
<tr>
<td>compaperrate</td>
<td>annual growth rate of commercial paper outstanding 1981M9-2012M9</td>
</tr>
<tr>
<td>moneyrate</td>
<td>annual growth rate of money stock (zero maturity) 1981M9-2012M9</td>
</tr>
<tr>
<td>nfibsurv</td>
<td>%credit was harder to get than last time 1981M9-2012M9</td>
</tr>
<tr>
<td>migoodsurv</td>
<td>%good-%bad conditions for buying large goods 1981M9-2012M9</td>
</tr>
<tr>
<td>mihousesurv</td>
<td>%good-%bad conditions for buying a house 1981M9-2012M9</td>
</tr>
<tr>
<td>miautosurv</td>
<td>%good-%bad conditions for buying a car 1981M9-2012M9</td>
</tr>
<tr>
<td>vix</td>
<td>VIX (monthly average) 1990M1-2012M9</td>
</tr>
<tr>
<td>jumbospread</td>
<td>Jumbo rates - 30-year conventional rates 1998M6-2012M9</td>
</tr>
<tr>
<td>OIS spread</td>
<td>3-month libor rates - overnight index swap rates 2001M12-2012M9</td>
</tr>
<tr>
<td>highyieldspre</td>
<td>High-yield corporate rates – Baa corporate rates 1997M1-2012M9</td>
</tr>
<tr>
<td>oil price</td>
<td>price of oil relative to a 2-year moving average 1981M9-2012M9</td>
</tr>
</tbody>
</table>
Table 2 – Posterior Inclusion Probabilities for Covariates (full sample).

<table>
<thead>
<tr>
<th>Covariate</th>
<th>FASTVAR_r</th>
<th>FASTVAR</th>
</tr>
</thead>
<tbody>
<tr>
<td>10y</td>
<td>0.63</td>
<td>0.65</td>
</tr>
<tr>
<td>FFR3msp</td>
<td>0.42</td>
<td>0.43</td>
</tr>
<tr>
<td>2y3msp</td>
<td>0.40</td>
<td>0.40</td>
</tr>
<tr>
<td>10y3msp</td>
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</tr>
<tr>
<td>baa10ysp</td>
<td>0.96</td>
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<td>30mort10ysp</td>
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<td>0.82</td>
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<td>tedsp</td>
<td>0.65</td>
<td>0.62</td>
</tr>
<tr>
<td>creditsp</td>
<td>0.70</td>
<td>0.70</td>
</tr>
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<td>exchrate</td>
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<td>0.48</td>
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<tr>
<td>wlrate</td>
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<td>0.89</td>
</tr>
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<td>houseinf</td>
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<td>0.65</td>
</tr>
<tr>
<td>creditrate</td>
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<td>0.39</td>
</tr>
<tr>
<td>compaperrate</td>
<td>0.68</td>
<td>0.71</td>
</tr>
<tr>
<td>moneyrate</td>
<td>0.50</td>
<td>0.49</td>
</tr>
<tr>
<td>nfbtsurv</td>
<td>0.67</td>
<td>0.69</td>
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<td>mgoodsurv</td>
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<td>mihousesurv</td>
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</tr>
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<td>vix</td>
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<td>0.74</td>
</tr>
<tr>
<td>jumbospread</td>
<td>0.66</td>
<td>0.66</td>
</tr>
<tr>
<td>OIS spread</td>
<td>0.70</td>
<td>0.67</td>
</tr>
<tr>
<td>highyieldspre</td>
<td>0.97</td>
<td>0.96</td>
</tr>
<tr>
<td>oil price</td>
<td>0.44</td>
<td>0.49</td>
</tr>
</tbody>
</table>

Note: FASTVAR_r restricts the VAR coefficients such that there is no dynamic spillovers between macro variables and the factor. Based on 15000 draws of the posterior distribution (25000 draws with 10000 discharged).