

Credit Shocks, Monetary Policy, and Business Cycles: Evidence from a Structural Time Varying Bayesian FAVAR

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Abstract

I estimate a Bayesian factor-augmented vector autoregression model using a large panel of macroeconomic and credit spread data from the United States for the period 1926-2009. The model has time varying parameters and volatilities. I identify a number of episodes with high volatility in the common component of credit spreads. Often, though not always, these episodes coincide with (or lead) NBER recessions. I find that, during these episodes, credit spread shocks and monetary policy shocks have much stronger effects on macroeconomic variables than on average. The degree of amplification of those responses reaches at its peak a factor of up to ten. These amplified responses tend to exhibit a larger persistence.¹

JEL codes: C11, C15, C22, C53, N12, E32, E37, E44, E47, E51, E52,

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1 Introduction

The recent disruptions in the financial market, its spread to a variety of other asset markets and the subsequent contraction in the real economy has centered attention on the linkages of financial factors and real activity explaining business cycle fluctuations. The compelling response by monetary and fiscal authorities around the globe witnessed by means of sharp interest rate cuts, introduction of new alternative monetary policy instruments and extraordinary financial stimulus packages suggests its potential importance.

In this paper I address the following questions: To what extent do credit spread shocks² and monetary policy shocks in the presence of credit market frictions contribute to business cycle fluctuations? Is the relationship between the credit market, the real economy and the transmission mechanism of shocks constant or subject to changes in both, parameters and volatilities governing the dynamics?

Since the Great Depression the U.S. economy has been characterized by substantial changes in institutions, shifts in the structure of the economy, changes in macroeconomic policy regimes and varying volatility of the real, nominal and financial sector. Particular prominent periods are the "*Great Events*" such as the "*Great Depression*" which marked the severest financial crisis and recession in the U.S. history. The "*Great Inflation*"³ describes the period covering the 70s and early 80s characterized by simultaneous high inflation, high interest rates and high macroeconomic volatility with large swings in the real and nominal cycle coinciding with non-active monetary policy responding weakly to inflation. The "*Great Moderation*" is characterized by a decline in the volatility of output growth and inflation starting from the mid 1980's after the Chairmanship of Paul Volcker and his disinflationary monetary policy regime, see Kim and Nelson (1999), McConnell and Pérez-Quirós (2000) and Stock and Watson (2002). Recently the term "*Great Contraction*" has been coined by Kenneth Rogoff to describe the contraction experienced in the most recent recession preceded by the financial market turmoil.

To shed light on the linkages and mechanisms at play during the past century I analyze a large panel of U.S. macroeconomic data and credit spreads from corporate bond yields covering the period 1926-2009. To cope with the different sources of changes in U.S. business cycle I employ a structural Bayesian factor-

²By credit spread shock I mean a widening in a common factor describing the key common movement of a large panel of nominal bond yields data of major groups at different ratings from which a proxy for the risk free rate has been subtracted.

³See Blanchard and Simon (2001), Stock and Watson (2002), Sims and Zha (2006), Primiceri (2005) and Cogley and Sargent (2005) for a discussion about the causes of the Great Inflation.

augmented vector autoregression (henceforth FAVAR) model with time varying parameters and volatilities. I identify different states in the evolution of the respective sector volatility which are converging in some periods, e.g. during the Great Depression overall volatilities increase, and diverging in others, e.g. like during the Great Moderation where macroeconomic volatility decreases while financial market indicators' volatility increases. Furthermore I identify the effects of credit spread shocks and monetary policy shocks to quantify their impact and contribution in explaining fluctuations in the real economy at business cycle frequencies.

I identify a number of episodes with high volatility in the common component of credit spreads. During many recession periods and financial disruptions these episodes coincide with or are led by a widening in the credit spread factor. I find that, during these episodes, credit spread shocks and monetary policy shocks have much stronger effects on macroeconomic variables than on average. The degree of amplification of those responses reaches at its peak a factor of up to ten. Simultaneously these responses exhibit a larger persistence at the three year horizon considered. The highest volatility periods of the credit spread factor are during the Great Depression, the decade of the 70s and the current crisis labeled as the "*Great Contraction*". However the impact on real variables during the Great Depression is much stronger than during the recent recession period. There is clear evidence on changes in the transmission mechanism of both shocks analyzed affecting the amplification and propagation. During the periods of strong responses to both monetary policy and credit spread shocks the variation explained in business cycle fluctuations is significantly higher. Comparing different pairs of periods I find evidence on changes in the persistence of inflation and output growth. The recent decade compared to the Great Moderation period shows a high probability of an increase in the persistence of inflation. These considered recent years coincide with an increase in the volatility of macroeconomic, nominal and financial factors.

For the analysis of financial factors and shocks I focus on credit spreads. Changes in the spread reflects changes in "pay off", "default risk" or "liquidity risk" affecting the external financing position of firms through which effects can be feed back amplified to the real economy. The theoretical foundation for the particular importance of credit market frictions comes from the concept of the "financial accelerator" introduced to the literature most prominently by the work of Bernanke and Gertler (1989), Bernanke, Gertler and Gilchrist (1996,1999). This concept relates fixed income asset prices and real output through the external finance premium. This measure is defined as the difference between the costs of raising external funds to the opportunity costs of internal funds faced by a bor-

rower. Assuming financial frictions the external finance premium is positive and depends inversely on the strength of the borrower's financial position. A widening in the external finance premium is related to a widening in credit spreads. A higher external finance premium - or equivalently, a deterioration in the cash flow and balance sheet positions of a borrower - makes borrowing more costly, reduces investment and thus overall aggregate economic activity creating a channel through which otherwise short lived economic or monetary policy shocks may have long-lasting effects. Furthermore the financial accelerator is known to deliver the credit channel of monetary policy providing the theoretical underpinning why a monetary contraction might have accelerated real effects through a tightening in effect in credit conditions. This is the building block of many recent theoretical attempts to model financial frictions in DSGE models like Christiano, Motto and Rostagno (2003,2007), De Fiore and Uhlig (2005), Gertler and Gertler and Kiyotaki (2009). Other recent promising attempts to model credit frictions in theoretical models are the work of Curdia and Woodford (2009a,b,c) who model credit frictions and credit spreads within the standard New Keynesian model describing implications for optimal monetary policy. Gilchrist, Yankov and Zakrajasek (2009) also identify credit market shocks and its impact on economic fluctuations. They employ a FAVAR model for the U.S. economy covering the period 1990-2008 with constant parameters. My approach differs from the ones previously mentioned because, firstly I am not only considering the credit market as a channel amplifying and propagating monetary policy shocks but also the impact of perturbations originating directly in the credit market. Secondly, I consider a much longer time period of the U.S. business cycle and finally I explicitly allow for different sources of nonlinearities that are important in order to detect and characterize potential changes in the transmission mechanism of shocks and their contribution to business cycle fluctuations.

