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Financial Stress Regimes and the Macroeconomy*

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Abstract

Some financial stress events lead to macroeconomic downturns, while others appear to be isolated to financial markets. We identify financial stress regimes using a model that explicitly links financial variables to macroeconomic outcomes. The stress regimes are identified using an unbalanced panel of financial variables with an embedded method for variable selection. Our identified stress regimes are associated with corporate credit tightening and with NBER recessions. An exogenous deterioration in our financial condition index has strong negative effects in economic activity, and negative amplification effects on inflation in the stress regime. We employ a novel factor-augmented vector autoregressive model with smooth regime changes (FAST-VAR).

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

JEL codes: C3, E3.

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1 Introduction

In the aftermath of the 2008-2009 worldwide downturn, research in macroeconomics has emphasized models with financial frictions able to describe nonlinearities in how shocks to the financial sector affect the macroeconomy.[1] These models typically characterize two regimes: a normal, low-stress regime and a high-stress regime—or high-systemic-risk regime—where financial constraints are binding and shocks to the financial sector have stronger negative effects on investment (He and Krishnamurthy, 2014). The financial stress 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 (2015) 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.[2]

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. This suggests two possible alternative characterizations of financial stress: one whose effects are limited to financial markets and emphasizes regulatory solutions and one that has consequences for macroeconomic activity that implies the use of economic stabilization policy. Because most financial stress indexes are focused on financial variables alone, this second, possibly important characterization has been relatively absent in the literature.

In this paper, we use a novel econometric approach with nonlinear dynamic links between the financial sector and the macroeconomy to compute a financial conditions factor using

[1] See for example, Brunnermeier and Sannikov (2014), He and Krishnamurthy (2014),Akinci and Queralto (2014).

[2] Additionally, Dahlhaus (2014) examines how changes in financial stress can alter the channels through which monetary policy acts.

a large unbalanced panel of financial variables. The approach includes a built-in selection mechanism such that the financial condition factor considers only the subset of financial variables that better describe linkages between the financial sector and the macroeconomy. The nonlinear dynamics are described by the occurrence of high- and low-stress regimes lead by the jointly estimated financial conditional factor. Our main empirical result is that the financial variables that are strongly linked to the macroeconomy are (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 are consistent with those of He and Krishnamurthy (2014), 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 financial condition factor has a correlation of around 60% with alternative measures of financial stress such as the excess bond premium in Gilchrist and Zakrajsek (2012) and financial stress indexes published by regional Federal Reserve banks. In general, 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). Although we start with a similar set of variables to Hatzius et al. (2010), the use of a variable selection mechanism to estimate a factor within a nonlinear dynamic model where macroeconomic variables are also fitted explains the low correlation between our estimates and alternatives. As a result, our financial condition factor is able to better explain fluctuations in economic activity and inflation than alternatives because the model filters out events in the financial sector that have no macroeconomic consequences. The identified stress regimes have a stronger correlation with NBER recessions than regimes identified with alternative published measures of financial stress.

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-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.[3]

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. If instead we employ a traditional measure of financial conditions to identify regime changes in the VAR dynamics, we find asymmetries in line with significant negative effects of financial shocks on industrial production only in the high stress regime. This implies that our model is able to measure well macro-financial linkages such that exogenous innovations to the estimated financial condition

[3] Gilchrist, 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 have usually large negative effects on economic activity in both regimes.

We evaluate our econometric modeling approach to identify periods of high-stress regimes with macroeconomic consequences 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) and Hubrich and Terasvirta (2013)) 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 use the extended Kalman filter to draw the factor conditional on all parameters. 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 (2014) using model averaging in FAVAR models.

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

2 The Empirical Model

In this section, we propose a method to simultaneously measure financial stress and 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 $\mathbf{z}_t$ 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 $\mathbf{y}_t = [\mathbf{z}_t', f_t]'$, where the ordering of f_t last is intentional and provides the identifying restriction used to construct impulse responses.[4] The VAR in question is then

$$\mathbf{y}_t = \mathbf{A}\left(L\right)\mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{1}$$

[4] Our identifying assumption is that the financial stress shock does not affect the macroeconomic variables contemporaneously. In our baseline specification, a monetary policy instrument is not included in $\mathbf{z}_t$.

where $\mathbf{A}(L)$ is a matrix polynomial in the lag operator, $\boldsymbol{\varepsilon}_t \sim N(0, \Omega)$, and we have suppressed any constants and trends. The matrixes $\mathbf{A}(L)$ drive the transmission of financial shocks—shocks to f_t—to macroeconomic variables $\mathbf{z}_t$. 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

$$\mathbf{y}_t = [1 - \pi_t(f_{t-1}; \gamma, c)] \mathbf{A}_1(L) \mathbf{y}_{t-1} + \pi_t(f_{t-1}; \gamma, c) \mathbf{A}_2(L) \mathbf{y}_{t-1} + \boldsymbol{\varepsilon}_t, \tag{2}$$

where $\mathbf{A}_1(L)$ and $\mathbf{A}_2(L)$ are matrices of lag polynomials, $\boldsymbol{\varepsilon}_t \sim N(\mathbf{0}_{N_z+1}, \boldsymbol{\Omega}_t)$, and Ω_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 $\mathbf{A}_1(L)$ and $\mathbf{A}_2(L)$ on the path of $\mathbf{y}_t$.

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

$$\pi_t(f_{t-1}; \gamma, c) = [1 + \exp(-\gamma(f_{t-1} - c))]^{-1}, \tag{3}$$

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, $A_1(L)$.[5] The coefficient γ 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

[5] This analysis implicitly assumes that the transition variable delay is equal to 1. Because financial condition factors are typically persistent time series, the assumption that the delay is equal to 1 is not very restrictive.

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).

The advantage of using a smooth transition model instead of a threshold specification is that we are not required to assume abrupt changes between regimes, since they can be smooth. In comparison with Markov-Switching models (Hamilton, 1989), the advantage of the smooth transition specification is that a model with constant transition probabilites, as the one applied by Chauvet (1998) and Hubrich and Tetlow (2015), does not allow the financial stress to affect the state of the world, which we view as critical in identifying stress regimes.

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

$$\mathbf{\Omega}_t = \left[1 - \pi_t\left(f_{t-1}; \gamma, c\right)\right] \mathbf{\Omega}_1 + \pi_t\left(f_{t-1}; \gamma, c\right) \mathbf{\Omega}_2,$$

where $\mathbf{\Omega}_1$ and $\mathbf{\Omega}_2$ are $((N_z + 1) \times (N_z + 1))$ symmetric matrices. A STVAR specification with regime-dependent heteroskedasticity as above but with $c = 0$ and a calibrated γ 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 with effects in the macroeconomy? As a consequence, we estimate the financial conditions index as a factor within a FASTVAR based on a vector of financial variables, $\mathbf{x}_t$.

Let f_t be the factor that summarizes the comovements across N_x demeaned financial series, $\mathbf{x}_t$:

$$\mathbf{x}_t = \boldsymbol{\beta} f_t + \mathbf{u}_t, \tag{4}$$

where $\boldsymbol{\beta}$ is the matrix of factor loadings and u_{it} are iid $N\left(0, \sigma_i^2\right)$. 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 $\mathbf{x}_t$. For example, Kliesen et al. (2012) surveyed 11 different indexes constructed from 4 to 100 indicators. While some indicators are more frequently included and appear to be more important than others, the composition of the variables used to construct the index is important. 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 get at this issue, we start with a baseline composition of variables (e.g., those in Hatzius et al. (2010)) and 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 ith element of $\mathbf{x}_t$ to zero. We can then rewrite (4) as

$$\mathbf{x}_t = (\mathbf{\Lambda} \odot \boldsymbol{\beta}) f_t + \mathbf{u}_t. \tag{5}$$

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

2.2.1 Estimation and Possible Identification Issues

We estimate the model using the Gibbs sampler with three Metropolis-in-Gibbs steps. Let Θ collect all of the model parameters. We can partition the set of model parameters into blocks: (1) $\mathbf{\Psi} = [\mathbf{A}_1(L), \mathbf{A}_2(L)]$, the VAR coefficients; (2) $\mathbf{\Omega}_1$ and $\mathbf{\Omega}_2$, which are the regime-specific VAR variance-covariance matrixes; (3) γ and c, the transition speed and the threshold; (4) β, Λ and $\mathbf{f}_T = \{f_t\}_{t=1}^{T}$, the factor loadings, the inclusion indicators and the factor, respectively; and (5) $\{\sigma_{it}^2\}_{i=1}^{N_x}$, the variances of financial variables. The Gibbs sampler is a Bayesian algorithm that samples from the posterior distribution of each block conditional on past draws of 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.

We assume a normal prior for the VAR coefficients and the factor loadings; the VAR covariance matrices have an inverse Wishart prior; the financial variable innovations have an inverse gamma prior. The inclusion indicators have a Bernoulli prior weighted a priori to exclude variables from the model. The transition speed has a gamma prior and the threshold has a uniform prior whose support is restricted to lie inside the extrema of the factor draws.

The draws of most of the parameters are conjugate, but the model requires three Metropolis steps and a nonlinear filtering step to draw the factors. First, we follow Lopes and Salazar (2005) and jointly draw the transition function parameters γ and c from gamma and uniform proposal distributions, respectively.[6] Second, we jointly draw the factor loadings $\boldsymbol{\beta}$ and the inclusion dummies $\boldsymbol{\Lambda}$. Third, we use a Wishart proposal for Ω_t, the variance-covariance matrix of each regime, and use a decision rule based on the likelihood, prior and proposal when considering each new draw.[7] All the Metropolis steps have tuning parameters that control the percentage of rejections over the sampling procedure. We set the tuning parameter values such as the acceptance rate is around 30% using 10,000 initial discarded draws. We use 25,000 draws and discarded the initial 10,000 to compute posterior distributions. Parameterization of the prior and details for the sampler, including our implementation of the extended Kalman filter to draw the factors, are available in the Appendix.

Terasvirta (2004) argues that it might be difficult to estimate γ in short time series even if there is strong nonlinearity because only few observations will be available around the threshold value c. We address this issue as follows: First, we estimate the model with monthly series as to have a reasonable number of observations (around 372). Second, we make the smoothing parameter γ scale free by writing the transition function as $\pi_t(f_{t-1}; \gamma, c) = [1 + \exp(-(\gamma/\sigma_f)(f_{t-1} - c))]^{-1}$ so it is easier to set priors and tuning parameters. Third, we set the support of the prior distribution for the threshold such that at least 10% of the observations in each regime even if γ is large. This implies that the estimation procedure will not capture outliers as a regime.

