Monetary Policy Transmission during Financial Crises: An Empirical Analysis

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Abstract

This paper studies the effects of a monetary policy expansion in the U.S. during times of financial crises. The analysis is carried out by introducing a Smooth Transition Factor Model where the transition between states (“normal” times and financial crises) depends on a financial condition index. The model is estimated using Bayesian MCMC methods. Employing a quarterly dataset over the period 1970Q1-2009Q2 containing 108 U.S. macroeconomic and financial time series, I find that a monetary expansion during financial crises has stronger and more persistent effects on macroeconomic variables, such as output, consumption, and investment than during “normal” times. Differences in effects among the regimes seem to originate from non-linearities in the credit channel.

JEL classification: C11; C32; E32; E44; G01
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1 Introduction

The U.S. economy has experienced several financial crises in the last 40 years. Although financial conditions have long been understood to play an important role for macroeconomic dynamics, only the recent financial crisis has strengthened the interest in exploring the interactions between monetary policy and financial market imperfections. Policymakers reduced interest rates to historical lows in order to alleviate the financial stress and its contractionary effects on the economy. Central Banks were pursuing monetary policy under high financial stress and uncertainty. Some interesting and natural questions arise: are the effects on economic activity of conventional monetary policy, i.e., decreasing the Federal Funds rate, different during periods of high financial stress from what is usually observed in good or “normal” times? Has the transmission of monetary policy in the U.S. been different during the financial crises of the last forty years?

This paper aims to shed light on these questions and introduces an empirical model which allows for nonlinearities in the dynamic propagation of monetary policy shocks along financial conditions. In particular, I study the transmission of monetary policy during times of low (“normal”) and high financial stress. So far, little empirical work has been devoted to the investigation of monetary policy transmission during financial crises. The paper that the analysis carried out here may be relate to the closest is the paper by Hubrich and Tetlow (2011). Using an empirical model which switches between “normal” and high financial stress regimes, they find that responses of the Federal Funds rate to industrial production shocks as well as financial shocks depend on the underlying financial conditions. They conclude that monetary policy has reacted differently in times of financial stress, implying that inference based on constant parameter models might be inappropriate. The novel contribution of this paper is that the analysis not only lays down the existence of differences in monetary policy transmission during financial crises but rather exploits where these differences stem from.

However, the literature has not reached a common consensus of whether and how responses of macroeconomic variables to monetary policy shocks differ in times of high financial stress from what is usually observed in “normal” times. On the one hand, it has been argued that monetary policy has not been effective during financial crises. This view is motivated by the fact that during the recent financial crisis of 2008/09 credit standards...
tightened and the cost of credit increased further, despite the Federal Reserve reducing interest rates substantially (see Krugman (2008)). On the other hand, one might argue that monetary policy has been effective and actually more potent during financial crises because it not only lowers interest rates on default-free securities, but also helps to lower credit spreads. As shocks from the recent financial crisis were unusually large versions of shocks previously experienced (Stock and Watson (2012)), one might argue that monetary policy was simply not able to offset these massive contractionary shocks (see Mishkin (2009)).

The latter view can be linked to the credit channel of monetary policy or the so-called financial accelerator mechanism (see the seminal contributions of Bernanke and Gertler (1989), Bernanke et al. (1996) and Bernanke et al. (1999)). The key premise of the financial accelerator is the inverse relationship between the premium borrowers have to pay when they ask for external credit in the banking system (the so-called External Finance Premium (EFP)) and the financial condition of the borrower. The impact of the financial accelerator is assumed to be non-linear, i.e., its effects are stronger the lower the financial fundamentals such as the net worth of firms or the higher the cost of credit. During “normal” times when financial stress is low, firms and households are less sensitive to changes in their cost of credit whereas during times of high financial stress or crises, firms and households would be more sensitive to any change in their cost of credit. Therefore, changes in the net worth induced by, for example, monetary policy may yield large changes in the cost of credit for low-net-worth borrowers (borrowers during financial crises) but should not much affect the cost of credit for borrowers with wide internal finance (borrowers in “normal” times).

The possibility of a non-linear credit channel has been noted in the literature by, for example, Bernanke and Gertler (1989), Gertler and Gilchrist (1994), and Bernanke et al. (1999). Bernanke et al. (1999) using a two-sector model with the financial accelerator find that the response of firms with relatively poor access to external credit markets to an expansionary monetary policy shock is stronger than that of firms with better access to credit. Moreover, Gertler and Gilchrist (1994) provide empirical evidence that the performance of small firms is more sensitive to interest rate changes the weaker the balance sheets of the firms, suggesting that financial accelerator effects should be stronger the higher the financial

\(^2\)Note that during financial crises, when asset prices are low firms are likely to be liquidity constrained and in need of external financing.
stress. Finally, Ravn (2012) introduces a model in which the strength of the financial accelerator is non-linear. The asymmetric financial accelerator is modeled by assuming different values of the elasticity of the EFP with respect to the net worth of firms. This implies that when the entrepreneurs’ wealth is already low, such as during financial crises, the EFP reacts more strongly to small changes in the net worth.

As the questions at hand demand a non-linear environment, I introduce the Smooth Transition Factor Model (STFM) which is a regime dependent factor model where the transition between regimes (“normal” and high financial stress times) is smooth. Since I am especially interested to explore where differences in effects of a monetary policy shock stem from, the STFM allows me to obtain conditional regime-dependent responses from a broad set of macroeconomic and financial variables. As a conditioning factor I use the financial condition index summarizing information from financial market variables. The STFM is estimated using Bayesian MCMC methods, i.e., a Metropolis-within-Gibbs sampler.

Estimating the model using 108 macroeconomic and financial variables over the period 1970Q1 to 2009Q2 I find the following main results:

1. A monetary expansion has stronger and more persistent effects on macroeconomic variables such as output, consumption, and investment during financial crises than during “normal” times.

2. Differences in effects among the regimes seem to originate from non-linearities in the credit channel.

More specifically, I find that a monetary expansion decreases the EFP and increases stock prices, i.e., the entrepreneurs’ wealth, in the financial crises as well as the “normal” regime. The effects on the EFP and stock prices are stronger during financial crises. This provides supportive evidence for the existence of a balance sheet channel which is more pronounced during times of high financial stress. Moreover, an expansionary monetary policy shock increases loans during financial crises while it seems to have no significant effects on loans during times of low financial stress, indicating the potential existence of a bank lending channel during periods with severe disruptions in financial markets. Summing up, a monetary expansion during financial crises increases loans and asset prices by more than in times of low financial stress, leading to a higher decrease of the EFP which, in turn,
provokes the stronger effects of macroeconomic variables such as output, investment, and consumption.

The remainder of this paper is organized as follows: Section 2 introduces the STFM and discusses identification issues; the Metropolis-within-Gibbs sampler used to estimate the model is described in Section 3; Section 4 lays down the empirical results of the paper and Section 5 concludes.

2 The Model

This section introduces the Smooth Transition Factor Model (STFM). The model is based on the dynamic factor model (see, e.g., Forni et al. (2009)) in which I introduce a non-linear relation among the common factors. In order to allow for responses being different across “normal” times and times of high financial stress, i.e., financial crises, I employ a smooth transition vector autoregression for the factors (STVAR)(see for example Weise (1999) and Auerbach and Gorodnichenko (2012)). The STVAR is a multivariate extension of the smooth transition autoregressive models developed in Granger and Terasvirta (1993).