Recent advances in empirical macroeconomics have emphasized the role of dynamic factor analysis and FAVARs for the analysis of large panels of disaggregated data to capture the key driving factors that explain business cycle fluctuations in a parsimonious and flexible way. See Stock and Watson (2002a,b,2005), Bernanke and Boivin (2003), Bernanke, Boivin and Elias (2005). Bayesian approaches to the large scale dynamic factor analysis employing likelihood-based Markov Chain Monte Carlo (MCMC) methods have been provided first by Otrok and Whiteman (1998). Amir Ahmadi and Uhlig (2009) combine a Bayesian FAVAR model with sign restrictions for an improved identification of monetary policy shocks. The first authors to consider time variation in the context of dynamic factor analysis are Del Negro and Otrok (2008). The analysis of monetary policy in the time varying framework goes back to the work by Sims and Zha

(2006), Cogley and Sargent (2005) and Primiceri (2005). Sims and Zha (2006) employ a Markov-Switching VAR and find a key role for drifts in Volatilities only. In the paper by Cogley and Sargent (2005) and Primiceri (2005) there is some evidence on some changes also in parameters and not only volatilities.

Literature on the interaction of financial factors, monetary policy and business cycle fluctuations is rare particularly considering the long run that is subject to several instabilities in the economic structure. The few papers to analyze interwar U.S. data are Ritschl and Woitek (2004) employing a Bayesian VAR with time varying parameters and Amir Ahmadi and Ritschl (2009) employing a monetary FAVAR model. To the best knowledge of the author, this paper is the first attempt to incorporate the role of financial factors on business cycle fluctuations covering data from the Great depression up to now, explicitly modeling the changes in volatilities and parameters. My approach allows characterizing changes in the transmission mechanism of financial and monetary policy shocks covering a number of recessions and crisis in the U.S. business cycle.

2 Empirical Strategy

The key idea behind dynamic factor analysis and FAVAR models is to parsimoniously represent the comovements in a large set of cross-sectional data by only a limited number of unobserved latent factors. These models involve dimension reduction techniques which allow to represent the dynamics in both the common component - represented by these factors and their respective factor loadings - and the variable-specific idiosyncratic component in a parsimonious way. The factor-augmented vector autoregression (henceforth FAVAR) model is a hybrid between a dynamic factor model (henceforth DFM) and the standard structural VAR model: a joint VAR is specified for some series of interest f_t^y and some factors f_t^m that are extracted from a large panel of informational time series x_t . The working hypothesis of the FAVAR model is that while a narrow set of variables f_t^y , notably the policy instrument of the central bank, are perfectly observable and have pervasive effects on the economy, the underlying dynamics of the economy are less perfectly observable, and hence a VAR in just a few key variables would potentially suffer from omitted variable bias. As increasing the size of a VAR is impractical due to problems of dimensionality, the FAVAR approach aims to extract the common dynamics from a wide set of informational indicator series x_t^m , and to include these in the VAR, represented by a small number of factors f_t^m . This approach is well suited for structural analysis such as impulse response analysis and variance decomposition (in particular for the problem at

hand). For the estimation procedure the model has to be cast in a state-space representation. The informational variables x_t included in the observation equation are assumed to be driven by observable variables with pervasive effects on the economy (e.g. the central bank's policy instrument), f_t^y , a small number of unobservable common factors, f_t^m , which together represent the main "driving forces" of the economy, and an idiosyncratic component e_t .

2.1 Modeling Choices

In order to have a flexible model that allows for the previously mentioned drifts in parameters and volatilities. A decision has to be made as to where to model dynamics and time variation. I will model time variation in the factor coefficients and stochastic volatility in the factors residual covariance matrix and time variation in the contemporaneous relation of the shocks following augments put forward by Primiceri (2005) in the VAR framework. The parameters are modeled as driftless random walk processes as proposed in Cogley and Sargent (2005) for a VAR model. Stochastic volatilities follow a driftless geometric random walk. This follows the belief that changes due to policy, structure or luck, are permanent rather than transitory hence this specification is preferred over a stationary process as in Del Negro and Otrok (2008). Unlike Del Negro and Otrok (2008) I model all the time varying dynamics in the process for the common factors and leave the parameters and hyperparameters in the observation equation constant. The motivation comes from the different questions addressed in this paper. Here I aim to capture changes in the structure of the economy and the conduct of policy that are common across the informational variables rather than detecting shifts in idiosyncratic forces. Therefore the flexibility in terms of time variation is devoted to the state equation only. Adding time variation and stochastic volatility in the process of the idiosyncratic components comes at high computational cost, and aggravates on the degree of freedom problem without explicitly adding insights to the questions at hand. The drawback of imposing the stability condition of the process for the state equation over a rather long period can be computationally high and forces to choose to short lag length a priori.

2.2 The Econometric Model

The model to be derived here is a Bayesian FAVAR with both time-varying coefficients and multivariate stochastic volatility in the common factors residual covariance matrix set up in a general (parametric) state space form. These different sources of time variation are designed to capture possible nonlinearities in the

process of the factors driving the key common dynamics of the potentially large panel of data. The time-variation in the coefficients is meant to capture nonlinearities in the lag structure of the model, e.g. possible changes in policy regimes and institutional changes affecting the propagation mechanism. The latter independent source of variation is designed to capture possible heteroskedasticity of the exogenous (structural) shocks and nonlinearities in the simultaneous relations among the common factors of the model affecting the size of shocks and hence determines the scale of the impulse of shocks⁴. The objective is to propose a likelihood estimation approach to capture the rich interrelations of the real, nominal and financial sector in a parsimonious model in order to identify and analyse the different sources of nonlinearity and its transmission mechanism. The model takes the form

$$\begin{aligned} x_t &= \lambda^c f_t^m + \lambda^y f_t^y + \lambda^{cs} f_t^{cs} + e_t \\ e_t &\sim N(0, R) \end{aligned} \quad (2.1)$$

where $x_t = (x_t^{m'}, x_t^{y'}, x_t^{cs'})'$ of dimension $[(N_m + N_y + N_{cs}) \times 1]$ denotes the time t grouped data vector containing macroeconomic data x_t^m , core VAR data x_t^y and credit spread data x_t^{cs} .⁵ The total number of time series is denoted by $N = (N_m + N_y + N_{cs})$. The factor loading matrices λ^m , λ^y and λ^{cs} of respective dimension $[N \times K_m]$, $[N \times K_y]$ and $[N \times K_{cs}]$ relate the observable data in x_t to the common time t factors $f_t = (f_t^{m'}, f_t^{y'}, f_t^{cs'})'$ of dimension $[K_m \times 1]$, $[K_y \times 1]$ and $[K_{cs} \times 1]$ respectively which themselves follow a time-varying parameter VAR(P) process with stochastic volatility. The time t observation residual is denoted by the vector $e_t = (e_t^{m'}, 0_{N_y \times 1}', e_t^{cs'})'$ of dimension $[N \times 1]$. The innovation term e_t has mean 0 and covariance R , which is assumed to be diagonal and including zero elements for the variances of the core VAR process f_t^y in the FAVAR. Hence the error terms of the observable variables are mutually uncorrelated at all leads and lags, namely

$$\begin{aligned} E[e_{i,t} f_t] &= 0 \\ E[e_{i,t} e_{j,s}] &= 0 \end{aligned}$$

where the latter hold for $\forall i, j = 1, \dots, N \wedge t, s = 1, \dots, T$ and $i \neq j \wedge t \neq s$. The joint dynamics of the factors f_t are given by the following VAR(P) process with

⁴See Primiceri (2005) for a detailed description of these modeling features for a VAR model on which the introduced nonlinearities of my model draw.