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 the transmission of shocks differs even though the size and sign of the shocks are invariant. We split

[6] Our prior differs from Bauwens, Lubrano and Richard (1999), whose prior for the autoregressive parameters depend on γ. Our procedure differs from Gefang and Strachan (2010), who draw γ and c independently. Note also that Auerback and Gorodnichenko (2012) calibrate the values of γ and c such that they guarantee that γ is small and the transition function is smooth.

[7] This step differs from Auerback and Gorodnichenko (2012), who draw the variance-covariance parameters via its lower triangular decomposition in an element-by-element Metropolis step and is motivated by the homoscedastic case where the Wishart distribution provides closed-form posterior distribution for variance-covariance matrix.

the data on macroeconomic variables and a factor f_t (for $t = 1, ..., T$) 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, $\pi_t(f_{t-1}; \gamma, c) > 0.5$.[8] 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 $\mathbf{y}_{t+h}$ with and without the shock to compute responses:

$$IRF_{h,v,s} = \frac{1}{T_s} \sum_{t=1}^{T_s} \left\{ E[\mathbf{y}_{t+h} | \mathcal{F}_t^{(s)}, v_t = v] - E[\mathbf{y}_{t+h} | \mathcal{F}_t^{(s)}] \right\}, \tag{6}$$

where T_s is the number of histories in regime s, $\mathcal{F}_t^{(s)}$ is a history from regime s (typically including $\mathbf{z}_t, ..., \mathbf{z}_{t-p+1}$ and $f_t, ..., f_{t-p+1}$) 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 (6), we are implicitly assuming a fixed set of parameters of the FASTVAR ($\mathbf{A}_1(L)$, $\mathbf{A}_2(L)$, γ, c, Ω_1, Ω_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

[8] We check the robustness of this assumption. Qualitative results in section 3.5 do not change if we the define the upper as $\pi_t(f_{t-1}; \gamma, c) > 0.9$ and the lower regime as $\pi_t(f_{t-1}; \gamma, c) < 0.1$.

distribution, and we plot the posterior mean for $IRF_{h,v,s}$ and 68% confidence intervals.

3 Empirical Results

3.1 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. Because the series start at different points in time, the panel is unbalanced with a start data in 1981. 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.

3.2 Financial Conditions Factor

Figure 1 presents the estimates of the financial conditions factor obtained with the FASTVAR with $p = 1$, including 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. Figure 1 results suggest that if large positive factor values are normally associated with financial stress periods, then stress regimes that may be identified by the principal-component approach may differ from those using the FASTVAR approach.

Table 2 presents the posterior means of the inclusion dummies (λ_i) for each financial variable for both the restricted. The variables selected over more than 84% of the posterior distribution are (i) two credit spreads (baa10ysp and highyieldspread), (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 selected. However, variables such as term spreads are not very important to define financial stress regimes. Our variable selection takes into account the link between the financial factor and future economic activity, so our support to measures of credit conditions as measure of financial stress are in agreement with Gilchrist and Zakrajsek (2012), who show that credit spreads lead economic activity.

We compute the correlation between the factor obtained with FASTVAR presented in Figure 1 and alternative estimates of financial tightening and/or financial stress. First, the correlation with the principal component estimate, also shown in Figure 1, is of 64%, providing additional evidence that the factor estimated within a model that links financial variables to the macroeconomy and includes a covariate selection step is not very similar than one computed simply by principal components as in Hatzius et al. (2010). Second, the correlation with the excess bond premium of Gilchrist and Zakrajsek (2012) is of 64%. Although our financial condition index selects credit spread very frequently, the contribution of other variables such as equity returns imply only a moderate correlation with the excess bond premium measure. Finally, in comparison with financial stress indexes published by regional Federal Reserve Banks, we find a correlation of 74% with the Kansas Fed Stress index, of 63% with the St. Louis Fed index, 56% with the Chicago Fed index, and of 52% with the Cleveland index. As a consequence, our financial conditions factor based on similar set of financial variables differs from others available in the literature because the FASTVAR model extracts the information on financial variables that actually matters for the macroeconomy.

Figure 1 indicates four peaks for the financial condition factor. These peaks are during each one of the four recessions that have occurred during the period. The first one is in July 1982 and it is associated with the failure of the Penn Square bank. The second one is in February 1991 and it is within the 1990-92 credit crunch period when the Resolution Trust Corporation was actively dealing with bankrupt Savings and Loan associations. The third peak is in October 2001, which is the month that the Enron scandal was first revealed. Finally, the last peak is on April 2009, which is the month that Chrysler filed for bankruptcy. These events all describe financial stress in the corporate environment, in agreement with the results of our covariate selection relying mainly in corporate spreads.

3.3 Alternative Specifications

In this subsection, we compare our baseline FASTVAR specification with alternative specifications. We use a Bayesian Information criterion (BIC) for the comparison. We apply the criterion for the fit of the two macroeconomic observables (IP growth and inflation) such that we can compare linear and nonlinear models and models with observed and unobserved factors. We compute the BIC for each kept MCMC draw and the results presented in Table 3 are average over draws.

First, we consider specifications that impose restrictions on the baseline FASTVAR specification. The first specification is the FASTVAR_r that imposes that no direct dynamic effects of the macroeconomic variables on the financial factor—that is, the only nonzero coefficients in the factor equation are the factor's own AR coefficients. This might have the effect of giving more weight to financial variables (since VAR dynamics is restricted) in the estimation of the financial condition factor. The second specification is a FASTVAR with no variable selection—that is, all financial variables in Table 1 are loaded into the financial conditions factor. Third, we consider a linear specification with no variable section—that is, a FAVAR model estimated via Gibbs sampling.

We also consider the smooth transition VAR models as described in Section 2.1 with observed factors. These specifications do not require the estimation of the factor and factor loadings, but they still use the steps described in the Appendix to draw the parameters of the transition function and the regime-dependent variance-covariance matrices. We employ two observed financial factors that are chosen based on their monthly availability for the 1981-2012 period so obtained results are comparable with the FASTVAR results. We use the excess bond premium by Gilchrist and Zakrajsek (2012) and the Chicago Fed Financial Condition Index.[9]

Table 3 clearly indicates that the baseline FASTVAR is the modelling approach that better fits IP growth and inflation dynamics. All alternatives raise the BIC substantially. Interestingly, the STVAR specifications with observed factors do not improve over the linear FAVAR specification, while our FASTVAR does. This suggests that estimating the factor within the model improves the fit when the objective is to obtain changes in financial conditions that affect macro variables. The results also suggest that to capture nonlinearity over the 1981-2012 period, the excess bond premium (EPB) is a better transition variable than the Chicago Fed Financial conditions index.

3.4 Regime Changes

Figure 2 presents the posterior mean of the transition function, equation (3), for the FASTVAR. As opposed to the Markov-switching VAR model, in the FASTVAR 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.[10] Values near zero imply that the economy is in the lower stress regime; NBER recessions are shaded in gray.

The weights on the second regime's coefficients, which we classify as the financial stress regime, are higher than 80% during most of the NBER recessions. The estimates in Figure 2 can also be interpreted 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

[9]The excess bond premium is obtained from http://people.bu.edu/sgilchri/Data/data.htm and the Chicago Fed Financial Conditions Index is obtained from the FRED database at the St. Louis Fed.

[10]The posterior mean estimates of the parameters of the transition function are $\bar{\gamma} = 12.77$ and $\bar{c} = 0.474$.

the unobserved factor and the transition function within the FASTVAR model, the model is able to detect financial stress regimes correlated with recessions.

Figure 3 presents the posterior mean estimate of the transition function computed using two STVAR specifications: the first employs the Chicago FCI and the second the EBP as transition variable. These specifications were also in the analysis in the previous section. The stress regimes identified by the Chicago FCI show no evidence of high stress during the 2001 recession, but they classify the period from June 1987 up to February 1991 as a long high stress regime, which includes the months following the Black Monday (October, 1987). In contrast, stress regimes identified by the EBP are more strongly correlated with recessions but the high stress regime is also identified in expansion periods such as from May 1986 to May 1987 and from May 1989 to April 1990. The period just after Black Monday, however, is not identified as high stress, as in the case of the FASTVAR.

Figure 4 represents the posterior mean of the transition function and 68% confidence bands for the FASTVAR and also the FASTVAR_r specification that constrains the dynamic of the factor as described in the previous section. 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 5 presents the square root of the posterior mean of the diagonal of $\mathbf{\Omega}_t$, which is the regime-dependent variance-covariance matrix of the disturbances, for the FASTVAR. 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%. If we use the posterior distribution to compute the standard deviation of these estimates for each regime, we find that the high-stress regime financial volatility is one-standard deviation larger than the one in the low stress regime, while differences across regime for the other shocks are generally smaller than one standard deviation.

3.5 Impulse Responses

Figure 6 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 (ν in equation (6)) such that the size of the shock is the same for both regimes; thus, 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 5. 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. Regime 2 is the financial stress regime.

The responses suggest that 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%, but the response is zero after 3 years (68% confidence bands include zero). 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 are, in general, compatible with typical recession characteristics. They are also compatible with the results of Caldara, Fuentes-Albero, Gilchrist and Zakrajsek (2016), who, in a constant parameter model, found a similar sized variation in industrial production as response to a shock that raises financial market tightening. Recall also that our high-stress regime is strongly correlated with recessions, so our results agree with Ng and Wright (2013) who argue that is hard of find evidence of asymmetries over business cycles in responses of aggregate economic activity to shocks.

If we apply the same methodology described to compute the responses in Figure 6 to a STVAR with Chicago FCI as observed transition variable, we obtain the results in Figure 7 for full sample average standard deviation shock. They clearly indicate that negative responses of economic activity to the financial condition shocks are stronger in the high stress than in the low stress regime, while inflation responses are positive in the lower stress regime and negative in the high stress regime. We investigate these differences between the FASTVAR and the STVAR results by comparing their posterior mean VAR coefficients estimates in each regime. The STVAR estimates suggest that the lagged coefficient of the FCI on IP growth is very small in the low stress regime, but it is larger and negative in the high stress regime. In the case of the FASTVAR estimates, however, the coefficient on the lagged estimated factor is large and negative in low stress regime, and the coefficient value is reduced further in the high stress regime, but then by a small amount. These results support our claim that the FASTVAR performs a better job in identifying a measure of financial conditions that is strongly linked with macroeconomic fluctuations in both low and high stress regimes.

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 3.4 suggest we should expect larger financial shocks.