The key advantage of estimating a STVAR for the factors rather than estimating SVARs for each regime separately is that with the latter I may have relatively few observations in a regime, especially for financial crises, which renders estimates unstable and imprecise. In contrast, specifying the factors as a STVAR the dynamics of the common factors may be determined by both regimes, with one regime having more impacts in some times and the other regime having more impacts in other times. Therefore, the model makes use of more information by exploiting variation in the probability of being in a particular regime so that estimation for each regime is based on a larger set of observations.

2.1 The Smooth Transition Factor Model

Let \( x_t = (x_{1t}, x_{2t}, ..., x_{Nt})' \) be a N-dimensional vector of macroeconomic variables at time \( t, t = 1, ..., T \). \( x_t \) follows the following factor model representation:

\[
x_t = \chi_t + e_t = \Lambda'f_t + e_t,
\]
where $f_t$ is a $r \times 1$ vector of unobserved "common" or "static" factors and $\Lambda$ is a $r \times N$ matrix of factor loadings associated with $f_t$. The linear combination of the $r$ factors, i.e., $\chi_t = \Lambda'f_t$, is called the common component of $x_t$ which is responsible for comovements between macroeconomic variables. $e_t$ is the idiosyncratic component of $x_t$ and it is assumed to be normally distributed and cross-sectionally uncorrelated, i.e., $e_t \sim i.i.d. N(0, H)$.

As mentioned before, the factors are assumed to follow a STVAR where the choice between the two regimes is operated by a nonlinear transition function, $F(z_{t-1}, \nu)$, which takes values between zero and one. The dynamic behaviour of the factors depends on the observable transition variable, $z_t$, and the transition function parameters, $\nu$.

$$f_t = (1 - F(z_{t-1}, \nu)) \sum_{i=1}^{p} D^{(1)}_i f_{t-i} + F(z_{t-1}, \nu) \sum_{i=1}^{p} D^{(2)}_i f_{t-i} + u_t$$

(2)

$$Var(u_t) = Q$$

with $u_t$ being normally distributed with zero mean and constant covariance matrix, $Q$, over the two regimes. Note that differences in the transmission of shocks come from differences in the lag polynomials, i.e., $D^{(1)}(L)$ and $D^{(2)}(L)$. For estimation purposes it is useful to rewrite the factors in Equation (2) as

$$f_t = \sum_{i=1}^{p} D^{(1)}_i f_{t-i} + F(z_{t-1}, \nu) \sum_{i=1}^{p} \Pi_i f_{t-i} + u_t$$

(3)

where $\Pi = D^{(2)} - D^{(1)}$ is the contribution to the regression of considering a second regime.

Equation (3) can be written as

$$D_t(L)f_t = u_t$$

(4)

$$D_t(L) = I - \left[D^{(1)}_1 + F(z_{t-1}, \nu)\Pi_1\right]L - \ldots - \left[D^{(1)}_p + F(z_{t-1}, \nu)\Pi_p\right]L^p$$

Therefore, using Equations (1) and (4) macroeconomic variables can be described as

$$x_t = \Lambda'(D_t(L))^{-1}u_t + e_t$$

(5)

The regime changes are assumed to be captured by a logistic smooth transition function.

$$F(z_t, \nu) = \frac{1}{1 + \exp(-\gamma(z_t - c))}$$

(6)

where $\nu = (\gamma, c)$ is a vector containing the transition function parameters. The parameter, $\gamma > 0$, is responsible for the smoothness of the function, $F$. For high values of $\gamma$ the model
switches sharply at a certain threshold. The location or threshold parameter, \( c \), is the point of inflection of the function and therefore it is the threshold around which the dynamics of the model change. The transition variable, \( z \), is observable and normalized to unit variance so that \( \gamma \) is scale invariant. Moreover, \( z \) is dated by \( t - 1 \) to avoid contemporaneous feedbacks.

### 2.2 Factor Identification

As any factor model the STFM is not identified without imposing further restrictions (see for example Del Negro and Schorfheide (2011), Otrok and Whiteman (1998) or Lopes and West (2004) for identification issues in linear factor models). Two identification problems arise.

First, the model is rotationally invariant. Specifically, for a given \( r \times r \) nonsingular matrix, \( A \), premultiplying the factors, \( f_t \), and its lags, \( f_{t-i} \), as well as \( u_t \) by \( A \) and post-multiplying the loadings, \( \Lambda' \), and the coefficient matrices, \( D^{(1)}_i \) and \( D^{(2)}_i \), by \( A^{-1} \) does not change the distribution of the observables, \( x_t \). Define \( \Lambda' = [\Lambda'_1 \ \Lambda'_2]' \), where \( \Lambda_1 \) is the first \( r \times r \) matrix of loadings and \( \Lambda_2 \) is the remaining \( r \times N-r \) matrix of loadings. In order to address the issue described above, I follow Geweke and Zhou (1996) and restrict \( \Lambda'_1 \) to be lower triangular. Moreover, the covariance matrix of the factor specification in (2) is restricted to be equal to the identity matrix, i.e., \( Q = I_r \).

Second, the signs of the factors, \( f_t \), and the loadings, \( \Lambda' \), are not separately identified. This is handled by setting the loadings on the diagonal of \( \Lambda'_1 \) equal to one\(^3\).

### 2.3 Shock Identification

It is well known that the innovations, \( u_t \), from Equation (2) which represents a reduced-form model do not correspond to economically identified (structural) shocks, \( \eta_t \), but instead to a linear combination of them (\( u_t = S\eta_t \) with \( \eta_t \) being iid such that \( \eta_t'\eta_t = I \)). In order to recover the underlying structural shocks, it is necessary to impose some restrictions on the matrix \( S \). The most famous identification method (called Cholesky) consists in proposing

\(^3\)Note that this restriction is overidentifying the model as restricting the loadings on the diagonal of the first \( r \times r \) matrix of loadings to be positive should be enough to identify the factor model. However, in the empirical application of this paper this set of restrictions turned out to work best in guaranteeing convergence of the latent factors.
S to lower triangular and \( Q = S'S \). It is then possible to recover recursively the structural shocks. Therefore, multiplying Equation (4) by \( S^{-1} \) yields

\[
S^{-1}D_t(L)f_t = \eta_t
\]

Consequently, the identification restrictions needed to identify the factor model (see Section 2.2) identify u_t as the structural macroeconomic shocks. To see this, note that I can write \( \Lambda' = [S^{-1}, \Lambda_2']' \), as \( \Lambda_1' \) is lower triangular. Moreover, as I restrict \( Q = I_r \), u_t are orthogonal innovations. Therefore, having identified the factor model, Equation (5) provides a definition of the structural impulse-responses.

\[
x_t = \Lambda'(D_t(L))^{-1}u_t + e_t
\]

where u_t are the structural economic shocks now and \( B_t(L) = \Lambda'(I - D(L)_t)^{-1} \) are the associated impulse-response functions which are varying over time. Therefore, assuming a recursive identification scheme which imposes zero restrictions on the impact effects, i.e, \( B_t(0) \), of a set of variables used for identification, the choice and order of the first \( r \) variables of \( x_t \) in the restricted STFM directly identifies the structural shocks. Moreover, note that assuming \( F(z_{t-1}, \nu) = 1 \) or \( F(z_{t-1}, \nu) = 0 \), I can obtain the impulse response function of each pure regime.