⁵Throughout the paper the superscript m , y and cs will denote the reference to macroeconomic data, the core VAR and credit spread data respectively unless explicitly stated.

drifting parameters and volatilities

$$\begin{aligned} f_t &= \sum_{p=1}^P B_{t,p} f_{t-p} + u_t \\ u_t &\sim N(0, Q_t) \end{aligned} \quad (2.2)$$

where

$$\begin{aligned} Q_t &= A_t^{-1} \Sigma_t A_t^{-1'} \\ u_t &= A_t^{-1} \Sigma_t^{.5} v_t \\ E_t[v_t v_t'] &= I_K \end{aligned}$$

where u_t is the time t vector of innovations and v_t is the time t vector of structural shock both of dimension $[K \times 1]$. The contemporaneous relations of the shocks and the factors are represented through the matrix A_t of dimension $[K \times K]$. From the above triangular reduction it follows that

$$A_t = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ a_{21,t} & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{K1,t} & \cdots & a_{KK-1,t} & 1 \end{bmatrix}, \quad \Sigma_t = \begin{bmatrix} \sigma_{1,t} & 0 & \cdots & 0 \\ 0 & \sigma_{2,t} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{K,t} \end{bmatrix}.$$

The dimensions of the factors are $[K_m \times 1]$, $[K_y \times 1]$ and $[K_{cs} \times 1]$ respectively, where $K = [K_m + K_y + K_{cs}]$ denotes the total number of factors including the perfectly observables ones. Please note that $K_y \equiv N_y$ as it represents an identity in the companion form of the state space representation of the model to be estimated.

The model in the state space form is given by equation (2.2) and (2.3). Vectorizing and stacking the coefficients in the state equation (2.3) delivers $b_t = (b_{1,t}, \dots, b_{p,t})$ where the time t lag p vectorized matrix of coefficients is given by $b_{p,t} = \text{vec}(B_{p,t})$. Similarly the diagonal elements of the time t stochastic volatility matrix $\Sigma_t^{.5}$ and the time t lower diagonal and non one elements of A_t row-wise stacked denoted by a_t are given by $\log(\sigma_t) = (\log(\sigma_{1,t}), \dots, \log(\sigma_{K,t}))$, $a_t = (a_{21,t}, \dots, a_{KK-1,t})$ respectively. The drifting parameters and log volatilities follow a driftless random walk process of the form

$$\begin{aligned} b_t &= b_{t-1} + \omega_t^b \\ a_t &= a_{t-1} + \omega_t^a \\ \log(\sigma_t) &= \log(\sigma_{t-1}) + \omega_t^\sigma. \end{aligned}$$

The vector of all innovations in the model is given by $\varepsilon_t = (e_t, v_t, \omega_t^b, \omega_t^a, \omega_t^\sigma)$ and is assumed to be jointly normally distributed given by

$$\varepsilon_t = \mathcal{N} \left(\begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} R & 0 & 0 & 0 & 0 \\ 0 & I_K & 0 & 0 & 0 \\ 0 & 0 & \Omega^b & 0 & 0 \\ 0 & 0 & 0 & \Omega^a & 0 \\ 0 & 0 & 0 & 0 & \Omega^\sigma \end{bmatrix} \right).$$

Note that the $R, \Omega^b, \Omega^a, \Omega^\sigma$ are positive definite matrices. As pointed out by Primiceri (2005) the implied restrictions of block diagonal structure are not essential and could be easily abstracted from⁶. However considering a more generic correlation structure of the covariance matrix of the vector of shocks is not of direct interest for the economic questions at hand and goes beyond the scope of this paper.

2.3 Identification of Macroeconomic and Credit Spread Factors

Identification of the model against rotational indeterminacy requires normalization and additional restrictions. For better exemplification of the factor identification I will restate the observation equation in (2.2) with the model in mind and the resulting implied zero restrictions on the factor loading matrix.

$$\begin{bmatrix} x_t^m \\ x_t^y \\ x_t^{cs} \end{bmatrix} = \begin{bmatrix} \lambda^m & \lambda^y & 0 \\ 0 & I_{K_y} & 0 \\ 0 & 0 & \lambda^{cs} \end{bmatrix} \begin{bmatrix} f_t^m \\ f_t^y \\ f_t^{cs} \end{bmatrix} + \begin{bmatrix} e_t^m \\ 0 \\ e_t^{cs} \end{bmatrix}.$$

In what follows I partly follow the approach of Bernanke, Boivin and Elias [2005] and normalize the upper $[K_m \times K_m]$ block of λ^m to the identity matrix and restrict the upper $[K_c \times N_y]$ block of λ^y to only contain zeros.

In dynamic factor analysis and therefore also in the FAVAR approach it is of great importance to impose further restrictions for the model parameters and the factors to be uniquely identified against rotational, scale and sign indeterminacy. This task is of crucial importance as the likelihood is salient about the specific unique rotation that separately identifies factors, loadings and parameters. Different rotations are observationally equivalent resulting with the same likelihood although the model can be very different. There are different assumptions one can impose depending on the purpose of the analysis. One standard approach to the identification of factor models is the approach goes back to Geweke and

⁶For a discussion see Primiceri (2005)

Zhou [1996]. They restrict the upper $K \times K$ (where K denotes the total number of factors) block of the factor loading matrix λ to be lower triangular. See also Mönch [2006] for an implementation in the FAVAR framework. Alternatively one could impose the upper $K \times K$ to be identity as is done in Bernanke, Boivin and Elias [2005]. Note that this restriction is over-identified however very convenient as no further restrictions are required for the scale and sign determinacy. A third alternative is to group the data according to some model the researcher has in mind e.g. blocking the data according to some regional concepts and extract the respective factors solely from these predefined blocks of data. This approach has implied restrictions on the factor loading matrix resulting in over-identification from a purely statistical sense but required given the possibility to label the factors according to some economic model the researcher has in mind. One possibility is to impose restrictions on the factor loading matrix such that the factors refer to specific economic concepts, like economic activity or inflation factors the data refers to (see Belviso and Milani [2006]) or distinguish between economic concepts geographical aggregates, like world, regional and country specific business cycles as in Otrok and Whiteman (1998) and Del Negro and Otrok (2004,2008). In this paper I employ a semi-structural identification of the factors due to the pre-blocking of the data and the imposed block-diagonal restrictions on the loading matrix are designed to deliver "*macro factors*" and "*credit spread factor*". It is furthermore required to set the first $[K_i \times K_i]$ where K_i denotes the number of factors to be sampled from the respective block, to identity as a normalization. The data is ordered and blocked according to respective economic concepts designed to reflect. Note that the grouping of the data and the block-diagonality assumptions are additional restrictions imposed for the factors to represent solely the economic concepts. Hence the structure of the factor loading imposed combines the normalization and the additional restrictions. For unique identification of factors and loadings it is sufficient to set the upper $[K \times K]$ block to identity and no further restrictions are required. But then there is no interpretation of the factors as economic concepts which is not what we want. For that the additional assumptions of block diagonality according to the respective groups of data is required. This way the extracted factors are consistent with the respective economic concept as each data block only loads with one of the corresponding factors.