3.6 Identifying financial stress regimes during 2007-2010

One of the possible uses of the empirical model proposed in this paper is to predict financial stress regimes with macroeconomic consequences. 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 7 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 (20,000 draws with the initial 5,000 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 the results in Section 3.4, the unrestricted model exhibits more uncertainty in identifying the financial stress regime than the restricted model.[11] 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 September 2012, 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 9 presents the posterior mean of the λ_is for each window of data finishing at the indicated date, computed using the restricted specification (results are similar for the unrestricted one). For data windows up to January 2009, many variables are selected more

[11] 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.

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.

3.7 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 $\mathbf{z}_t$ in equation (2). While the fed funds rate can be used as the measure of monetary policy for the period prior to 2008, it does not account for the unconventional policy implemented by the Fed after the nominal funds rate hits the zero lower bound. This explains why we did not include the fed funds rate in our baseline specification, differing from the specification of Bernanke et al. (2005) and Hubrich and Tetlow (2015). 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 $\mathbf{z}_t$.

Figure 10 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 3.5. 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.

We also check if the covariate selection and regime histories change if we use data only up through 2007—that is, if we exclude the Great Recession. Table 4 suggests that there are more variables that are frequently selected but these variables are still mainly related with corporate credit conditions. Figure 11 indicates the identification of additional high stress periods in particular during the 1983-1990 period that do not overlap recessions. As consequence, the identification of high stress regimes when excluding the recent financial crisis resembles the identification obtained when the EBP is employed as observed transition variable.

4 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 the financial conditions factor have not only large negative effects on economic activity as in Caldara et al. (2016), 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.

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A FASTVAR Estimation

We estimate the model using the Gibbs sampler with a Metropolis-in-Gibbs step. Let Θ collect all of the model parameters. We can partition the set of model parameters into blocks: (1) $\mathbf{\Psi} = [\mathbf{A}_1(L), \mathbf{A}_2(L)]$, the VAR coefficients; (2) $\mathbf{\Omega}_1$ and $\mathbf{\Omega}_2$, which are the regime-specific VAR variance-covariance matrixes; (3) γ and c, the transition speed and the threshold; (4) β, Λ and $\mathbf{f}_T = \{f_t\}_{t=1}^{T}$, the factor loadings, the inclusion indicators and the factor, respectively; and (5) $\{\sigma_{it}^2\}_{i=1}^{N_x}$, 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.

A.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

$$\begin{bmatrix} \mathbf{z}_t \\ \mathbf{x}_t \end{bmatrix} = \begin{bmatrix} \mathbf{I} & 0 \\ 0 & (\mathbf{\Lambda} \odot \boldsymbol{\beta}) \end{bmatrix} \begin{bmatrix} \mathbf{z}_t \\ f_t \end{bmatrix} + \begin{bmatrix} 0 \\ \mathbf{u}_t \end{bmatrix}; u_t \sim iidN(0, \sigma_i^2). \tag{7}$$

This differs from the FAVAR specification of Bernanke et al. (2005) by excluding the macroeconomic variables $\mathbf{z}_t$ as observable factors in the measurement equation of the financial variables $\mathbf{x}_t$.

The state equation is

$$\begin{bmatrix} z_{1,t} \\ z_{2,t} \\ f_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \\ a_{30} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} z_{1,t-1} \\ z_{2,t-1} \\ f_{t-1} \end{bmatrix} \tag{8}$$
$$+\pi_t(f_{t-1};\gamma,c) \left\{ \begin{bmatrix} d_{10} \\ d_{20} \\ d_{30} \end{bmatrix} + \begin{bmatrix} d_{11} & d_{12} & d_{13} \\ d_{21} & d_{22} & d_{23} \\ d_{31} & d_{32} & d_{33} \end{bmatrix} \begin{bmatrix} z_{1,t-1} \\ z_{2,t-1} \\ f_{t-1} \end{bmatrix} \right\} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{ft} \end{bmatrix},$$

where $\varepsilon_t \sim N(0, \Omega)$, $\pi_t(f_{t-1}; \gamma, c) = [1 + \exp(-\gamma(f_{t-1} - c))]^{-1}$ and $d_{ij} = a_{2,ij} - a_{1,ij}$ measures the change in the autoregressive coefficients across regimes. Note that the intercepts are allowed to change with the regime as they have an important role to characterize business cycle regimes in Clements and Krolzig (1998).

Formally, we estimate the model using the specification in (8) so that the sampler does not fail even if γ is small while imposing that $\gamma \geq 0$. Similar strategies have also being employed by Gefang and Strachan (2010). The state-space representation of the FASTVAR model above is helpful to understand identification requirements for estimating the parameters in the transition function $\pi_t(f_{t-1}; \gamma, c)$. Based on equation (8), it is clear that if there is no nonlinearity—that is, the parameters do not change across regimes—then γ and c are not identified. However, if we find strong evidence of nonlinearity, that is, the d_{ij} parameters are typically nonzero, as it is the case with our application, then we should be able to estimate γ and c. Because the d_{ij} are nuisance parameters when $\gamma = 0$, we cannot employ the posterior distribution of γ to assess evidence of nonlinearity.

A.2 Priors

Table A: Priors for Estimation			
Parameter	Prior Distribution	Hyperparameters	
$vec\left(\boldsymbol{\Psi}\right)$	$N\left(\mathbf{m}_0, \mathbf{M}_0\right)$	$\mathbf{m}_0 = \mathbf{0}_N$; $\mathbf{M}_0$=$10\mathbf{I}_N$	$N = 2N_z\left(N_z+1\right)P + 2N_z + 2P$
$\boldsymbol{\Omega}_1^{-1}, \boldsymbol{\Omega}_2^{-1}$	$W\left(\frac{\nu_0}{2}, \frac{D_0}{2}\right)$	$\nu_0 = 1000$; $D_0 = \mathbf{I}_N$	$\Delta_{\Omega_1} = \Delta_{\Omega_2} = 150$
γ	$\Gamma\left(\mathbf{g}_0, \mathbf{G}_0\right)$	$\mathbf{g}_0 = 6$; $\mathbf{G}_0 = 3$	$\Delta_\gamma = 0.01$
c	$Unif\left(\mathbf{c}_L, \mathbf{c}_H\right)$	$\mathbf{c}_L = f_{0.10}$; $\mathbf{c}_H = f_{0.90}$	
σ_n^{-2}	$\Gamma\left(\omega_0, W_0\right)$	$\omega_0 = 1$; $W_0 = 1$	$\forall n$
β_n	$N\left(\mathbf{b}_0, \mathbf{B}_0\right)$	$\mathbf{b}_0$= $-\mathbf{100}$; $\mathbf{B}_0$=0.01	$\forall n$
λ_n	ρ_0	$\rho_0 = 0.01$	$\forall n$

We assume a proper normal–inverse-Wishart prior for the VAR(P): Each regime-dependent coefficient matrix has a multivariate normal prior; the regime-dependent 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 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 Δ_γ, Δ_{Ω_1} and Δ_{Ω_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 10,000 initial (discarded) draws out of total 25,000 draws.

A.3 Drawing $\boldsymbol{\Psi}$ conditional on $\Theta_{-\boldsymbol{\Psi}}, \mathbf{f}_T, \mathbf{z}_{d,T}$ and $\mathbf{x}_T$

Conditional on $\pi_t\left(f_{t-1}\right)$, 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 $\mathbf{y}_t = [\mathbf{z}'_t, f_t]'$ as follows:

$$\mathbf{y}_t = \boldsymbol{\theta}_t \widetilde{\boldsymbol{\Psi}} + \varepsilon_t, \tag{9}$$

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

$$\boldsymbol{\theta}_t = \begin{bmatrix} I_{N_z} \otimes \widehat{\mathbf{y}}_{t-1} & \mathbf{0}_{2P} \\ 0 & \widehat{\mathbf{f}}_{t-1} \end{bmatrix},$$

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

$\mathbf{y}^p_{t-1} = \left[1, \mathbf{y}'_{t-1}, ..., \mathbf{y}'_{t-p}\right]$,

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

and $\mathbf{f}^p_{t-1} = \left[f'_{t-1}, ..., f'_{t-p}\right]'$. Then, given the prior $N(\mathbf{m}_0, \mathbf{M}_0)$, the (stacked) joint parameter vector can be drawn from

$$\boldsymbol{\Psi} \sim N(\mathbf{m}, \mathbf{M}),$$

where

$$\mathbf{M} = \left(\mathbf{M}_0^{-1} + \sum_{t=1}^{T} \boldsymbol{\theta}'_t \Omega_t^{-1} \boldsymbol{\theta}_t\right)^{-1}$$

and

$$\mathbf{m} = \mathbf{M}\left(\mathbf{M}_0^{-1}\mathbf{m}_0 + \sum_{t=1}^{T} \boldsymbol{\theta}'_t \Omega_t^{-1} \mathbf{y}_t\right).$$

A.4 Drawing $\widetilde{c}, \widetilde{\gamma}$ conditional on $\Theta_{-[\widetilde{c},\widetilde{\gamma}]}, \mathbf{f}_T, \mathbf{z}_{d,T}$ and $\mathbf{x}_T$

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

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

and

$$c^* \sim Unif\left(\mathbf{c}_L, \mathbf{c}_H\right),$$

where the superscript $[i-1]$ represents the values retained from the past Gibbs iteration and Δ_γ 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

$$\begin{aligned} A \quad = \quad & \frac{\prod_t \phi\left(\mathbf{z}_t | \pi_t\left(f_{t-1} | \gamma^*, c^*\right), \mathbf{\Psi}, f_t\right)}{\prod_t \phi\left(\mathbf{z}_t | \pi_t\left(f_{t-1} | \gamma^{[i-1]}, c^{[i-1]}\right), \mathbf{\Psi}, f_t\right)} \\ & \times \frac{dUnif\left(c^* | \mathbf{c}_L, \mathbf{c}_H\right)}{dUnif\left(c^{[i-1]} | \mathbf{c}_L, \mathbf{c}_H\right)} \frac{dG\left(\gamma^* | \left(\gamma^{[i-1]}\right)^2 / \Delta_\gamma, \gamma^{[i-1]} / \Delta_\gamma\right)}{dG\left(\gamma^{[i-1]} | \left(\gamma^{[i-1]}\right)^2 / \Delta_\gamma, \gamma^{[i-1]} / \Delta_\gamma\right)}, \end{aligned}$$

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

A.5 Drawing β, and Λ conditional on $\Theta_{-\beta,\Lambda}, \mathbf{z}_{d,T}$, $\mathbf{f}_t$ and $\mathbf{x}_T$

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 Λ via a reversible-jump Metropolis step; however, a new candidate Λ^* invalidates the β from the previous draw. Thus, it is more efficient to draw β and Λ 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, Λ^*, from $q(\Lambda^*)$. Then, conditional on these candidates, we draw a candidate factor loading, β^*, from $q(\beta^*|\Lambda^*)$. This allows us to simplify the acceptance probability of the joint candidate.