### 3 Estimation

The parameters and unobserved latent factors of the STFM are estimated using a Metropolis-within-Gibbs sampling procedure. The Gibbs sampler allows me to sample from conditional distributions for a subset of the parameters conditional on all the other parameters instead of sampling from the joint posterior distribution which would be a rather complex problem. Note that conditional on \( \nu = (\gamma, c) \), the STFM becomes a linear factor model. Bayesian estimation of linear factor models is discussed for example in Del Negro and Schorfheide (2011) and Otrok and Whiteman (1998). Therefore, my Gibbs sampling procedure reduces to three main blocks. First, I draw the factors, \( f_t \), using the standard algorithm for state space models of Carter and Kohn (1994) given the model’s parameters \( \gamma, c, Q, H, \Lambda, D_{1}^{(1)} , ..., D_{p}^{(1)}, \Pi_1, ..., \Pi_p \). In the second block I draw the linear parameters, \( H, \Lambda, \) and \( D_{1}^{(1)} , ..., D_{p}^{(1)}, \Pi_1, ..., \Pi_p \). Conditional on the factors, Equation (1) are just \( N \) normal linear
regression models. Given the factors, Equation (3) also becomes a normal multivariate regression. In the third block, the transition function parameters \( \gamma \) and \( c \) are drawn using a Metropolis-Hastings step.

3.1 Notation

Before presenting further estimation details it is useful to rewrite the STFM. Define the \( 1 \times rp \) vector \( w_t = (f_t'_{t-1}, ..., f_t'_{t-p}) \) and the \( 1 \times 2rp \) vector \( w_t^{ST} = (w_t F(z_{t-1}, \nu)w_t) \). Next I stack the vectors over \( t \) to generate the \( T \times r \) matrix \( F = (f_1, f_2, ..., f_T)' \), the \( T \times 2rp \) matrix \( W^{ST} = (w_1^{ST}, ..., w_T^{ST})' \), the \( 2rp \times r \) matrix \( D = (D^{(1)}_1, ..., D^{(1)}_p, \Pi_1, ..., \Pi_p)' \), the \( T \times N \) matrix \( X = (x_1, ..., x_T)' \), the \( T \times N \) matrix \( E = (e_1, ..., e_T)' \), and the \( T \times r \) matrix \( U = (u_1, ..., u_T)' \).

\[
X = FA + E \tag{9}
\]

\[
F = W^{ST}D + U, \tag{10}
\]

where \( E \sim N(0, H) \) and \( U \sim N(0, Q) \), for \( t = 1, ..., T \). Vectorizing Equations (1) and (3) the STFM is transformed into

\[
x = (I_N \otimes F)\lambda + e \tag{11}
\]

\[
f = (I_r \otimes W^{ST})d + u, \tag{12}
\]

where \( x = \text{vec}(X) \), \( \lambda = \text{vec}(\Lambda) \), \( d = \text{vec}(D) \), \( e = \text{vec}(E) \), \( f = \text{vec}(F) \), \( u = \text{vec}(U) \), \( e \sim N(0, H \otimes I_T) \) and \( u \sim N(0, Q \otimes I_T) \). Therefore, the likelihood of the STFM can be shown to be of the standard normal Wishart form. See Appendix A for details.

3.2 Block I: Factors

In the first block of the Gibbs sampler I draw the factors conditional on all the parameters, i.e., the linear and the transition function parameters. Before I apply the algorithm developed by Carter and Kohn (1994) to draw from the posterior distribution of the factors the
STFM has to be rewritten in state space form.

\[
x_t = \begin{pmatrix}
\Lambda & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & \cdots & 0
\end{pmatrix}
\begin{pmatrix}
0 \\
\vdots \\
0
\end{pmatrix}
\begin{pmatrix}
f_t \\
f_{t-1} \\
\vdots \\
f_{t-p+1}
\end{pmatrix} + e_t \quad e_t \sim N(0, H)
\]

\[
\begin{pmatrix}
D_{tt} & D_{2t} & \cdots & D_{pt} \\
I & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & I & 0
\end{pmatrix}
\begin{pmatrix}
0 \\
\vdots \\
0
\end{pmatrix}
\begin{pmatrix}
0 \\
\vdots \\
0
\end{pmatrix}
\begin{pmatrix}
Q \\
0 \\
\vdots \\
0
\end{pmatrix}
\]

where \( D_{it} = [D_i^{(1)} + F(z_{t-1}, \nu_i)] I_i \) for \( i = 1, \ldots, p \). I am therefore ready to draw the factors using the Kalman filter and smoother algorithm by Carter and Kohn (1994). Details about the procedure can be found in Appendix A.

3.3 Block II: Linear Parameters

In the second block I draw the linear parameters, i.e., the loadings, the idiosyncratic variances, and the regime-dependent coefficients. Given the factors and the transition function parameters the STFM is a linear factor model. Therefore, drawing from the conditional distribution of the linear parameters requires to split these parameters into the two parts that refer to the observation equation in (9) and to the Equation (10), respectively. The blocks can be sampled independently from each other conditional on the extracted factors, the data, and the transition function parameters.

3.3.1 Loadings and Idiosyncratic Variances

First, I draw the loadings, \( \Lambda \), and the idiosyncratic variances, \( H \). Conditional on the factors and the transition function parameters, \( \nu \), Equation (9) represents simply \( N \) normal linear regression models and therefore the conditional posterior distributions are of standard forms. Since the idiosyncratic errors, \( E \), are independent across equations, the sampling can be
implemented one equation at a time. Note that the subscript \( n \) refers to the \( n \)-th equation and that \( \sigma_n^2 \) denotes the \( n \)-th diagonal element of \( H \).

Using an improper prior for the idiosyncratic variances might result in a Bayesian analogue of the Heywood problem which takes the form of multi-modality of the posterior of \( \sigma_n^2 \) with one mode lying at 0 (Martin and McDonald (1975)). To avoid this potential problem I assume natural conjugate priors, i.e.,

\[
\lambda_n \sim N(\Delta_n, \sigma_n^2 V_n) \\
\sigma_n^2 \sim IG(\nu/2, \delta/2)
\]

The variance of the normal prior for \( \lambda_n \) depends on \( \sigma_n \) because this allows joint drawing of \( \Lambda \) and \( \sigma_1, \ldots, \sigma_N \).