2.4 Identification of Structural Shocks

2.4.1 Factor generalization of Cholesky Identification

In order to identify the effects of monetary policy shocks and credit spread shocks identifying assumptions have to be made to allow for structural interpretation. I employ the Cholesky identification imposing a contemporaneous recursive structure where the macroeconomic factors f_t^m are ordered first before the core VAR factors f_t^y and ordering last the credit spread factor f_t^{cs} endogenizing its contemporaneous response. The ordering in the core VAR of the benchmark case industrial production is ordered first before CPI inflation and the policy instrument is ordered last in f_t^y . Note that the time t reduced form errors u_t are parameterized as

$$\begin{aligned} u_t &= A_t^{-1} \Sigma_t^5 \nu_t \\ A_t^{-1} \Sigma_t A_t^{-1'} &= Q_t \end{aligned}$$

where the structural time t shocks is assumed to be $\nu_t \sim N(0, I)$. Here (A_t^{-1}) is lower triangular and captures the time t the contemporaneous relation of the shocks. I compute the impulse response functions for a pre-specified horizon h at each point in time therefore up to $t + h$ based on the current time t sampled factors, states parameters and hyperparameters of the MCMC algorithm.

2.4.2 Alternative Identification of Shocks via Sign Restrictions

Amir Ahmadi and Uhlig (2009) have shown that within large scale factor models the identification of monetary policy shocks leads to unreasonable price puzzles particularly when controlling for monetary policy regime consistent periods like the post-Volcker disinflation period. They suggest to combine dynamic factor analysis and sign restrictions for a successful identification of monetary policy shocks. It turns out that the results look more reasonable and the combined approach allows for a robustness check of identification avoiding the puzzling ambiguous effect of output to a contractionary monetary policy shock. Eliciting sign restriction priors related to the financial accelerator could be done by calibrating or estimating a model that explicitly involves the financial accelerator like the one by Bernanke, Gertler and Gilchrist (1999). I solved the model and calculated impulse responses to a monetary policy shock, a government spending shock and a technology shock which can be seen in figure (18) from which sign restrictions could be derived to be imposed on the empirical model. For more details regarding sign restrictions see Uhlig (2005), Mountford and Uhlig (2008), Canova and DeNicoló (2002) and Amir Ahmadi and Uhlig (2009).

2.5 Bayesian Estimation and MCMC Algorithm

Bayesian analysis treats the parameters of the model as random variables. In order to conserve notation let us define the space of parameters, hyperparameters and volatilities of the observation model and the state model respectively as:

$$\begin{aligned}\Theta^{State} &\equiv (B^T, A^T, \Sigma^T, \Omega^b, \Omega^a, \Omega^\sigma) \\ \Theta^{Obs} &\equiv (\lambda, R)\end{aligned}$$

We are interested in inference on the parameter space $\Theta \equiv (\Theta^{State}, \Theta^{Obs})$ and the factors F^T . Multi move Gibbs Sampling alternately samples the parameters Θ and the factors F_t , given the data. We use the multi move version of the Gibbs sampler because consisting of three blocks. The task is to derive the joint posterior density of:

$$p(F^T, \Theta)$$

which requires to empirically approximate the marginal posterior densities of F and Θ given the history of the data X^T :

$$\begin{aligned}p(F^T) &= \int p(F^T, \Theta | X^T) d\Theta \\ p(\Theta) &= \int p(F^T, \Theta | X^T) dF^T\end{aligned}$$

The procedure applied to obtain the empirical approximation of the posterior distribution is the previously mentioned multi move version of the Gibbs sampling technique by Carter and Kohn [1994] and Fruhwirth-Schnatter [1994]⁷.

2.5.1 Estimation Summary

In order to estimate the model we first start to set some set of starting values $(F_0^T, \Theta_0^{State}, \Theta_0^{Obs})$ and then cycle through the three blocks until convergence has been achieved. In order to further exemplify the basic estimation procedure I will briefly summarize the three blocking steps:

BLOCK 1: $p(F^T | X^T, \Theta^{Obs}, \Theta^{State})$. Conditional on the data X^T and a set of previous draws Θ_{i-1} we simulate factors given the model (1)-(17). Here I employ the widespread version by Kim and Nelson (1999).

⁷For a survey and more details see Kim and Nelson [1999]

BLOCK 2: $p(\Theta^{Obs} | X^T, F^T)$. Conditional on the data X^T and the loadings and idiosyncratic component's variance follow a normal-inverse Gamma density equation by equation due to the diagonality assumption of R .

BLOCK 3: $p(\Theta^{State} | X^T, F^T)$. Conditional on the data X^T and the simulated factors I estimate the sample, parameters, hyperparameters and volatilities of the state equation. The AR coefficients b_t and α_t are simulated via forward-filtering backward-sampling procedure described before after redefining the state space respectively (See Kim and Nelson (1999) for details). Hyperparameters Ω^a and Ω^b are drawn from the inverse Wishart distribution and each diagonal element of Ω^σ is drawn from the inverse gamma distribution. The log volatilities $ln(\Sigma_t)$ are drawn by the mixture of normals approach as described in Kim, Shepard and Chib (1998).

Summary of Steps at each Iteration .

- Step 0:** Initialize $p(F_0, \lambda_0, R_0, B_0^t, A_0^t, \Sigma_0^t, \Omega^b, \Omega^a, \Omega^\sigma)$
- Step 1:** Sample $F^T, p(F_g^T | X^T, \lambda_{g-1}, R_{g-1}, B_{g-1}^t, A_{g-1}^t, \Sigma_{g-1}^t, \Omega_{g-1}^b, \Omega_{g-1}^a, \Omega_{g-1}^\sigma)$
- Step 2:** Sample $R, p(R_g | X^T, F_g^T)$
- Step 3:** Sample $\lambda, p(\lambda_g | X^T, F_g^T, R_g)$
- Step 4:** Sample $B^T, p(B_g^T | X^T, F_g^T, A_{g-1}^t, \Sigma_{g-1}^t, \Omega_{g-1}^b)$
- Step 5:** Sample $A^T, p(A_g^T | X^T, F_g^T, A_{g-1}^t, \Sigma_{g-1}^t, \Omega_{g-1}^a)$
- Step 6:** Sample $\Sigma^T, p(\Sigma_g^T | X^T, F_g^T, A_{g-1}^t, \Omega_{g-1}^\sigma)$
- Step 7:** Sample Hyperparameters Ω_g^b, Ω_g^a from the inverse-Wishart density and the diagonal elements of Ω_g^σ from the inverse-Gamma density
- Step 8:** Set $g = g + 1$ and repeat iteration **Step 1** to **Step 7** many times until the chain has reached its ergodic distribution.

2.5.2 Choosing the Starting Values Θ^0

In general one can start the iteration cycle with any arbitrary randomly drawn set of parameters, as the joint and marginal empirical distributions of the generated parameters will converge at an exponential rate to its joint and marginal target

distributions as $S \rightarrow \infty$. This has been shown by Geman and Geman [1984]. Since Gelman and Rubin [1992] have shown that a single chain of the Gibbs sampler might give a “false sense of security”, it has become common practice to try out different starting values. We check our results based on four different strategies regarding the set of starting values. One out of many convergence diagnostics involves testing the fragility of the results with respect to the starting values. For the results to be reliable, estimates based on different starting values should not differ. Strictly speaking, the different chains should represent the same target distribution. In order to verify we start our Gibbs sampler with the following summarized starting values respectively.