A.5.1 Drawing the Inclusion Indicator Candidate

The financial factor may be sensitive to small shocks in the financial variables because of the nonlinearities in the transition function, making variable selection important. Let $\Lambda^{[i-1]} = \left[\lambda_1^{[i-1]}, ..., \lambda_{N_x}^{[i-1]}\right]$ 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 Λ^* is then

$$\Lambda^* = \left[\lambda_1^{[i-1]}, ..., \lambda_{n-1}^{[i-1]}, 1 - \lambda_n^{[i-1]}, \lambda_{n+1}^{[i-1]}, ..., \lambda_{N_x}^{[i-1]}\right],$$

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

A.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: $\beta_n^* \sim N(\mathbf{b}_n, \mathbf{B}_n)$, where

$$\mathbf{b}_n = \mathbf{B}_n^{-1}\left(B_0^{-1} b_0 + \sigma_n^{-2} f_T' \mathbf{x}_{nT}\right)$$

and

$$\mathbf{B}_n^{-1} = B_0^{-1} + \sigma_n^{-2} f_T' f_T.$$

A.5.3 Accepting the Draw

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

$$A_{n,\gamma} = \min\left\{1, \frac{|\mathbf{B}^*|^{1/2}}{|\mathbf{B}|^{1/2}} \frac{\exp\left(\frac{1}{2}\mathbf{b}^*\mathbf{B}^{*-1}\mathbf{b}^*\right)}{\exp\left(\frac{1}{2}\mathbf{b}\mathbf{B}^{-1}\mathbf{b}\right)} \frac{\pi\left(\Lambda^*\right)}{\pi\left(\Lambda^{[i-1]}\right)} \frac{q\left(\Lambda^{[i-1]}\right)}{q\left(\Lambda^*\right)}\right\}, \tag{10}$$

where $\mathbf{b}^*$ and $\mathbf{B}^*$ are defined and $\mathbf{b}_n$ and $\mathbf{B}_n$ are defined for $\Lambda^{[i-1]}$ and $\pi\left(.\right)$ is the value of the prior.

A.6 Drawing the Factor

To implement the extended Kalman filter, we rewrite the model in its state-space representation. The state variable is $\boldsymbol{\xi}_t = \mathbf{y}_t^p$ as defined above; let $\mathbf{Y}_t = [\mathbf{z}_t', \mathbf{x}_t']'$. Then,

$$\begin{aligned} \mathbf{Y}_t &= H\boldsymbol{\xi}_t + \mathbf{e}_t, \\ \boldsymbol{\xi}_t &= G\left(\boldsymbol{\xi}_{t-1}\right) + \mathbf{v}_t, \end{aligned}$$

where

$$H = \begin{bmatrix} \mathbf{I}_{N_z+1} & \mathbf{0}_{N_z\times 1} & \mathbf{0}_{N_z\times N_c} \\ \mathbf{0}_{N_x\times N_z+1} & \boldsymbol{\Lambda}\odot\boldsymbol{\beta} & \mathbf{0}_{N_x\times N_c} \end{bmatrix},$$

$\mathbf{e}_t = \left[\mathbf{0}_{N_z\times 1}', \mathbf{u}_t'\right]'$, $\mathbf{v}_t = \left[\boldsymbol{\varepsilon}_t', \mathbf{0}_{(N_c+1)\times 1}'\right]'$, $N_c = (N_x+1)(P-1)$, $E_t\mathbf{e}_t'\mathbf{e}_t = \mathbf{R}$ and $E_t\mathbf{v}_t'\mathbf{v}_t = \mathbf{Q}$. Note that, in general, both $\mathbf{Q}$ and $\mathbf{R}$ will be singular. The function $G\left(.\right)$ is

$$G\left(\boldsymbol{\xi}_{t-1}\right) = \left[1 - \pi_t\left(f_{t-1};\gamma,c\right)\right]A_1\left(L\right) + \left(\pi_t\left(f_{t-1};\gamma,c\right)\right)A_2\left(L\right)\right]\mathbf{y}_{t-1},$$

which is nonlinear in the state variable.

We can then draw $\boldsymbol{\xi}_T \sim p\left(\boldsymbol{\xi}_{T|T}, \mathbf{P}_{T|T}\right)$ 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, $\boldsymbol{\xi}_t \sim p\left(\boldsymbol{\xi}_{t|t}, \mathbf{P}_{t|t}\right)$. The distribution $\boldsymbol{\xi}_{T-1} \sim p\left(\boldsymbol{\xi}_{T-1|T}, \mathbf{P}_{T-1|T}\right)$ is obtained via smoothing and preceding periods are drawn recursively.

A.7 Drawing $\boldsymbol{\sigma}^2$ conditional on $\boldsymbol{\Psi}_{-\sigma^2}, \mathbf{Z}_T$ and $\mathbf{X}_T$

Given the inverse gamma prior, the measurement variances can be drawn from an inverse gamma posterior, $\sigma_i^{-2} \sim \Gamma\left(\omega_i, W_i\right)$, where

$$\omega_i = \frac{1}{2}\left(\omega_0 + T\right),$$

$$W_i = \frac{1}{2}\left(W_0^{-1} + \mathbf{u}_{it}\mathbf{u}_{it}'\right),$$

and

$$\mathbf{u}_{it} = \mathbf{x}_{it} - \Lambda_i f_t.$$

A.8 Drawing $\boldsymbol{\Omega}_1$ conditional on $\Theta_{-\boldsymbol{\Omega}_1}, \mathbf{f}_T, \mathbf{z}_{d,T}$ and $\mathbf{x}_T$

Under the assumption of homoskedasticity, $\boldsymbol{\Omega}_t = \boldsymbol{\Omega}$ 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 $\boldsymbol{\Omega}_1$ and $\boldsymbol{\Omega}_2$ are no longer conjugate and each requires Metropolis-in-Gibbs steps. Here, we describe the draw for $\boldsymbol{\Omega}_1$; the draw for $\boldsymbol{\Omega}_2$ is similar and can be inferred. To obtain a draw for $\boldsymbol{\Omega}_1$ conditional on $\boldsymbol{\Omega}_2$ and the other parameters, we draw a candidate $\widehat{\boldsymbol{\Omega}}_1$ from an inverse

Wishart distribution. Rewrite (2) in terms of the residual as

$$\boldsymbol{\varepsilon}_t = \mathbf{y}_t - \left[\left(1 - \pi_t\left(f_{t-1}\right)\right) A_1(L) + \pi_t\left(f_{t-1}\right) A_2(L)\right] \mathbf{y}_{t-1}.$$

Then, given the prior $W\left(\nu_0, D_0\right)$ for $\boldsymbol{\Omega}_1^{-1}$, the candidate is drawn from $\Omega_1^{-1} \sim W\left(\frac{D^2 \Delta_{\Omega_1}}{2}, \frac{\nu}{2\Delta_{\Omega_1}}\right)$, where

$$\nu = \nu_0 + \sum_t I(f_{t-1} < c) \ ,$$

$$D = D_0 + \sum_t \left(1 - \pi_t\left(f_{t-1}; \gamma^{(i)}, c^{(i)}\right)\right) \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t',$$

and Δ_{Ω_1} is a tuning parameter. The draw is then accepted or rejected similar to the step above.

Table 1. Financial Variables included in the FASTVAR estimation

	Description	Sample
10y	annual growth rate of the 10-year treasury rate	1981M9-2012M9
FFR3msp	fed fund rates – 3-month tbill rates	1981M9-2012M9
2y3msp	2-year treasury rates – 3-month tbill rates	1981M9-2012M9
10y3msp	10-year treasury rates – 3-month tbill rates	1981M9-2012M9
baa10ysp	Baa corporate rates – 10-year treasury rates	1981M9-2012M9
30mort10ysp	30-year mortgage rates – 10-year treasury rates	1981M9-2012M9
tedsp	TED spread	1981M9-2012M9
creditsp	Citibank corporate credit spread	1981M9-2012M9
exchrate	annual growth rate of the exchange rate	1981M9-2012M9
wilrate	annual growth rate of the Wilshire 5000	1981M9-2012M9
houseinf	annual growth rate of the national house index	1981M9-2012M9
creditrate	annual growth rate of bank credit of commercial banks	1981M9-2012M9
compaperrate	annual growth rate of commercial paper outstanding	1981M9-2012M9
moneyrate	annual growth rate of money stock (zero maturity)	1981M9-2012M9
nfibsurv	%credit was harder to get than last time	1981M9-2012M9
migoodsurv	%good-%bad conditions for buying large goods	1981M9-2012M9
mihousesurv	%good-%bad conditions for buying a house	1981M9-2012M9
miautosurv	%good-%bad conditions for buying a car	1981M9-2012M9
vix	VIX (monthly average)	1990M1-2012M9
jumbospread	Jumbo rates – 30-year conventional rates	1998M6-2012M9
OIS spread	3-month libor rates – overnight index swap rates	2001M12-2012M9
highyieldspre	High-yield corporate rates – Baa corporate rates	1997M1-2012M9
oil price	price of oil relative to a 2-year moving average	1981M9-2012M9

Note: The table lists the data used in the estimation of the factor, eq. (5). Sources: [1] FRED [2] Citi Global Markets via Haver Analytics [3] CoreLogic via Haver Analytics [4] NFIB via Haver Analytics [5] University of Michigan via Haver Analytics [6] Bloomberg/ Haver Analytics[7] FRED/ Bank of England via Haver Analytics [8]FRED/ Merrill Lynch via Haver Analytics

Table 2. Posterior Inclusion Probabilities for Covariates (full sample)

	FASTVAR
10y	0.65
FFR3msp	0.43
2y3msp	0.40
10y3msp	0.40
baa10ysp	**0.97**
30mort10ysp	0.82
tedsp	0.62
creditsp	0.70
exchrate	0.48
wilrate	**0.89**
houseinf	0.65
creditrate	0.39
compaperrate	0.71
moneyrate	0.49
nfibsurv	0.69
migoodsurv	**0.84**
mihousesurv	0.55
miautosurv	0.44
vix	0.74
jumbospread	0.66
OIS spread	0.67
highyieldspre	**0.96**
oil price	0.49

Note: The table shows the posterior inclusion probabilities based on 15,000 draws of the posterior distribution (25,000 draws with 10,000 discarded) for each of the data series listed in Table 1 for the factor estimated from eq. (5), jointly with eq's (2) and (3), the baseline FASTVAR model. Bold numbers represent series with posterior probability of inclusion greater than 84 percent.