Combining the likelihood of the STFM which is given in Appendix A with the prior distributions I obtain the following posterior distributions for \( \Lambda \) and \( \sigma_n^2 \):

\[
\lambda_n | \sigma_n^2, X, F, \nu \sim N(\bar{\lambda}_n, \sigma_n^2 V_n) \\
\sigma^2 | X, F, \nu \sim IG(\nu/2, \delta/2)
\]

where

\[
\bar{\lambda}_n = V_n(\bar{V}_n^{-1} \Delta_n + F' \hat{\lambda}_n) \\
\bar{V}_n = (\bar{V}_n^{-1} + F' F)^{-1} \\
\delta = \nu \delta + \hat{e}_n \hat{e}_n + (\hat{\lambda}_n - \Delta_n)'(\bar{V}_n + (F' F)^{-1})^{-1}(\hat{\lambda}_n - \Delta_n) \\
\nu = T + \nu
\]

Variables with a hat refer to their respective OLS estimates, i.e., \( \hat{\lambda}_n = (F' F)^{-1} F' x_n \) and \( \hat{e}_n = x_n - F \hat{\lambda}_n \)

### 3.3.2 Regime-Dependent Coefficients

The second part refers to the Equation (10) which is the STVAR of the factors. As mentioned before, conditional on the factors and the transition function parameters Equation (8) becomes a multivariate regression and, hence, conditional posterior distributions can be obtained in their standard forms. Since I restrict the covariance matrix \( Q \) to be the
identity matrix in order to identify the STFM, I only need to draw the regime-dependent coefficients, i.e., $D^{(1)}_1, \ldots, D^{(1)}_p$, $\Pi_1, \ldots, \Pi_p$.

Since I do not have any strong a priori beliefs about the parameter values of $D$ I choose the uninformative Jeffrey’s prior. Combining the likelihood with the prior I obtain a standard posterior distribution for $\text{vec}(D) = d$, i.e.,

$$
d|Q, X, F, \nu \sim N(\bar{d}, \bar{V}_d)
$$

$$
\bar{d} = \text{vec}\left((W^{ST\prime}W^{ST})^{-1}W^{ST\prime}F\right)
$$

$$
\bar{V}_d = Q \otimes (W^{ST\prime}W^{ST})^{-1}
$$

To ensure stationarity I truncate the draws of $D^{(1)}$ and $D^{(2)} = \Pi + D^{(1)}$. I discard the draws whenever not all of the roots of the characteristic polynomials $D^{(1)}(L)$, $D^{(2)}(L)$, as well as $D_t(L)$ lie outside the unit circle.

### 3.4 Block III: Transition Function Parameters

In the last block of the Gibbs sampler I draw the transition function parameters, i.e., the smoothness parameter, $\gamma$, and the threshold value, $c$. Since their full conditional distribution has no known form I update them jointly by using the Metropolis-Hastings algorithm following Lopes and Salazar (2006). I assume similar priors as proposed by Lopes and Salazar (2006), i.e.,

$$
\gamma \sim G(a, b)
$$

$$
c \sim N(m_c, \sigma^2_c)
$$

For given starting values $(\gamma^{(0)}, c^{(0)})$ at iteration $s$ of the Gibbs sampler the Metropolis-Hastings algorithm consists of two steps.

Step 1:
I generate draws from the following proposal densities:

$$
\gamma^* \sim G\left((\gamma^{(s-1)})^2/\Delta_\gamma, \Delta_\gamma/\gamma^{(s-1)}\right)
$$

$$
c^* \sim N\left(c^{(s-1)}, \Delta_c\right)
$$

The normal proposal density is truncated at the interval $[c_A, c_B]$ with $\hat{F}(c_A) = 0.05$ and $\hat{F}(c_B) = 0.95$ where $\hat{F}$ is the empirical distribution of the transition variable, $z$. 

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Step 2:
I set $(\gamma(s), c(s)) = (\gamma^*, c^*)$ with probability $\alpha(\gamma^*, c^*|\gamma(s-1), c(s-1)) = \min \{1, A\}$, where

$$A = \frac{\prod_{t=1}^{T} p_N(x_t|f_t^*, \Lambda^*, D^{(1)}(L)^*, D^{(2)}(L)^*, Q^*) \ p_G(\gamma^*|a, b)p_N(c^*|m_c, \sigma^2_c)}{\prod_{t=1}^{T} p_N(x_t|f_t, z_t-1, \Lambda, D^{(1)}(L), D^{(2)}(L), Q) \ p_G(\gamma(s-1)|a, b)p_N(c(s-1)|m_c, \sigma^2_c)}$$

$$\times \frac{p_G(\gamma(s-1)|\gamma^*|^2/\Delta_{\gamma}, \Delta_{\gamma}/\gamma^*)}{p_G(\gamma^*|(\gamma(s-1))^2/\Delta_{\gamma}, \Delta_{\gamma}/\gamma(s-1))} \ \Phi \left( \frac{c_B - c(s-1)}{\sqrt{\Delta_c}} \right) - \Phi \left( \frac{c_A - c(s-1)}{\sqrt{\Delta_c}} \right)$$

Otherwise $(\gamma(s), c(s)) = (\gamma(s-1), c(s-1))$. Therefore, $A$ is the product of the likelihood ratio, the prior ratio, and the proposal ratio. $p_N$ and $p_G$ denote the probability density function of the normal and gamma, respectively. $\Phi(.)$ denotes the cumulative distribution function of the standard normal distribution. $\Delta_{\gamma}$ and $\Delta_c$ are adjusted on the fly for the burn-in period to generate an acceptance probability which lies between 10% and 50%.

4 Empirical Results

In this section I present the results of the paper. First, I discuss the choice of the transition variable. Then, the data, the model specification, the identification of the monetary policy shock, and the particular choice of the prior hyperparameters are described. Next, I analyse the convergence of the proposed Gibbs sampler algorithm followed by estimation results of the transition function. Finally, I present results for the persistence of shocks among the different regimes and regime-dependent impulse responses to monetary policy shock.

4.1 Transition Variable

The transition variable, $z$, is chosen to be an index which reflects tensions in various credit markets. I prefer a broad measure of financial stress rather than a market specific measure since using only one measure potential stresses in other financial markets might be ignored. Here I choose the Financial Conditions Index (FCI) recently constructed by Hatzius et al. (2010). This FCI has several advantages. First, it has a large span of history. Second, the FCI pools information across 45 financial indicators, whereas other indices are relatively narrow and might exclude potentially important indicators. Third, the index by Hatzius et al. (2010) is purged of endogenous movements related to business cycle fluctuations or monetary policy. Figure 1 shows a time series plot of the FCI. An increase in the FCI
corresponds to an improvement in overall financial conditions while a decrease reflects a worsening. Therefore, \( z_{t-1} < c \) indicates the high financial stress (financial crises) regime with \( D^{(1)}(L) \) describing the behavior of the system in that regime, i.e., \( F(z_{t-1}, \nu) \approx 0 \). For sufficiently high values of the FCI, i.e., \( z_{t-1} > c \), \( D^{(2)}(L) \) describe the behavior of the system in the low financial stress (“normal”) regime, i.e., \( F(z_{t-1}, \nu) \approx 1 \).

4.2 Data and Model Specification

The data set I use here consists of 108 U.S. quarterly series covering the period 1970Q1 until 2009Q2. I start the sample in 1970 because the FCI (the transition variable) is not available for earlier dates. The series of the dataset are listed in Table 1 of the Appendix B and are mostly obtained from the FRED database. Some financial variables are obtained from IFS and the Flow of Funds Account provided by the Board of Governors. The series include national accounts data such as GDP, consumption, investment and the GDP deflator, labor market variables, e.g., hours worked, unemployment rate, employment, prices, industrial production, public sector variables and financial variables such as stock market returns and realized volatilities\(^4\), spreads and interest rates. All data series are transformed to reach stationarity. A list of transformations applied to the variables is given in the fourth column of Table 1. Moreover, I set the number of factors to 4. I experimented with changing the number of factors but it turns out that results are robust assuming more than 4 factors as well as less than 4 factors. Finally, results are based on assuming a lag length of a quarter, i.e., \( p = 1 \).