1. Randomly draw Θ_0 from (over)dispersed distribution
2. Set Θ_0 to results from principal component analysis.⁸In such a way the number of draws required for convergence can be reduced considerably.
3. Set Θ_0 to parameters of the last iteration of the previous run appending the chain.

2.5.3 Prior Specification

Regarding the choice of the priors I closely follow Primiceri (2005) as regards the states, parameters and hyperparameters of the state equation. In order to calibrate the priors for the estimation I rely on estimating a training sample on the initial 5 years of the data for a constant FAVAR model. This is standard practice. The details of the prior and posterior derivation can be found in the appendix.

3 Empirical Evidence

In this section I present the main results of the paper. In particular, I identify the episodes with high volatility in the common component of credit spreads. Furthermore I find that, though not always, these episodes coincide with (or lead) NBER recessions. During these episodes, credit spread shocks and monetary policy shocks have much stronger effects on macroeconomic variables than on average. The degree of amplification of those responses reaches at its peak

⁸This strategy is particularly suited for large models as the ones studied here and has been proposed by Elias (2005).

a factor of up to ten simultaneously exhibiting a larger persistence in those responses. Before proceeding, however, I begin with a brief discussion of the data used.

3.1 Data

In this paper I will analyze two different data set which differ in the time period the cover and the cross sectional dimension. The first data set consist of 20 macroeconomic, interest rate, corporate, industrial and utility bond yield time series from January 1919 to August 2009 for the U.S. economy in monthly frequency. As a second step to check the robustness of the results and whether they are subject to omitted variable bias I redo the exercise by compiling a larger data set that includes the first on and adds a number of additional macroeconomic indicators. In total I have 55 time series for the second data set. However these are available only from January 1959 to August 2009. Note that the key results are not in conflict with the ones from the long term time span. The data on nominal bond of major groups is available for different (quality) ratings according to Moody's. The appendix provides the details along with the classification codes. To induce stationary, some of the data series were transformed. Again the details are provided in the appendix.

Table 1: Estimated R^2 s from regressions of individual series on Factors.

Description	R^2	Description	R^2
Consumption	1.00	Wages	0.65
PPI Inflation	1.00	CPI Inflation	0.71
Federal Funds Rate	1.00	Income	0.53
Industrial Production	0.93	Unemployment	0.85
Average Credit Spread	0.81	ISM Manufacturing Index	0.89

Data show the variance decomposition of the factors through the estimated R^2 s for selected series based on 7 factors for the post-WW II data set.

3.2 Model Specification

For the first long term data set I sample a single factor from the credit spreads. The core VAR in the FAVAR equation consists of industrial production, CPI inflation and the three month Treasury Bill. From the rest of the macroeconomic time series I sample the factor that explains the key variation in the data. This results

in a total number of $K = 5$ factors in the FAVAR equation. For the second data set results are reported from the model with $K_m = 3$ macroeconomic factors and $K_{cs} = 1$ the credit spread factor. The core VAR in the FAVAR equation consists of industrial production, CPI inflation and the Federal Funds Rate resulting in a total number of 7 factors $K = 7$. Due to the long time period and the stability condition in the first data set I impose the stability condition on the drifting process of the factors coefficients. Therefore I am forced to have a rather short lag length. This is standard in the time varying parameter literature. Due to the computational burden and the additional problem with the stability condition I chose to set the lag length to 1. Therefore I report results based on a single lag. However I experimented increasing the number of lags to two but the key results did not change.

3.3 Reduced Form Evidence

3.3.1 Model Fit

In order to assure that the methodology can represent the data in an adequate manner I report results that pursue to assess the models fit to the data. The first obvious check is to see how well the factors represent our panel of data series. To this end, I estimated the R^2 statistics from regressing the respective series onto the respective factors. Results are some selected series can be found in table (tab:R2Table) below. As can be seen, the overall fit is high; the factors do seem to capture the variance in the individual series very well. Hence, the factor model is informative in the sense that it describes the common components of the business cycle that I am interested in. Thus, a VAR in these factors or common components should not suffer from omitted variable bias, which implies that adding individual series to the FAVAR in above does not alter results substantially.

I performed several checks to see whether the model represents the data in an adequate manner. The first obvious check is to obtain the goodness of fit of the observation equation (2.2) for each series x_t . Results are listed in Table (1) below. As can be seen, the overall fit is high; the factors seem to capture the common components of the business cycle well. Thus, a VAR in eq. (2.3) should not suffer from omitted variable bias, which implies that adding individual series to the FAVAR in above does not alter results substantially. As an additional check, I increased the model dimensionality of the factors. However, the model fit did not change much, and the subsequent VAR analysis remained basically unaffected.

3.3.2 Credit Spread Factor

The upper panel of figure (3) shows the sampled credit spread factor covering the period 1926-2009 with the NBER recession chronology depicted by the grey shaded area. It is evident that most of the US recession periods either coincide or are led by a widening in the credit spread factor which marks a tightening in the credit market conditions. However during some periods there is a widening in the credit spread factor such as during the mid 1980's and around 1998 without coinciding with a recession. These are particular events of international financial market disruptions such as the LTCM crisis, the Russian default crisis and the Asian crisis without coinciding with severe declines in the U.S. real activity. Only the widening in the credit spread factor during the Great Depression and the current financial market starting (or the Great Recession) are comparable in magnitude. The period preceding the peak of the spread during the Great Depression coincides with increasing number of bank suspensions. The lower panel in figure (3) shows exactly the same credit spread factor marking some selected events of financial distress with the a red line described in the caption of the figure. Here it is evident how sudden widening coincides with events tightening credit conditions. As an example one can see that the Penn central commercial paper crisis in may 1970 and the oil shock in 1974 are led by a widening in the spread.

3.3.3 Evidence on Time Variation

I provide evidence on time variation in both the coefficients and the factor residual covariance structure. In figure (1) I compare the prior mean of the coefficients in the state equation to its posterior mean that is subject to a drifting process. As can be seen there some substantial time variation the process along the time particularly around the period covering the Great Depression and the periods from 1960-1980. To better track whether these changes are relevant from a statistical point of view I provide in figure (2) a comparison a time invariant model versus the time varying FAVAR. I plot the posterior median and the 68% equal tail error bands of the coefficients of the state equation in the constant model versus the ones resulting from the model allowing for time variation. The picture changes somewhat in the sense that there a some reduced parameters that are substantially subject to time variation whereas some others move with the error bands hence do not change. The conclusion about time variation in the coefficients remains. However it is important for a fair comparison to compare the constant versus the time varying model rather comparing the prior and posterior outcome of the same model to infer about the degree of time variation. This might

overstate the underlying drifts at play.

3.3.4 Evolution of uncertainty and Volatility

Figure (5) plots a smoothed measure that can be interpreted as the total amount of uncertainty entering the system that characterizes the economy at each point in time. The smoothed estimates clearly shows that the overall uncertainty the U.S. economy faced during the last century is clearly subject to substantial time variation. The upward spikes coincide with the NBER business cycle chronology. Furthermore the current recession of 2007, as well as the Great Depression, the breakdown of Bretton Woods, the oil shocks, and the Volcker recession is clearly visible by an increase in the measure.