Table 3. Bayesian Information Criteria for Different Specifications

	BIC
FASTVAR	**3760.8**
FASTVAR_r	4004.3
FASTVAR no cov selection	4508.4
FAVAR	5136.2
STVAR with Chicago FCI	7591.2
STVAR with EBP	7361.2

Note: The table shows the values of the average BIC across the 15,000 saved Gibbs iterations for alterntative specifications. In each case, the likelihood is computed with the VAR equations for IP growth and inflation to ensure that it is comparable across specifications. Penalization changes across specifications depending on the number of parameters required to describe IP growth and inflation dynamics. The FASTVAR is the baseline model with variable selection, eq. (2), (3), and (5). FASTVAR_r is the same model with zero restrictions on the feedback from the macro variables to the factor. FASTVAR no cov selection is the baseline model estimated with all variables in Table 1 included with probability 1, eq. (2), (3), and (4). FAVAR is the linear VAR with an estimated factor and no variable selection, eq. (1) and (4). STVAR with Chicago FCI and STVAR with EBP are the smooth transition VARs (eq (2) and (3)) estimated with observed factors. Bold number represent the lowest BIC.

Table 4. Posterior Inclusion Probabilities: Alternate Samples

	FASTVAR_2007	FASTVAR
10y	**1.00**	0.65
FFR3msp	0.30	0.43
2y3msp	0.00	0.40
10y3msp	0.00	0.40
baa10ysp	**1.00**	**0.97**
30mort10ysp	**1.00**	0.82
tedsp	0.40	0.62
creditsp	**0.96**	0.70
exchrate	0.00	0.48
wilrate	**1.00**	**0.89**
houseinf	0.80	0.65
creditrate	**1.00**	0.39
compaperrate	**1.00**	0.71
moneyrate	0.00	0.49
nfibsurv	**1.00**	0.69
migoodsurv	**1.00**	**0.84**
mihousesurv	0.78	0.55
miautosurv	0.36	0.44
vix	**0.96**	0.74
jumbospread	**0.89**	0.66
OIS spread	**0.86**	0.67
highyieldspre	**1.00**	**0.96**
oil price	0.00	0.49

Note: The table shows the posterior inclusion probabilities based on 15,000 draws of the posterior distribution (25,000 draws with 10,000 discarded) for each of the data series listed in Table 1 for the factor estimated from eq. (5), jointly with eq's (2) and (3), the baseline FASTVAR model. In this table, we use two samples: FASTVAR is the baseline full sample and FASTVAR_2007 is the sample ending in 2007M12. Bold numbers represent series with posterior probability of inclusion greater than 84 percent.

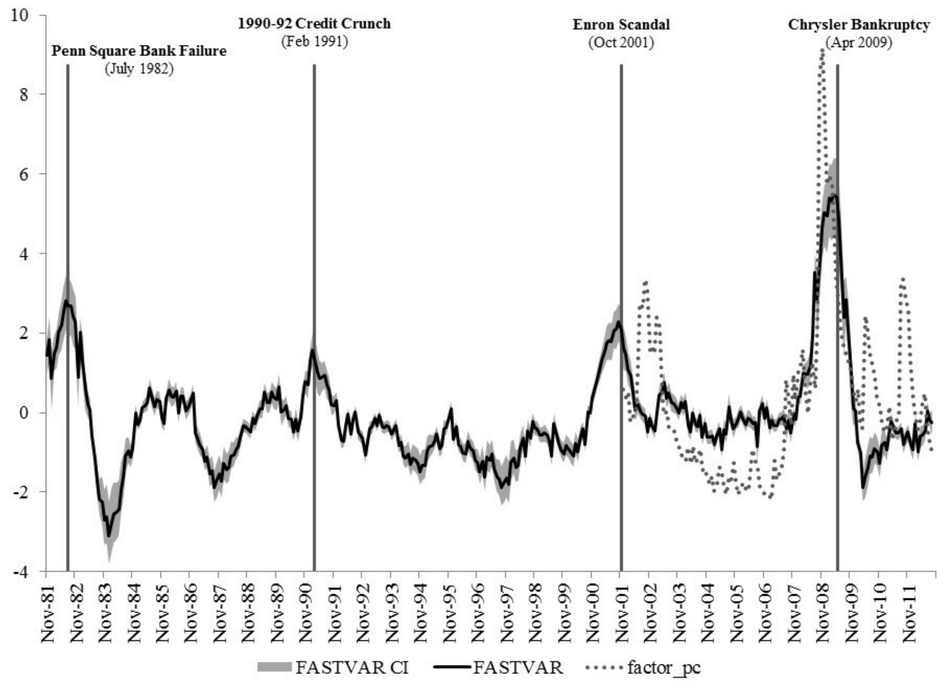

Figure 1: **Financial Factor Estimates.** The figure shows estimates using the unrestricted FASTVAR model, eq. (2), (3), and (5), estimated using an unbalanced panel, 1981M9 to 2012M9. The principal components factor is estimated with a balanced panel, leading to a shorter sample, 2001M12 to 2012M9. The 68-percent error bands for the unrestricted FASTVAR are shaded in gray. The figure also marks four significant financial stress events.

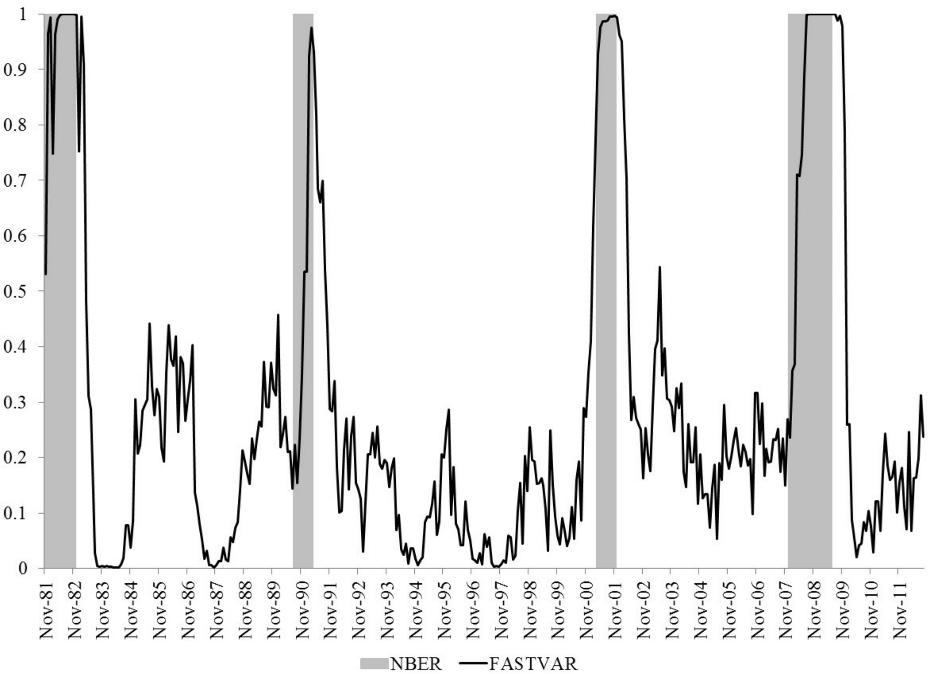

Figure 2: **Transition Function over time and NBER recessions.** The figure shows the values of the transition function, eq. (3), for the baseline FASTVAR. The NBER recessions are shaded in gray.

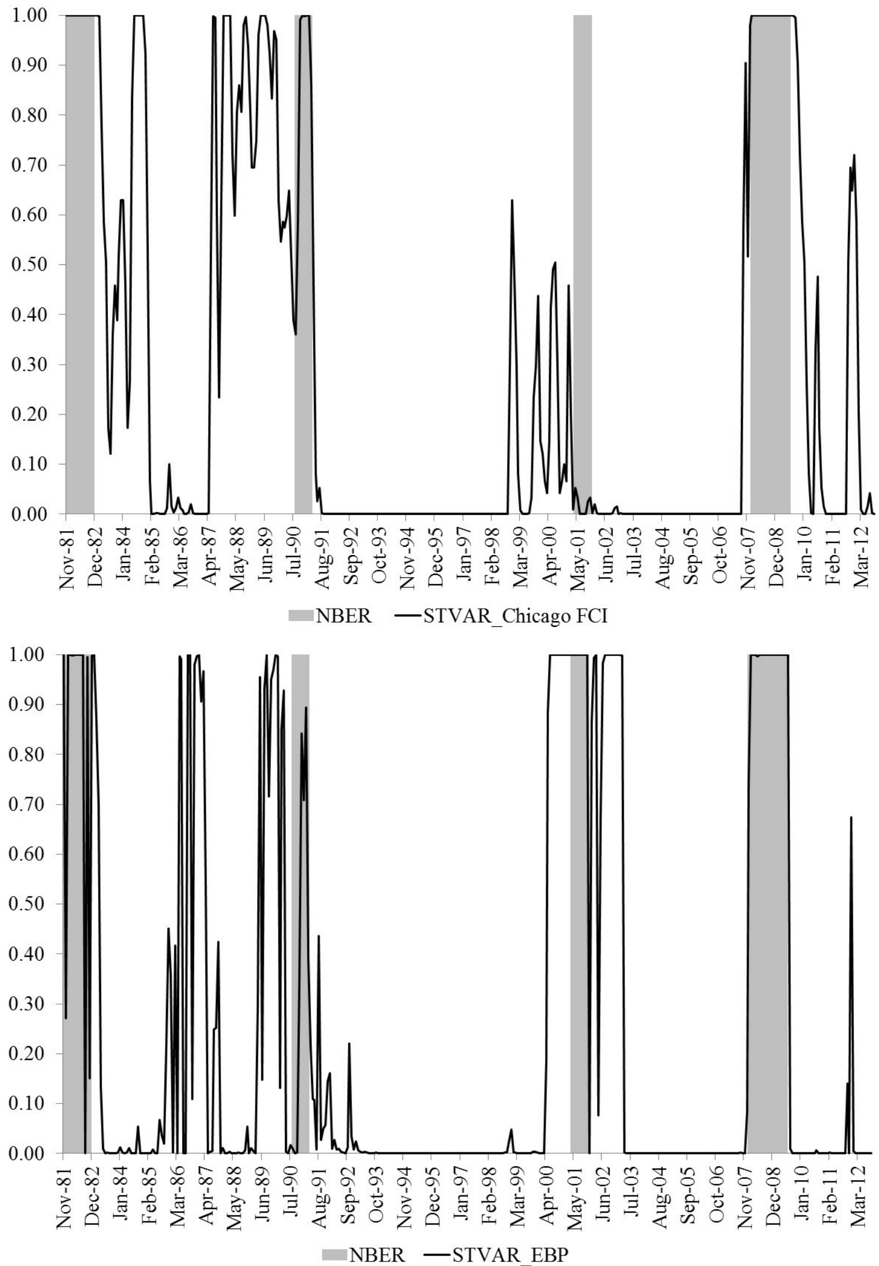

Figure 3: **Alternative Financial Stress Regimes.** The figure shows the values of the transition function, eq. (3), estimated from the STVAR model with an exoegenous factor: the Chicago FCI (top panel) or the EBP (bottom panel). The NBER recessions are shaded in gray.