4.3 Identification of the Monetary Policy Shock

Following most of the literature I assume a recursive scheme to identify a conventional monetary policy shock (e.g. Sims (1992), Bernanke et al. (2005), and Christiano et al. (1999)). As described in Section 2.3, the restrictions needed to identify the STFM (see Section 2.2) recover the structural shocks recursively. Therefore, the choice and order of the first \( r \) variables of my dataset allows me to identify a conventional monetary policy

\[^4\]The realized or historical volatility is calculated as the standard deviation of the daily equity index, i.e., \( \hat{\sigma}_t = \sqrt{\frac{1}{T-1} \sum_{t=1}^{T} (r_{\tau_t} - \mu_t)^2} \) where \( r_{\tau_t} \) is the price index at time \( \tau_t \) in quarter \( t \) and \( \mu_t \) is the average of the index over the quarter \( t \) (see Bloom (2009)).
shock. Assuming that output and prices react only with a lag to a monetary policy shock I order the GDP, GDP Deflator, CPI and Federal funds rate series first in my dataset. The CPI is ordered before the Federal funds rate since its inclusion can mitigate the price puzzle (Eichenbaum (1992)).

4.4 Prior Choices

Before I come to the estimation results and comment on the convergence of the simulation the choice of the prior hyperparameters has to be established.

The hyperparameters for the priors of the loadings and idiosyncratic variances are chosen to be the following: first, following, e.g., Lopes and West (2004) and Bernanke et al. (2005), I choose a vague prior for $\lambda_n$, i.e., $\Lambda_n = 0_{r \times 1}$, $\Sigma_n = I_r$; second, the hyperparameters for $\sigma^2_n$ are defined as $v = 0.001$ and $\delta = 6$ (See, for example, Otrok and Whiteman (1998) and Bernanke et al. (2005)). These values produce a quite diffuse though proper prior.

Concerning the priors of the transition function parameters $\gamma$ and $c$, the Gibbs sampling algorithm is sensitive to the choice of hyperparameters. In particular, if the priors are not sufficiently informative, the algorithm has difficulties converging. Therefore, I choose relatively informative hyperparameters values in order to obtain well mixing Markov chains and an adequate acceptance rate. Typically, the data is not very informative on the shape parameter as a wide range of values of $\gamma$ will lead to similar shapes of the transition function (Deschamps (2008) and Teräsvirta (1994)). Here I choose the hyperparameters, $a$ and $b$, of the prior for $\gamma$ such that the mean of $\gamma$ is equal to 3 and the variance is equal to 0.1. In order to set the values of the hyperparameters for $c$ consider Figure 1 which plots the FCI. As I am interested in high financial stress episodes/financial crises it seems intuitive that I choose the prior mean of $c$ in such a way that mainly financial crises episodes are considered for the estimation of $D^{(1)}$. Therefore, I choose $m_c = -1.35$ and $\sigma^2_c = 0.01$. This allows me to partly exclude the low values of the FCI in the beginning of the 1980s originating from monetary policy which was responsible for very high interest rates.

4.5 Convergence

In order to make sure that the results are based on converged simulations I follow various strategies. First, all my results are based on 20,000 draws of the Metropolis-within-Gibbs
sampler where the first 4,000 are discarded as burn-in. Second, to reduce possible autocorrelations of the sequence (as I have a Metropolis-Hastings step) I thin the draws by just considering every 4th draw. This yields adequate autocorrelations for the transition function parameters, i.e., $\text{Corr}(\gamma) = 0.75$ and $\text{Corr}(c) = 0.26$. Third, the Gibbs Sampler is run several times to compare the results obtained each time to assure that the chain is converging to the same stationary distribution. Moreover, I assess convergence visually by checking the trace plots which show the evolution of draws of the parameters and the log-likelihood. This is helpful for checking whether there are jumps in the level and variance of the respective parameter. Furthermore, to assure that the Gibbs sampler has moved to its target distribution I plot the estimated factors obtained in the first half of simulations against the ones obtained in the second half of the sampler (see Figure 2 in the Appendix B). Small deviations point out that the simulated chain has converged. Finally, to assess the precision of the Gibbs sampler I plot the estimated factors with their 95% confidence bands (Figure 3). As the estimated factors of the first and second half of simulations are nearly identical and the bands of the estimated factors are tight the chain seems to converge properly.

4.6 Weight on Financial Crises Regime

The time profiles of the transition function, $F(z_{t-1}, \nu)$, give a first insight of the regime changing behaviour of the model. The transition function can be interpreted as the weight on the “normal” and financial crises regime, respectively, where values close to one correspond to the “normal” regime and values close to 0 to the high financial stress regime.

First, I present the estimates of the transition function parameters, i.e., the smoothness parameter, $\gamma$, and the threshold value, $c$, which are calculated as the means of the respective parameter draws kept after thinning. As expected the estimated values of these parameters are close to their prior values. That is, the estimate for $\gamma$ is equal to 2.869 with the associated 95% confidence interval being $[2.286, 3.566]$ and the estimate of the threshold value, $c$, is equal to -1.354 with the 95% confidence interval $[-1.370, -1.331]$.

Using these parameter simulations Figure 4 (see Appendix B.2) plots the estimated transition function with its 95% confidence bands. As the confidence intervals of $\gamma$ and $c$ are relatively small the bands for the transition function are tight. Most of the time the model
is in the “normal” regime \((F(z_{t-1}, \nu) \text{ is close to 1})\). This is not surprising since financial crises are rather unfrequent events. Four high financial stress/financial crises periods can be spotted where the regime changes are rather abrupt. The first period in 1974 corresponds to the so called Franklin National crisis when the failure of the Franklin National Bank and the Herstatt Bank led to a crisis of confidence that brought the international banking system close to disaster. The second period of high financial stress in 1987 can be associated with the Black Monday when stock markets crashed worldwide. Another regime change from the “normal” to the financial crises regime takes place in about 2001 and matches up well with the burst of the dot-com bubble. The last period where the transition function reaches values close to zero in 2008/2009 corresponds to the recent financial crisis of 2008-2009. It is worth mentioning that the first three high financial stress episodes were rather short-lived while for the recent crisis the model stays longer in the high financial stress regime.

4.7 Persistence among Regimes

One may expect that there is a difference in the persistence of shocks between the “normal” and the financial crises regime. The persistence of shocks depends on the eigenvalues of the companion form of the regime-dependent coefficient matrices. More specifically, the closer the eigenvalues are to unity, the higher would be the persistence of shocks. In the case of greater than unity eigenvalues the impulse responses would be explosive. Note that the latter case is automatically excluded since I discard draws of the coefficient matrices which are associated to eigenvalues bigger or equal than one.

First, I present the results for the maximum eigenvalues of the extreme regime lag polynomials, \(D^{(1)}(L)\) and \(D^{(2)}(L)\), that corresponds to \(F(z_{t-1}, \nu) = 0\) and \(F(z_{t-1}, \nu) = 1\), respectively. The mean of the maximum eigenvalue associated with the draws of \(D^{(1)}(L)\) kept after thinning is equal to 0.903 with the 68% confidence interval being \([0.821, 0.979]\). Moreover, for the draws of \(D^{(2)}(L)\) the mean of the maximum eigenvalue is 0.646 and its confidence interval is given by \([0.551, 0.742]\). It seems that the persistence of shocks indeed varies with the two regimes.