Figure (4) reports the volatility of selected factor residuals over time. As regards output and Inflation the volatility has been very high particularly during the Great Depression. It is evident that the volatility is substantially higher than the recent crisis in the wake of the financial disruptions. Also interesting is the fact the decline of the volatility in inflation and output since the mid 80's termed as the Great Moderation shows signs of an increase suggesting the end of this low volatility era. My results suggest since the beginning of the new Millennium there is an upward trend in the volatility of inflation, interest rates and the credit market. There is a surge in the volatility of output that coincides with the current financial crisis. As expected there is a spike in the volatility series during the Great Depression showing the strongest spikes in industrial production by far.

3.3.5 Persistence and Predictability

Cogley, Sargent and Primiceri (2009) provide a time varying measure to access the persistence at a give given date in a time varying VAR model. The proposed measure requires to calculate the fraction of the total variation in a selected variable of interest $x_{n,t+j}$ that is due to shocks inherited from the past relative those that will occur in the future. They argue that this is equivalent to measure 1 minus the fraction of total variation due to future shocks. The measure relates the conditional to the unconditional variance and is given by

$$\begin{aligned}
 R_{x,t|T}^2 &= 1 - \frac{\text{var}_t(e_{f,t|T})}{\text{var}_t(e_{x,t|T})} \\
 \text{var}_t(e_{x,t|T}) &= \int_{-\pi}^{\pi} f_{x,t|T}(\omega) d(\omega) \\
 \text{var}_t(e_{f,t|T}) &= 2\pi \exp \left\{ \frac{1}{2\pi} \int_{-\pi}^{\pi} \log[f_{x,t|T}(\omega) d(\omega)] \right\}
 \end{aligned}$$

where $f_{x,t|T}(\omega)$ denotes the time varying spectral density of the selected series x and is given by

$$f_{x,t|T}(\omega) = s_x(I_K - B_{t|T}e^{i\omega})^{-1} \frac{Q_{t|T}}{2\pi} [(I_K - B_{t|T}e^{i\omega})^{-1}]' s_x'$$

Note that s_x is the selection vector for the series of interest. For a detailed explanation see Colgey and Sargent (2005) and Primiceri, Colgey and Sargent (2009).

Figure (6) depicts results for persistence comparison of different selected time spans. The idea is to access to the whether the persistence of the inflation and output growth have changed over time. For that matter I compare pairs of years and check whether the persistence has changed between the time spans. I do this analysis for the following time spans: 1930 – 1940, 1940 – 1960, 1960 – 1980, 1980 – 2000, 2000 – 2004, 2004 – 2009. What I find is that the persistence of both inflation and output has been subject to changes. Particularly the persistence of inflation has declined during the period of the Great moderation. However there is a tendency of increase in the persistence of inflation during the last decade which coincides with an increase in the volatility.

4 Structural Analysis

4.1 Constant Model

To identify the reaction function of credit spread shocks covering the period from the Great Depression up to the current period I first calculate the impulse responses to a credit spread shock in constant parameter model. These results serve as a benchmark to be compared with the nonlinear model that allows for time variation. This way one can assess first, the contribution of drifts in parameters and volatility states and report the degree of biased inference relying on a constant model. In figure (7) you can see that following a widening of the credit spread factor leads to a contraction in the U.S. economy. Industrial Production declines for a period of up to 18 month. We see a clear decline in CPI inflation that is persistent over the whole 2 year horizon and the 3 month T-Bill rate declines also showing a high persistence over the entire horizon considered.

4.1.1 Credit Spread Shocks

Figure (7) shows the impulse responses to a shock in the credit spread factor for a constant FAVAR model covering the period of 1964 – 2009. Output contracts following the unanticipated exogenous widening in the credit spread factor for

a short period, reaching its maximum impact already after 3 – 4 month reverting back to its pre-shock level rather fast afterwards. The response of inflation and the short term interest rate is immediate and shows a higher persistence. Inflation reaches its maximum response also after 3 – 4 month following the exogenous widening of the credit spread factor, but reverts much slower to the pre-shock level than industrial production. The response of the short-term interest rate declines more smoothly, reaching its maximum response at the end of the 48 month horizon considered. Credit spread indicators increase and revert back to the pre-shock level slowly after the 48 month horizon.

4.1.2 Monetary Policy Shocks

Figure (8) shows the impulse responses to a monetary policy shocks for a constant FAVAR model covering the period of 1964 – 2009. Industrial production immediately declines following a contractionary monetary policy shock in a rather persistent manner. This sharp and clear decline is in conflict with the standard result that output reacts with a delay and in a hump shaped manner (see Christiano, Eichenbaum and Evans (1999)). Also it is in conflict with the Result by Uhlig (2005) who shows that with a sign restriction approach the impact on output is ambiguous. Amir Ahmadi and Uhlig (2009) show how this the sign restriction approach combined with FAVAR analysis circumvents these puzzles successfully leading to reasonable results. However keep in mind that there is a substantial price puzzle in CPI inflation that persistently increases following a monetary policy shock. I interpret this as an anomaly due to both the disregard of nonlinearities and insufficient identification. On the other hand this could be seen as a piece of evidence of the financial accelerator, that the presence of credit market frictions amplify and propagate monetary policy shocks. In the following I will show that the key problem is the disregarded nonlinearities in parameters and volatilities that produce these results which are misleading.

4.2 Drifting Parameter Model

In this section I report the results for the model that explicitly allows for time variation in parameters and volatilities. A large list of impulse responses and forecast error variance decomposition are reported in the appendix (see figure (9)-(17)). I report here the posterior mean impulse response function and the corresponding forecast error variance decomposition of selected series to a credit spread shock over time. In figure (9)-(14) the upper two panels refer to the impulse response function and the lower two panels refer to the forecast error

variance decomposition. The respective right panels are the contour plots of the left ones to better assess the degree of persistence in the responses.

Figure (9) reports the results for unemployment. What is immediately clear from the figure is that there is substantial variation both in the amplification and propagation of unemployment to a widening in the credit spread factor shock. According to the mean estimates during the decade of the 70s unemployment increases much stronger than on average to a credit spread shock. During the beginning 90s and the current financial crisis unemployment responses show on average amplified responses though not as strong as during the high volatility periods of the 70s but still very strong. Compared to the average along time, the contour plot on the upper right panel shows that the unemployment response has a higher persistence during the mid and end 70s and again during the current recession indicating a change in the propagation of the credit spread transmission mechanism. As can be seen from the lower panels in figure (9), the fraction of variance explained is substantially higher on average. The explained variation during the periods of amplified and propagated responses is substantially higher than the average fraction. Note that these periods coincide with an overall higher volatility.

This pattern holds true for most of the real macroeconomic indicators. We see a much higher increase in unemployment during the recession periods of the seventies, the Volcker chairmanship and the mid nineties. The latter period is of interest as this is not a NBER recession period but coincides with financial disruptions. Furthermore there is a tendency that during those periods there is a high sensitivity to fluctuations in the credit market, not only the responses are stronger, they also exhibit a higher persistence. This also holds true for the response of consumption and other real indicator and price indicators (see figure (10)-(14)) which contract after a credit spread shock during strong recession periods in a much stronger manner. It holds also true that these specific periods coincide with a high macroeconomic and/or high financial volatility. The respective forecast error variance decompositions show that the contribution of credit market shocks and monetary policy shocks increase to a substantial amount during those periods compared to times where there is no recession are to the benchmark case assuming constant parameters.