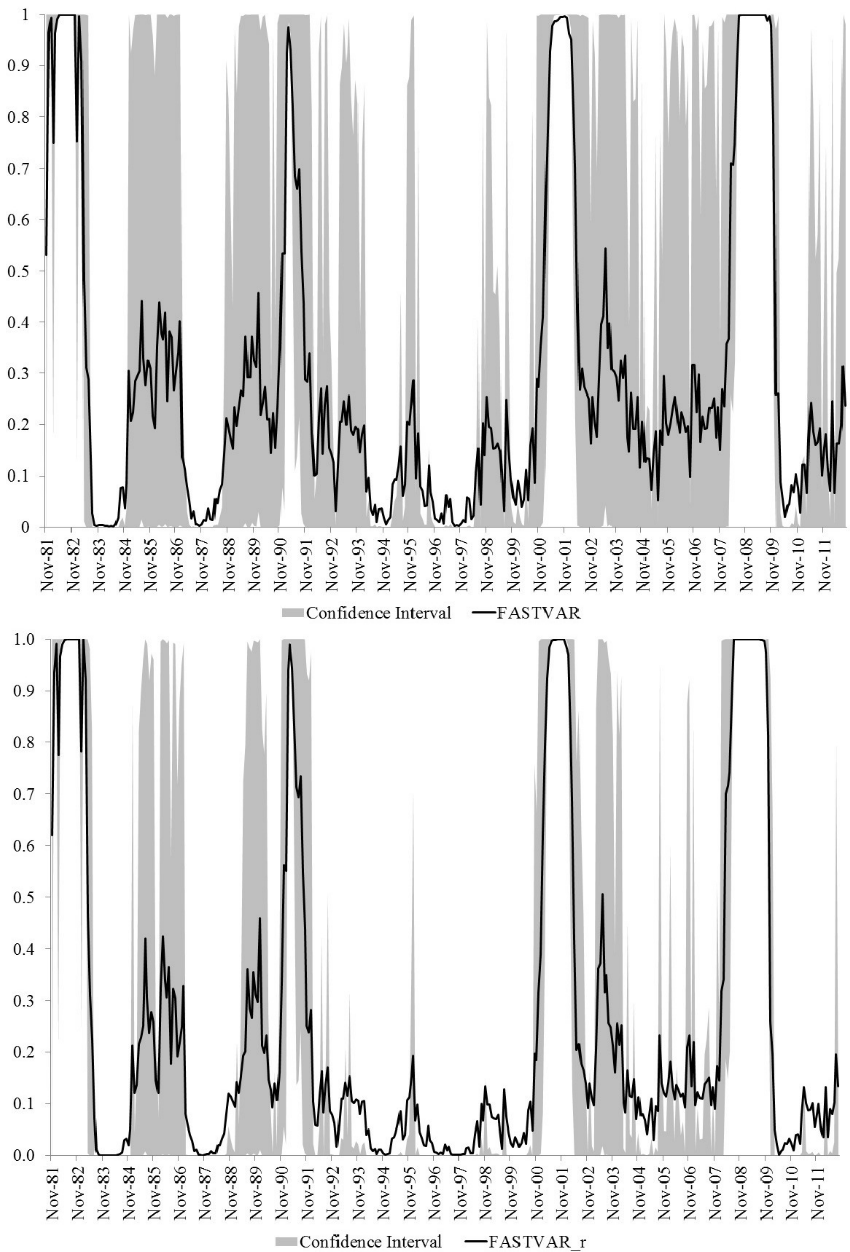

Figure 4: **Posterior Values of the Financial Stress Regime Weights.** The two panels show the mean value of the posterior distributions of the transition function, eq. (3), for the baseline unrestricted FASTVAR (top panel) and the restricted FASTVAR (bottom panel), where the VAR coefficients on the lagged macro variables in the factor equation are set to zero. The 68-percent error bands are shown shaded in grey.

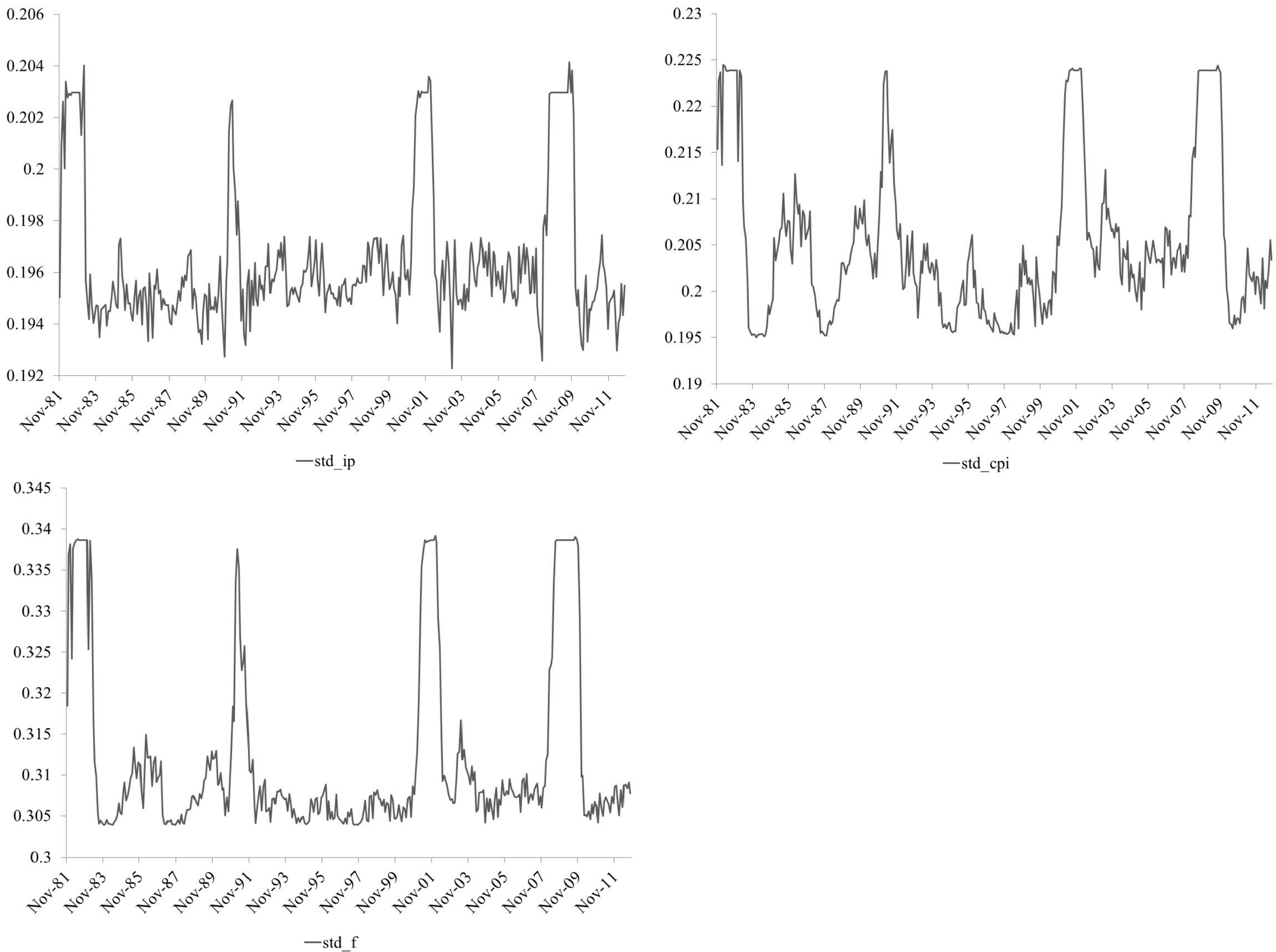

Figure 5: **Time-varying Volatilities.** The figure shows the square root of the diagonal elements of the posterior mean of the variance-covariance matrix for the FASTVAR (std) and the restricted FASTVAR (std_rest) specifications. The first panel shows the value for the IP growth equation, the second panel shows the value for the CPI inflation equation, and third is for the factor equation.