Next, the maximum eigenvalues associated to \(D_t(L)\) are obtained for each draw kept. This provides me with a plot of the mean and 68% confidence interval of the maximum eigenvalues for each point in time \(t\) (see Figure 5 in the Appendix B). Whenever, the model
is in the financial crises regime, i.e., in 1974, 1987, 2001 and 2008/2009 the plot shows an extremely high spike for the maximum eigenvalue. Therefore, it seems that shocks have more persistent effects during financial crises than in “normal” times.

4.8 Monetary Policy Shock

Impulse responses functions are the key statistics to shed light on the question of whether monetary policy transmission is different during “normal” times and times of high financial stress. This section lays down the results for the regime-dependent impulse responses of an expansionary monetary policy shock. Note that I construct impulse responses to monetary policy shocks conditional on a given regime. In other words, I assume that once the system is in a regime it can stay for a long time in that regime\(^5\). Moreover, as in Auerbach and Gorodnichenko (2012), impulse responses for the ”normal” and financial crises regimes are constructed using the pure regime lag polynomials \(D^{(2)}(L)\) and \(D^{(1)}(L)\), respectively. Therefore, impulse responses correspond to weights equal to \(F(z_{t-1}, \nu) = 1\) in the case of the “normal” regime and \(F(z_{t-1}, \nu) = 0\) in the case of the financial crises regime\(^6\). Note that \(F(z_{t-1}, \nu) = 0\) corresponds to the estimated weights during the recent financial crises (and maybe during the Black Monday). Hence, I could interpret the responses of the financial stress regime as responses to a monetary policy expansion during the financial crisis of 2008-2009.

Figures 6, 7, 8, 9, and 10 of the Appendix B show the mean impulse responses (of the draws kept after thinning) to a monetary policy shock decreasing the Federal funds rate by one standard deviation. Solid lines indicate responses in the financial crises regime while dashed lines indicate responses in the “normal” regime. The dotted lines are the respective 68% confidence bands.

Figure 6 presents the regime-dependent responses of the Federal Funds rate, GDP, prices\(^{5}\)The advantage of this approach is that, once a regime is fixed, the model is linear and hence impulse responses are not functions of history (for details see Koop et al. (1996)). Nevertheless, allowing for feedback from changes in \(z\) into the dynamics of macroeconomic variables I consider an interesting issue which is left for further research.

\(^6\)I also calculated impulse responses assuming weights between 0.8 and 1, i.e., \(0.8 \leq F(z_{t-1}, \nu) \leq 1\), for the “normal” regime and between 0 and 0.2, i.e., \(0 \leq F(z_{t-1}, \nu) \leq 0.2\) for the financial crises regime. The results are nearly identical.
and adjusted reserves. One of the most striking results is that an expansionary monetary policy shock has a larger effect on GDP during financial crises than during “normal” times. In the financial crises regime GDP significantly and persistently increases reaching the maximum raise, of about 1%, after about a year. The shape of the response of GDP in times of low financial stress is very similar to the one in the financial crises regime. However, there is a difference in the maximum increase that is reached at about 0.2% in the low financial stress (“normal”) regime. Moreover, prices increase significantly in the “normal” regime while they just increase for about a year in the financial crises regime. After a year the effects on prices become insignificant in the high financial stress regime. Although I cannot observe the so-called “price puzzle” in times of low financial stress, there seems to be a version of it in times of high financial stress as effects are non-significant after a year. Concerning adjusted reserves, the effects of a monetary policy shock are slightly higher in the financial stress regime for the first couple of quarters, reaching the maximum impact about one quarter earlier than the response of the “normal” regime. After about one year the response of adjusted reserve reverts back to the pre-shock level in the financial crises regime while the effects remain persistent in the “normal” regime. Note that this behavior might be due to the fact that the response of the Federal funds rate in the high financial stress state becomes insignificant after about a year while the effects are permanent in the low financial stress state.

In order to further analyze the differences among the two regimes, Figure 7 displays the impulse responses of consumption, investment, industrial production, and new orders. Most notably, for all four variables the responses to an expansionary monetary policy shock are stronger in high financial stress periods than in periods of low financial stress. As for consumption, during financial crises a decrease in the Federal funds rate increases consumption permanently by 3% while only about 0.8% in periods of low financial stress. Investment reacts with a maximum effect of about 1.3% in the financial crises state and of 0.1% in the “normal” state. The responses of industrial production and new orders are similar in both regimes. Summing up, variables from the business cycle seem to respond more extremely to a monetary policy shock during financial crises than during “normal” times.

So far, it is not clear where the differences in impulse responses come from. In order to gain insight of what might cause the differences in the transmission of the monetary policy shocks. More research is needed to understand the mechanisms behind these differences.
policy shock I plot impulse responses for credit spreads and stock market indices and their respective realized volatilities in Figure 8 and 9, respectively. Additionally, I consider the responses of bank loans to a monetary expansion (Figure 10).

The two upper rows of Figure 8 show the regime-dependent responses of the spread between the bank prime loan rate and the 3-month Tbill rate (95), and the spread between the bank prime loan rate and the 6-month Tbill rate (96). These spreads measure the premium entrepreneurs have to pay when they ask for credit in the banking system, i.e., when they raise funds externally. Therefore, I use these spreads as a proxy for the external finance premium (EFP) (see Bernanke et al. (1999)). An expansionary monetary policy shock has no impact effect on the EFP and then significantly decreases the EFP during “normal” as well as during high financial stress times. The maximum decrease is reached at about 3 quarters. Strikingly, the EFP reacts more extremely to a monetary expansion in the financial crises regime than in the “normal” regime, i.e., during financial crises the EFP decreases by double as much as it does during low financial stress periods. Moreover, the response of the EFP in the financial crises regime reverts back to the pre-shock level about two quarters later than the response of the “normal” regime. Therefore, a monetary expansion during financial crises decreases the cost of external funding by more than in times of low financial stress.

Additionally, Figure 8 presents the responses of the TED spread (103) which is a measure of the risk of default on interbank loans (counterparty risk) and therefore proxies the premium banks have of to pay when lending to each other. After an expansionary monetary policy the TED spread decreases on impact and reverts back to the pre-shock level after about a year in both regimes. The responses of the “normal” and the financial crises regime are nearly identical in the case of the TED spread. This suggests that even though a monetary expansion decreases the counterparty risk in both regimes, its effects are not asymmetric. Finally, the last row of Figure 8 depicts the regime-dependent impulse response of the Baa-Aaa spread (94), i.e., the corporate bond spread. The monetary policy shock increases the spread slightly on impact in both regimes. While in the “normal” regime the response of the corporate bond spread stabilises at the pre-shock level after about a year, the response of the financial stress regime turns negative after about two quarters and reverts back to the pre-shock level after about 2 years. Therefore, the monetary expansion
decreases the cost of bond financing via lower rated bonds than bond financing via high rated bonds during financial crises. Additionally, policy rate pass-through to this type of loan rates seems to be extremely sluggish in “normal” times.