Turning to the results for CPI (see figure (11)) I find again that the mean estimates during the decade of the 70s the CPI declines much stronger than on average to a credit spread shock. During the beginning 90s and 2001 recession CPI responses show on average amplified responses though not as strong as during the high volatility periods of the 70s. Compared to the average along time, the contour plot on the upper right panel shows that the CPI response

has a higher persistence during the mid and end 70s and again during the 2001 recession indicating a change in the propagation of the credit spread transmission mechanism. The fraction of variance explained in the two lower panels, is substantially higher on average in those periods of amplified and propagated responses. Note again that these are the periods that coincide with an overall higher volatility in macroeconomic, nominal and financial volatility.

In the appendix several figures of posterior mean impulse response function to both monetary policy and credit spread shocks. Here I compare the responses of selected recession periods to assess which recessions are associated with stronger and more persistent responses. I find that the responses during the Great Depression are by far the strongest ones. During that period responses show a significantly higher persistence. Again it holds true that in periods of high volatility the contribution of credit spread shocks increases substantially compared to the scale of normal times.

In figure (17) and (18) I report the impulse responses of selected series to a credit spread shock and a contractionary monetary policy shock respectively. The two figures compare the posterior median responses at different selected recession dates. The purpose is to assess the whether there are differences in the transmission mechanism during different recession periods. From the figure (17) it is evident that the Great Depression marks a particular recession period in which the economy responds substantially stronger to unanticipated exogenous changes in the credit spread factor. Responses during the Great Depression are much stronger on impact and show a much higher persistence all the series considered. Turning to the monetary policy shock, the distinction is not as evident. The response of the credit spread factor to a contractionary monetary policy shock is the strongest and most persistent one during the current crisis compared to other recession periods. However note that the monetary policy shocks shows strong price puzzles in the recession periods, which raises doubts about the correct identification. This is an indication for employing a better identification scheme, e.g. sign restrictions according to economic theory as is done in Amir Ahmadi and Uhlig (2009), Uhlig (2005), Canova and DeNicolò (2002). This is left for future research.

4.3 How does Monetary Policy React?

To assess the reaction of monetary policy when facing structural shocks I show in figure (15) the posterior mean impulse response functions of the Federal Funds rate to all the shocks in the time varying FAVAR system. Again you can see the pattern of time variation in the responses of monetary policy to structural shocks

reflecting potential changes in the systematic component of monetary policy. During the 70s responses of the Federal Funds rate is even increasing on average following a positive price shocks to CPI. Note that these come with error bands and that show that there is no clear declining response. This is an expected result given the large empirical evidence on the loose response of the monetary authority during the 70s. How much of the variation in the Federal Funds rate is explained by the different structural shocks? From figure (16) you can see that a monetary policy shock explain almost the whole variation in its own variation which is on average over 80% and remains high over up to the 24 month considered. Interestingly during the high volatility period the mid 70's where monetary policy is described as responding loosely to inflation and output growth violating the Taylor principle and the Volcker disinflation period the degree of explanation falls sharply the initial impact down to 40%. Also the persistence of the impulse response function of the Federal Funds rate to its own show declines during the first half of the 90's and the 2001 crisis which coincided with the event of 9/11 and the dotcom bubble. It is also interesting to note that the variation in the monetary policy instrument due to a credit spread shock of on average around 10% is rather. But the forecast error variance decomposition surge up during the aforementioned crisis periods up to around 30% and 20% on average.

5 Conclusion

The recent disruptions in the financial market and the subsequent contraction in the real economy have centered attention on the linkages of financial factors and real activity explaining business cycle fluctuations. In this paper I address the question to what extent this is true. Furthermore I ask whether this relationship is stable over time or subject to time variation. I employ a Bayesian factor-augmented vector autoregression model using a large panel of macroeconomic and credit spread data from the United States for the period 1926-2009. The model has time varying parameters and volatilities. In my analysis I identify a number of episodes with high volatility in the common component of credit spreads. I find that the transmission mechanism of both, monetary policy and credit spread shocks is subject to changes over time. I find real effects of both credit spread shocks and monetary policy shocks. The effects are much stronger on average during episodes of high financial and macroeconomic volatility. Often, though not always, these episodes coincide with (or lead) NBER recessions. The degree of amplification of those responses reaches at its peak a factor of up to ten while simultaneously exhibiting a larger persistence.

References

- [1] Amir Ahmadi, Pooyan and Harald Uhlig (2009) "*Measuring the Effects of a Shock to Monetary Policy: A Bayesian Factor Augmented Vector Autoregression (BEAVAR) approach with agnostic identification*", mimeo
- [2] Amir Ahmadi, Pooyan and Albrecht Ritschl (2009) "*Depression Econometrics: A FAVAR Model of Monetary Policy During the Great Depression*", CEPR Discussion Paper 7546
- [3] Belviso, Francesco, and Fabio Milani, 2005, Structural Factor-Augmented VAR (SFAVAR) and the Effects of Monetary Policy, *mimeo*, Princeton University
- [4] Bernanke, Ben. (1983). *Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression.*" *American Economic Review* 73, 257-76.
- [5] Bernanke, Ben, (1995), "*The Macroeconomics of the Great Depression: A Comparative Approach*", *Journal of Money, Credit and Banking* 27, 1-28.
- [6] Bernanke, Ben, M. Gertler, and S. Gilchrist (1999), "*The Financial Accelerator in a Quantitative Business Cycle Framework*", in *The Handbook of Macroeconomics*, ed. by J. Taylor, and M. Woodford, pp. 1341-1393. Elsevier Science B.V., Amsterdam, The Netherlands.
- [7] Bernanke, Ben and Jean Boivin (2003), "*Monetary Policy in a Data-Rich Environment*"; *Journal of Monetary Economics* 50(3), pp. 525-546
- [8] Bernanke, Ben, Jean Boivin and P. Elias (2005), "*Measuring the Effects of Monetary Policy: a Factor-Augmented Vector Autoregressive (FAVAR) Approach*"; *Quarterly Journal of Economics* 120, pp. 387-422
- [9] Blanchard, O., and J. Simon (2001), "*The Long and Large Decline in U.S. Output Volatility*", *Brookings Papers on Economic Activity*, 1, 135-164.
- [10] Bordo, Michael D., Christopher Erceg and Charles Evans. (2000). "*Money, Sticky Wages, and the Great Depression.*" *American Economic Review* 90, 1447-1463.
- [11] Canova, Fabio and Gianni De Nicrolo (2002), "*Monetary Disturbances Matter for Business Cycle Fluctuations in the G-7*"; *Journal of Monetary Economics*; 49, pp. 1131-59