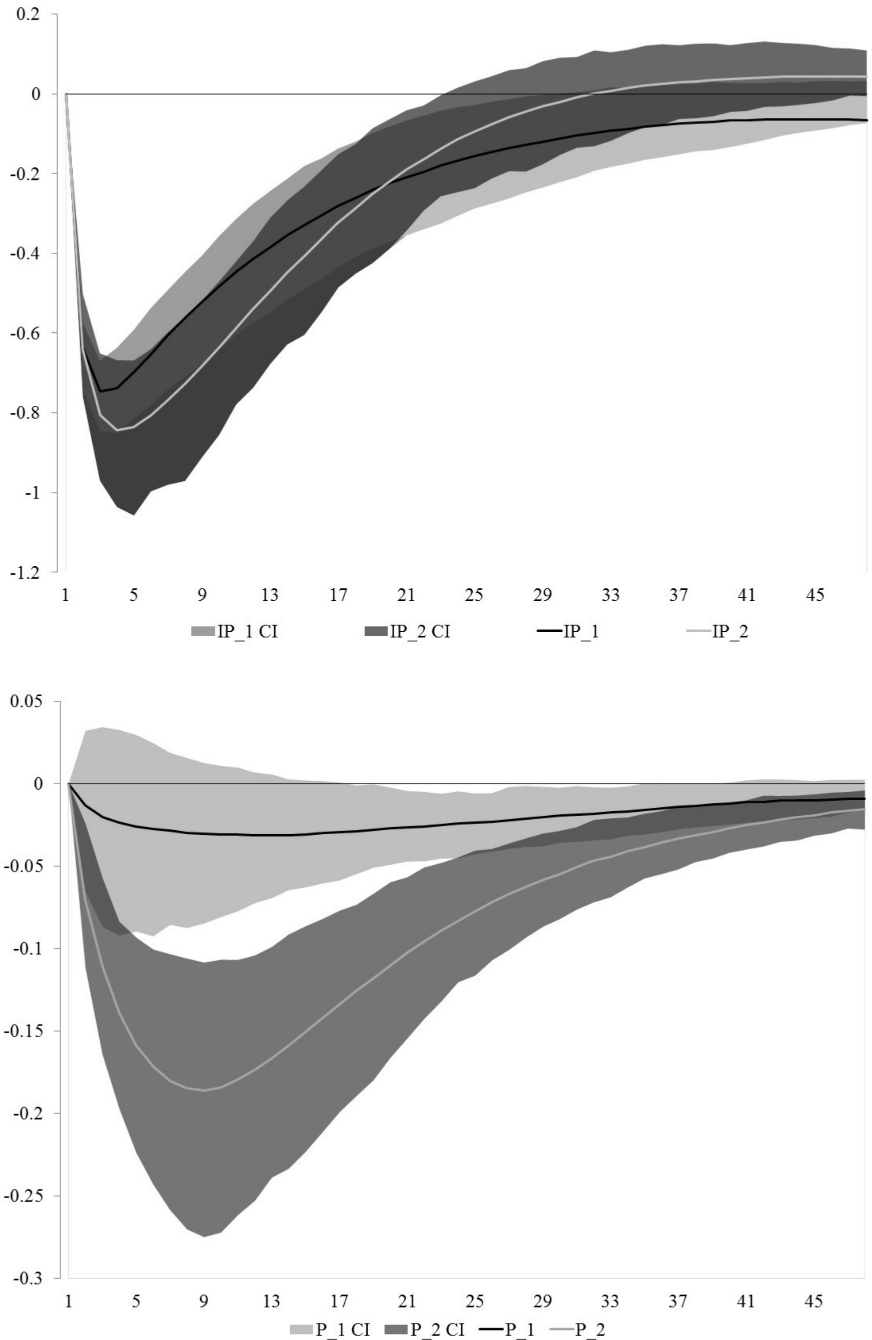

Figure 6: **Impulse responses to a financial factor shock.** The figure shows the generalized impulse responses, eq. (6), to a shock to the financial factor that occurs in the low stress regime (denoted by "_1" in black with light grey error bands) and that occurs in the high stress regime (denoted by "_2" in grey with dark grey error bands). The responses are computed from the baseline FASTVAR, eq. (2), (3), and (5). The responses of IP growth are shown in the top panel and the responses of CPI inflation are shown in the bottom panel. The generalized impulse responses are computed with 200 draws from the historical shock distribution for every hundredth draw from the Gibbs sampler.

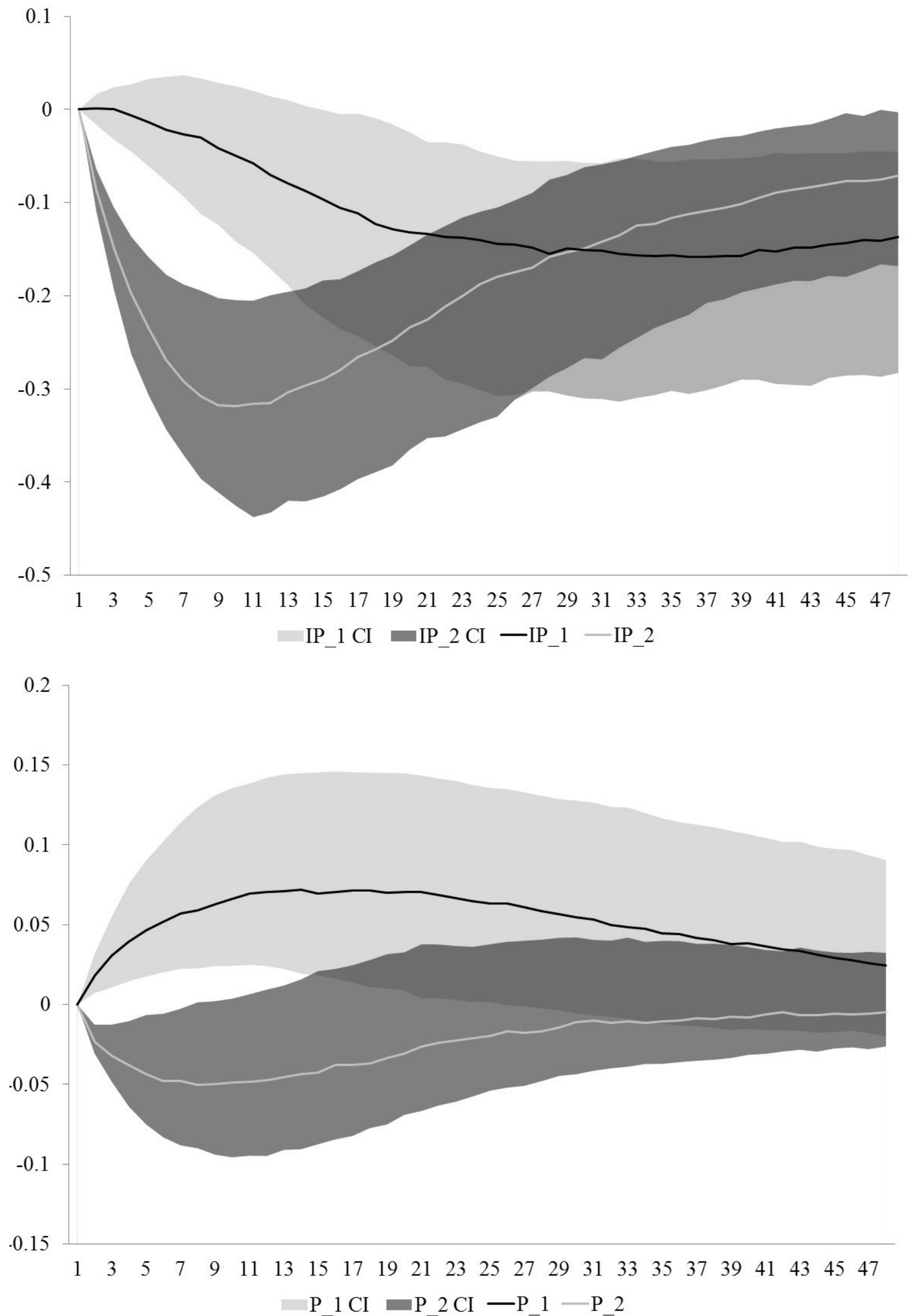

Figure 7: **Impulse responses to a exogenous financial shock.** The figure shows the generalized impulse responses, eq. (6), to a shock to an exogenous financial factor that occurs in the low stress regime (denoted by "_1" in black with light grey error bands) and that occurs in the high stress regime (denoted by "_2" in grey with dark grey error bands). The responses are computed from the STVAR, eq. (2) and (3), using the Chicago FCI as an exogenous financial factor. The responses of IP growth are shown in the top panel and the responses of CPI inflation are shown in the bottom panel. The generalized impulse responses are computed with 200 draws from the historical shock distribution for every hundredth draw from the Gibbs sampler.

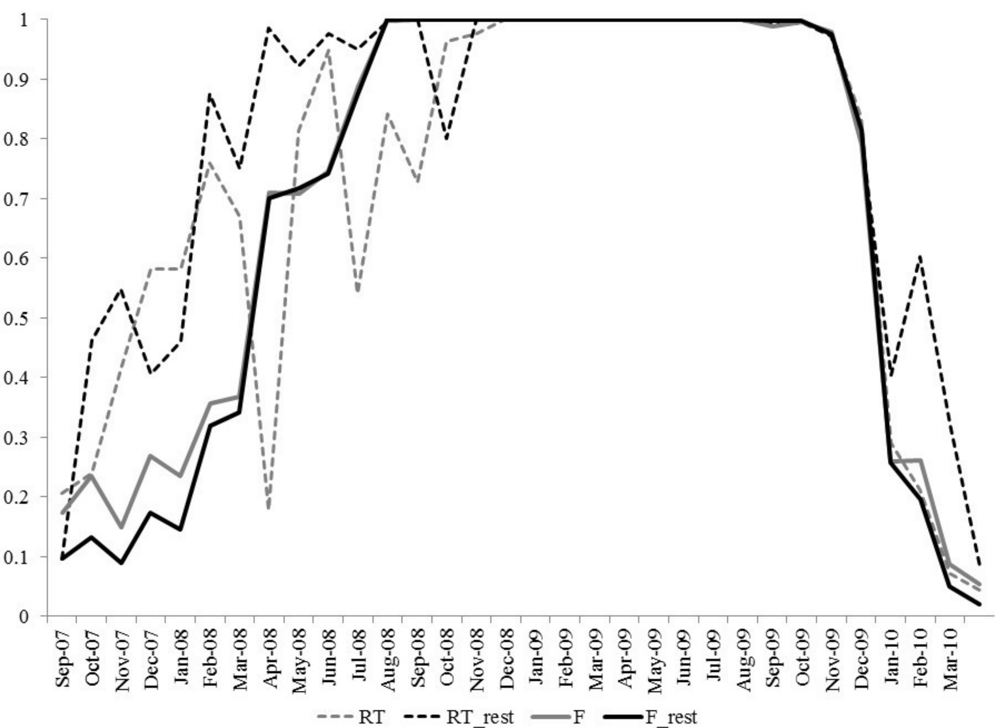

Figure 8: **Probabilities of Financial Stress Regime during 2007-2010.** The figure shows in-sample (F) and pseudo-out-of-sample (RT) estimates of the transition function, eq. (3), of the financial stress regime for the Great Recession period starting September 2007 and ending April 2010. The solid lines are the in-sample estimates of the transition function for the restricted (black line) and the unrestricted (grey line) models. The dashed lines are the pseudo-out-of-sample estimates of the transition function 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.