Figure 9 displays the regime-dependent impulse responses of the S&P 500 and NYSE price index, and of their respective realized volatilities. An expansionary monetary policy shock significantly and permanently increases both stock price indices. The S&P 500 index increase about 0.2% on impact in both regimes. While the response of the financial crises state reaches its maximum increase of about 1% after a year and then stabilises at a little bit less than 1%, the response of the ”normal” state stabilises at around 0.5% after two quarters. A very similar pattern arises for the regime-dependent responses of the NYSE index. As the stock market indices can be seen as a proxy for entrepreneurs’ wealth, a monetary expansion during financial crises increases the worth of a firm by nearly double as much as during periods of low financial stress. Moreover, a monetary policy shock seems to have no effects on the volatility of stocks in the “normal” regime as the responses are not significantly different from zero (except for a slightly positive effect on impact). Nevertheless, in the financial crises regime the response of the realized volatility significantly decrease after a monetary expansion reverting to the pre-shock level after about 1.5 years. This indicates that a monetary expansion decreases the uncertainty about the value of assets during financial crises while it has no effects on this uncertainty in “normal” times.

Finally, I consider the effects of a monetary expansion on several loans at commercial banks (see Figure 10). A similar pattern arises for all the different types of loans. During financial crises commercial and industrial loans, consumer loans, total loans, and real estate loans at commercial banks increase significantly and permanently after an expansionary monetary policy shock. On the contrary, I cannot observe any clear-cut effects on the different types of loans in the “normal” regime. Responses of loans during times of low financial stress are insignificant, except that one might argue that the response of consumer loans is slightly increasing. Therefore, a monetary expansion has asymmetric effects on loans, i.e., while a monetary expansion during “normal” times does not have any significant effects on loans, it raises loans during financial crises.

These findings for the financial market variables have various implications. First, the negative response of the credit risk spreads, i.e., EFP, in the financial crises as well as
in the “normal” regime, suggests that monetary policy and the premium entrepreneurs have to pay when they ask for external credit may be linked. Therefore, this finding provides supportive evidence for the existence of a credit channel which is also referred to as the financial accelerator (see the seminal contributions of Bernanke and Gertler (1989), Bernanke et al. (1996) and Bernanke et al. (1999)). The credit channel can be broken down into two components: the balance sheet channel and the bank lending channel (Bernanke and Gertler (1995)). Consequently, the positive response of entrepreneurs’ wealth, i.e., the S&P 500 and NYSE index, in both regimes supports the potential existence of a balance sheet transmission channel. More specifically, the balance sheet channel suggests that an expansionary monetary policy shock increases the net worth of borrowers via the increase in asset prices, forcing down the external finance premium, which decreases the effective cost of credit, and therefore further stimulates investment and output. I can observe these balance sheet effects for the high financial stress as well as for the low financial stress regime, whereas the effects are stronger during high financial stress times. Moreover, a monetary policy expansion may also affect the EFP by shifting the supply of intermediated credit, in particular, loans by commercial banks. Consequently, the positive response of loans in the financial crises regime may suggest the existence of a bank lending channel at least during financial crises when financial market imperfections are high.

Second, and more important for the question at hand, is the fact that effects on the EFP are stronger in the financial crises regime than in the “normal” regime. Moreover, the responses of stock prices, volatilities, and loans are stronger in the case of high financial stress. This may indicate that the financial accelerator is stronger when the financial fundamentals, e.g., the entrepreneurs’ wealth, are low, that is, during financial crises. This possibility of non-linear balance sheet effects was discussed for example in Bernanke and Gertler (1989), Gertler and Gilchrist (1994), and Bernanke et al. (1996). More specifically, in a high financial stress regime a monetary expansion increases the asset prices and decreases the EFP by more than in the low financial stress regime. This translates to a stronger increase of investment, output, and other variables describing the state of the economy such as consumption, industrial production, and new orders.
5 Conclusion

This paper investigates whether monetary policy transmission during financial crises differs from what is usually observed in low financial stress or “normal” times. In order to do so I introduce the STFM which is a regime-dependent factor model where the transition between states (“normal” and high financial stress times) depends on a financial conditions index.

My analysis shows substantial evidence that the transmission of a conventional monetary policy shock is different in times of financial crises. More specifically, I find that a monetary expansion during financial crises has stronger and more persistent effects on macroeconomic variables such as output, consumption, and investment than during “normal” times. These differences in effects among the regimes seem to originate from non-linearities in the credit channel. That is, a monetary expansion increases asset prices and loans by more during financial crises than in “normal” times, leading to a higher decrease in the EFP which, in turn, provokes the stronger effects on macroeconomic variables such as output, investment, and consumption.

For future work, I anticipate investigating the role of conventional monetary policy allowing for endogenous switches in the state, i.e., allowing for feedback from changes in the transition variable, $z$, into the dynamics of macroeconomic variables. Moreover, introducing regime-dependent covariance matrices in the factor relation I consider an interesting issue as this allows for differences in contemporaneous effects among the two regimes.


A Details of Gibbs Sampler

A.1 Likelihood

Under the normality assumptions the likelihood of the model can be expressed as:

\[
L(\Lambda, F, D, H, Q, \nu) \propto |H|^T/2 \exp \left\{ -\frac{1}{2} tr \left[ (X - FA)'H^{-1}(X - FA) \right] \right\} \times (14)
\]

\[
|Q|^T/2 \exp \left\{ -\frac{1}{2} tr \left[ (F - W^{ST}D)'Q^{-1}(F - W^{ST}D) \right] \right\},
\]

where the first factor of the product is the likelihood of the observation equation and the second factor is the likelihood of the measurement equation. After some manipulations I can rewrite the likelihood in the standard way as

\[
L(\Lambda, F, D, H, Q, \nu) \propto |H|^T/2 \exp \left\{ -\frac{1}{2} tr \left[ (\lambda - \hat{\lambda})'(H^{-1} \otimes F'F)(\lambda - \hat{\lambda}) \right] \right\} \times (15)
\]

\[
\exp \left\{ -\frac{1}{2} tr \left[ (X - FA)'H^{-1}(X - FA) \right] \right\} \times
\]

\[
|Q|^T/2 \exp \left\{ -\frac{1}{2} tr \left[ (F - W^{ST}D)'Q^{-1}(F - W^{ST}D) \right] \right\} \times
\]

\[
\exp \left\{ -\frac{1}{2} tr \left[ (d - \hat{d})'(Q^{-1} \otimes W^{ST}W^{ST})(d - \hat{d}) \right] \right\} \times
\]

\[
\exp \left\{ -\frac{1}{2} tr \left[ (F - W^{ST}\hat{D})'Q^{-1}(F - W^{ST}\hat{D}) \right] \right\}.
\]

Now the likelihood of each equation in the model given in (6) and (7) can be seen to be the product of an Inverse Wishart density for \( H \) and \( Q \), respectively and a normal density for \( \lambda \) and \( d \), respectively.

A.2 The Kalman Filter and Smoother Algorithm

Let \( X^t = (x_1, x_2, ..., x_t) \), \( \bar{F}^t = (\bar{f}_1, \bar{f}_2, ..., \bar{f}_t) \) and \( \bar{D}^t = (\bar{D}_1, \bar{D}_2, ..., \bar{D}_t) \) be the history from period 1 to \( t \) of \( x_t \), \( \bar{f}_t \) and \( \bar{D}_t \) which are from the state space representation given by Equation 10. As in Carter and Kohn (1994) the conditional distribution of the whole history of the factors at time \( t \) is the following:

\[
p (F^T|X^T, D^T, \Lambda, Q, H, \nu) = p (\bar{f}_T|X^T, D^T, \Lambda, Q, H, \nu) \prod_{t=1}^{T-1} p (\bar{f}_t|\bar{f}_{t+1}, X^t, D^t, \Lambda, Q, H, \nu) \]  

(16)

Since the state space model in (10) is linear and Gaussian the distribution of the factors is given by

\[
\bar{f}_T|X^T, D^T, \Lambda, Q, H, \nu \sim N (\bar{f}_T|T, P_T|T) \quad (17)
\]

\[
\bar{f}_t|\bar{f}_{t+1}, X^t, D^t, \Lambda, Q, H, \nu \sim N (\bar{f}_t|t+1, P_t|t+1) \quad t = T - 1, ..., 1. \]

(18)
First, I run the Kalman filter to obtain $\bar{f}_{T|T}$ and $P_{T|T}$. Starting with $\bar{f}_{0|0} = 0_{r \times p}$ and $P_{0|0} = I_{r \times p}$ the Kalman filter recursion over $t = 1, ..., T$ is given by

\[
\begin{align*}
\bar{f}_{t|t-1} &= D_t \bar{f}_{t-1|t-1} \\
P_{t|t-1} &= D_t P_{t-1|t-1} D_t' + \bar{Q} \\
\hat{f}_{t|t} &= \hat{f}_{t|t-1} + P_{t|t-1} \bar{\Lambda}' (\bar{\Lambda} P_{t|t-1} \bar{\Lambda}' + H)^{-1} (x_t - \bar{\Lambda} \hat{f}_{t|t-1}) \\
P_{t|t} &= P_{t|t-1} - P_{t|t-1} \bar{\Lambda}' (\bar{\Lambda} P_{t|t-1} \bar{\Lambda}' + H)^{-1} \bar{\Lambda} P_{t|t-1}
\end{align*}
\] (19)

Then, having the draw of $\bar{f}^T$ and the results of the filter I run the Kalman smoother to obtain $\bar{f}_{T-1|T}$ and $P_{T-1|T}$. This backward updating provides me with a draw of $\bar{f}_{T-1}$ and in the next updating step with a draw of $\bar{f}_{T-2}$ and so on until I arrive at $\bar{f}_1$. More specifically, the Kalman smoother steps for $t = T - 1, ..., 1$ are the following:

\[
\begin{align*}
\bar{f}_{t+1|t} &= \bar{f}_{t|t} + P_{t|t} D_t' (D_t P_{t|t} D_t' + \bar{Q})^{-1} (\bar{f}_{t+1} - D_t \bar{f}_{t|t}) \\
P_{t+1|t} &= P_{t|t} + P_{t|t} D_t' (D_t P_{t|t} D_t' + \bar{Q})^{-1} D_t P_{t|t}
\end{align*}
\] (20)

If the lag order $p$ exceeds one then lags of the factors appear in $\bar{f}_t$ and $\bar{Q}$ is singular. In this case in the Kalman smoother steps rather than conditioning on the full vector $\bar{f}_{t+1}$ when drawing $\bar{f}_t$, I only can use the first $p$ elements of $\bar{f}_{t+1}$. See Kim and Nelson (1999) for more details.
# B Tables and Figures

## B.1 Tables

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<td>Real Exports of Goods &amp; Services</td>
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<td>Corporate Profits After Tax/GDP deflator</td>
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<td>NPCPATAX/GDPDEF</td>
<td>Nonfinancial Corporate Business: Profits After Tax/GDP deflator</td>
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<td>Nonfarm Business Sector: Hours of All Persons</td>
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<td>Nonfarm Business Sector: Output Per Hour of All Persons</td>
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<td>Producer Price Index: Crude Materials for Further Processing</td>
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<td>Producer Price Index: Finished Consumer Goods</td>
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<td>Producer Price Index: Finished Goods</td>
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<td>3-Month Treasury Bill: Secondary Market Rate</td>
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<td>Moody's Seasoned Aaa Corporate Bond Yield</td>
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<td>MPRIME-TB6MS</td>
<td>Bank Prime Loan Rate minus 6-Month Treasury Bill</td>
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<td>Excess Reserves of Depository Institutions</td>
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<td>Real Net Taxes</td>
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Table 1: Transformations of $x_t$: $1 = x_t$, $2 = \Delta x_t$, $5 = \Delta \log x_t$, $6 = \Delta^2 \log x_t$
B.2 Figures

Figure 1: The black line shows the FCI of Hatzius et al. (2010). The red line is the estimated threshold value, $c$. The estimate has been obtained as the mean of the threshold value draws of the Metropolis-within-Gibbs sampler kept after thinning.
Figure 2: This figure plots the estimated factors obtained in the first half of the Gibbs sampler against the ones obtained in second half. The estimates are calculated as the mean of the factor draws of the sampler kept after thinning.
Figure 3: This figure plots the estimated factors and their 95% confidence bands. The estimates have been obtained as the mean of the factor draws of the Gibbs sampler kept after thinning.

Figure 4: This figure provides a time plot of the mean of the weight on the financial crises regime together with its 95%-confidence interval.
**Figure 5:** This figure provides a plot of the mean of the maximum eigenvalues of $\bar{D}_t$ together with its 68%-confidence intervals over time.

**Figure 6:** This figure plots the impulse responses to an expansionary monetary policy shock of the Federal funds rate (4), GDP (1), Prices (2), and adjusted reserves (107). Solid lines indicate the responses for the financial crises regime and dashed lines indicate the responses for the “normal” regime. Dotted lines are the respective 68%-confidence intervals.
Figure 7: This figure plots the impulse responses to an expansionary monetary policy shock of consumption (14), investment (10), industrial production (40), and new orders (78). Solid lines indicate the responses for the financial crises regime and dashed lines indicate the responses for the “normal” regime. Dotted lines are the respective 68%-confidence intervals.
Figure 8: This figure plots the impulse responses to an expansionary monetary policy shock of the 1st measure of the external finance premium (95), the 2nd measure of the external finance premium (96), the TED spread (103) and the corporate bond spread (94). Solid lines indicate the responses for the financial crises regime and dashed lines indicate the responses for the “normal” regime. Dotted lines are the respective 68%-confidence intervals.
Figure 9: This figure plots the impulse responses to an expansionary monetary policy shock of the S&P 500 index (97), the NYSE index (104), the realized volatility of the S&P 500 (99), and the realized volatility of the NYSE index (105). Solid lines indicate the responses for the financial crises regime and dashed lines indicate the responses for the “normal” regime. Dotted lines are the respective 68%-confidence intervals.
Figure 10: This figure plots the impulse responses to an expansionary monetary policy shock of commercial and industrial loans (62), consumer loans (63), total loans (64), and real estate loans (65). Solid lines indicate the responses for the financial crises regime and dashed lines indicate the responses for the “normal” regime. Dotted lines are the respective 68%-confidence intervals.