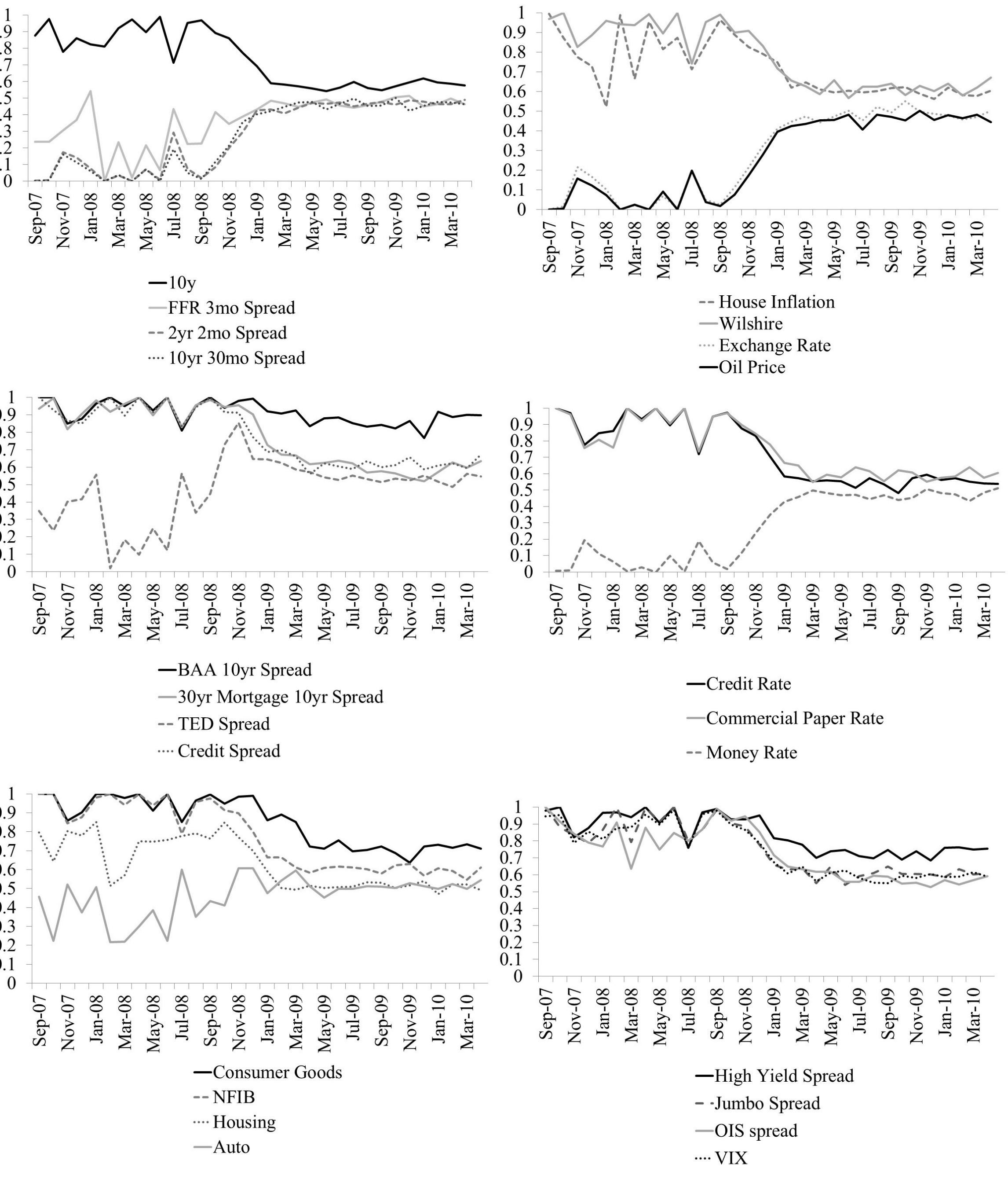

Figure 9: **Posterior Inclusion Probabilities for Covariates during 2007-2010.** The figure shows the posterior inclusion probabilities estimated from eq. (5) for select variables for samples ending in the period from 2007M9 to 2010M4. The posterior inclusion probability is the mean of the estimate of the inclusion dummy across Gibbs iterations computed using data up to t.

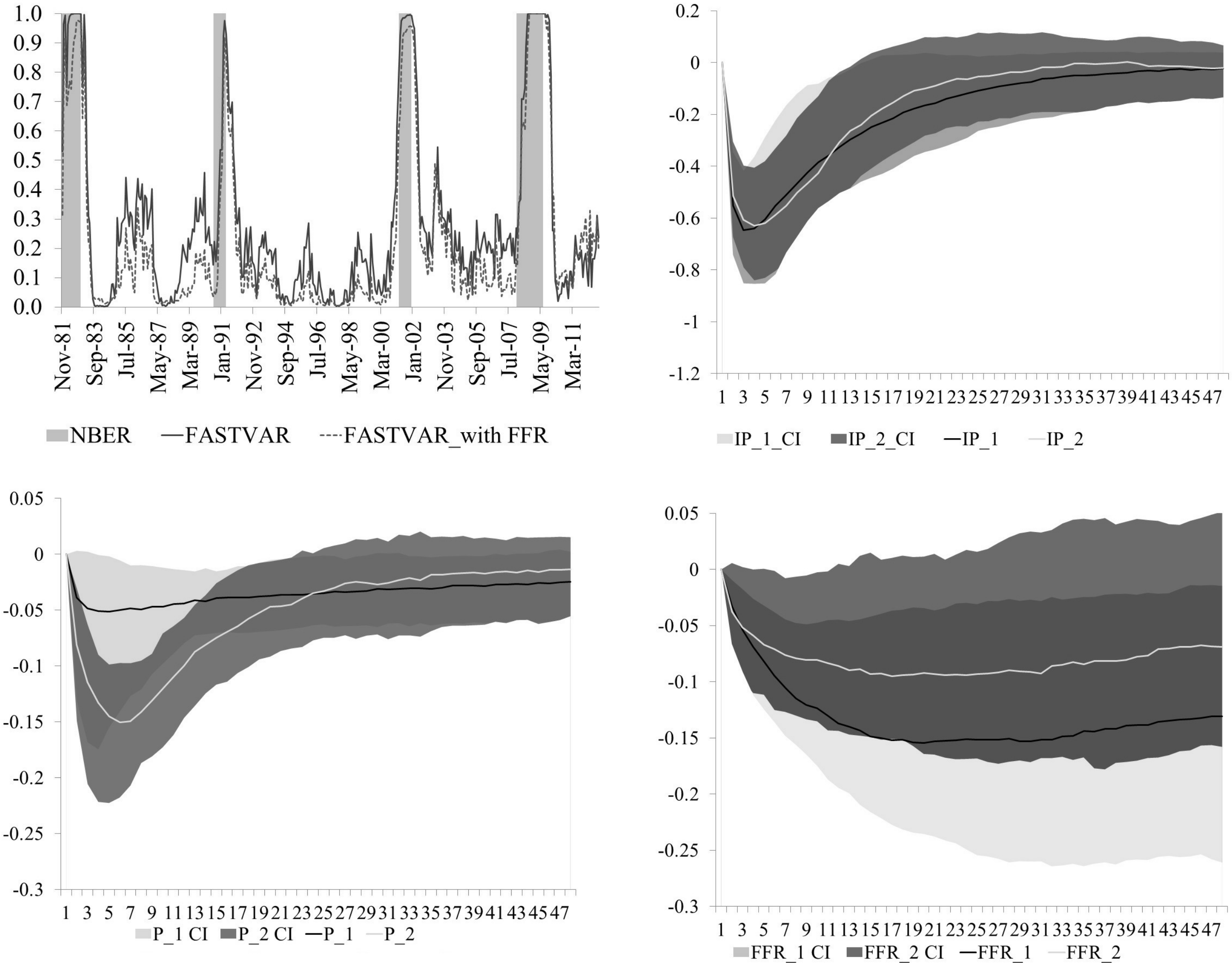

Figure 10: **Results for the FASTVAR model with the Fed rate.** Panel A shows the posterior means of the transition function for the FASTVAR model, eq. (2), (3), and (5), for the benchmark model (black line) and for the model where the fed fund rates is included in the VAR (grey line). The NBER recessions are shaded in grey. Panels B-D show the generalized impulse responses, eq. (6), of IP growth (panel B), CPI inflation (panel C), and the fed funds rate (panel D) to a shock to the factor that occurs in the low stress regime (denoted by "_1" in black with light grey error bands) and that occurs in the high stress regime (denoted by "_2" in grey with dark grey error bands). The generalized impulse responses are computed with 200 draws from the historical shock distribution for every hundredth draw from the Gibbs sampler.

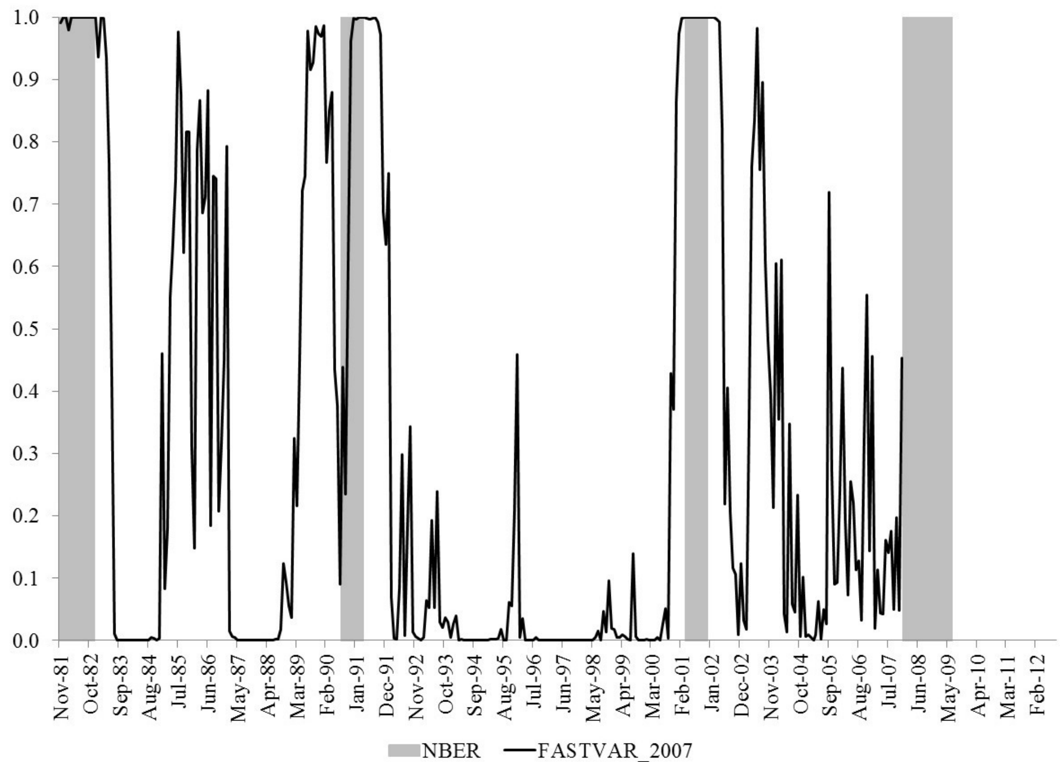

Figure 11: **Transition Function over time computed with data up to 2007M12 and NBER recessions.** The figure shows the values of the transition function, eq. (3), for the baseline FASTVAR estimated with data ending before the Great Recession (1981M9 to 2007M12). The NBER recessions are shaded in gray.