- [12] Timothy Cogley and Thomas J. Sargent, (2003), "*Drifts and volatilities: Monetary policies and outcomes in the post WWII U.S.*"; Working Paper 2003-25, Federal Reserve Bank of Atlanta.
- [13] Carlstrom, C., and T. Fuerst (1997), "*Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis*", *American Economic Review*, 87(5), 893-910.
- [14] Carter, C.K. and P. Kohn (1994), "*On Gibbs Sampling for State Space Models?*"; *Biometrika* 81, pp. 541-53
- [15] Curdia, Vasco and Michael Woodford (2009a), "*Conventional and Unconventional Monetary Policy*", Federal Reserve Bank of New York Staff Reports, Number 404,
- [16] Curdia, Vasco and Michael Woodford (2009b), "*Credit Spreads and Monetary Policy* ", Federal Reserve Bank of New York Staff Reports, Number 385,
- [17] Curdia, Vasco and Michael Woodford (2009c), "*Credit Frictions and Optimal Monetary Policy* ", working paper Federal Reserve Bank of New York
- [18] De Fiore, Fiorella, and Harald Uhlig (2005). "*Bank Finance versus Bond Finance: What explains the Difference Between US and Europe?*" Working Paper Series, 547, European Central Bank,
- [19] Del Negro, Marko and Chris Otrok (2008). "*Dynamic Factor Models with Time-Varying Parameters: Measuring Changes in International Business Cycles*", working paper, Federal Reserve Bank of New York
- [20] Friedman, Milton, and Anna Jacobson Schwartz. (1963). "*A Monetary History of the United States, 1867-1960*. Princeton: Princeton University Press.
- [21] Christiano, Lawrence J., Roberto Motto and Massimo Rostagno (2003). "*The Great Depression and the Friedman-Schwartz hypothesis*," *Journal of Money, Credit, and Banking* 35, 1119-1197.
- [22] Geman, S. and D. Geman (1984), "*Stochastic Relaxation, Gibbs Distribution and the Bayesian Restoration of Images*"; *IEEE Transactions of Pattern Analysis and Machine Intelligence* 6, pp. 721-41
- [23] Geweke, John, (1977) "*The Dynamic Factor Analysis of Economic Time Series*", in Dennis J. Aigner and Arthur S. Goldberger (eds.) *Latent Variables in Socio-Economic Models* (Amsterdam: North-Holland).

- [24] Geweke, John F., and Guofu Zhou, 1996, Measuring the Price of the Arbitrage Pricing Theory, *The Review of Financial Studies* 9(2), 557-587
- [25] Gilchrist, Simon, Vladimir Yankov and Egon Zakrajsek, (2009), Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets forthcoming *Journal of Monetary Economics*
- [26] Jermann, U., and V. Quadrini (2008) "*Financial Innovations and Macroeconomic Volatility*," NBER Working Paper 12308.
- [27] Kadiyala, Rao and Sune Karlsson (1997) "*Numerical Methods for Estimation and Inference Bayesian VAR-Models*"; *Journal of Applied Econometrics* 12, pp. 99-132
- [28] Kim, Chang-Jin, and Charles R. Nelson, 1999, *State-Space Models with Regime Switching*, The MIT Press, Cambridge, Massachusetts
- [29] Kose, M. Ayhan, Otrok, Christopher, and Charles H. Whiteman, 2004, Understanding the Evolution of World Business Cycles, *American Economic Review*, forthcoming
- [30] Kim, C.-J., and C. R. Nelson (1999) "*Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of Business Cycle*," *Review of Economics and Statistics*, 81(4), 608-616.
- [31] Leeper, Eric, Christopher Sims, and Tao Zha (1996) "*What Does Monetary Policy Do?*"; *Brookings Papers on Economic Activity* 2, 1-63
- [32] McConnell, M. M., and G. Pérez-Quiros (2000), "*Output Fluctuations in the United States: What Has Changed Since the Early 1980's?*", *American Economic Review*, 90(5), 1464-1476.
- [33] Mönch, Emanuel (2008) "*Forecasting the Yield Curve in a Data-Ritch Environment: A No-Arbitrage Factor-Augmented VAR Approach*"; *Journal of Econometrics*, Vol. 146, No. 1
- [34] Mönch, Emanuel (2005) "*Term Structure Surprises: The Predictive Content of Curvature, Level, and Slope*"; mimeo
- [35] Ritschl, Albrecht, and Ulrich Woitek (2000) "*Did Monetary Forces Cause the Great Depression? A Bayesian VAR Analysis for the U.S. Economy*", CEPR Discussion Paper 2547, Centre for Economic Policy Research.

- [36] Sargent, Thomas J. and Christopher A. Sims, (1977) *"Business Cycle Modeling without Pretending to Have Too Much A Priori Economic Theory"* in Christopher A. Sims (ed.) *New Methods in Business Research* (Minneapolis: Federal Reserve Bank of Minneapolis).
- [37] Schwartz, Anna Jacobson (1981), *"Understanding 1929-1933"*; in K. Brunner, editor, *Great Depression Revisited*
- [38] Sims, Christopher (1980) *"Macroeconomics and Reality"*, *Econometrica* 48, pp. 1-48
- [39] Stock, J. H. and M. W. Watson (1989), *"New Indexes of coincident and leading economic indicators"*, *NBER Macroeconomics Annual*, 351-393
- [40] Stock, J. H. and M. W. Watson (1991), *"A probability model of the coincident economic indicators"*, in G. Moore and K. Lahiri, eds. *The leading Economic Indicators: New Approaches and Forecasting Records* (Cambridge University Press) 63-90
- [41] Stock, James, and Mark Watson (2002), *"Has the Business Cycle Changed and Why?"*, *NBER Macroeconomics Annual*, NBER Working Paper 9127.
- [42] Stock, James, and Mark Watson (2005), *"Implications of Dynamic Factor Models for VAR Analysis"*, NBER Working Paper 11467, National Bureau of Economic Research.
- [43] Uhlig, Harald (1994) *"What macroeconomists should know about unit roots: a Bayesian perspective"*, *Econometric Theory*, vol. 10, pp. 645-71
- [44] Uhlig, Harald (1997) *"Bayesian Vector Autoregressions with Stochastic Volatility"*, *Econometrica*, vol. 65, no. 1, pp. 59-73
- [45] Uhlig, Harald (2005) *"What Are the Effects of a Shock to Monetary Policy? Results from an Agnostic Identification Procedure"*, *Journal of Monetary Economics* 52, pp. 381-419

A MCMC Algorithm and Model Estimation

Bayesian analysis treats the parameters of the model as random variables. In order to conserve notation let us define the space of parameters, hyperparameters and volatilities of the observation model and the state model respectively as:

$$\begin{aligned}\Theta^{State} &\equiv (B^T, A^T, \Sigma^T, \Omega_b^T, \Omega_a^T, \Omega_\sigma^T) \\ \Theta^{Obs} &\equiv (\lambda^T, R)\end{aligned}$$

We are interested in inference on the parameter space $\Theta \equiv (\Theta^{State}, \Theta^{Obs})$ and the factors F^T . Multi move Gibbs Sampling alternately samples the parameters Θ and the factors F_t , given the data. We use the multi move version of the Gibbs sampler because consisting of three blocks. The task is to derive the joint posterior density of:

$$p(F^T, \Theta)$$

which requires to empirically approximate the marginal posterior densities of F and Θ given the history of the data X^T :

$$\begin{aligned}p(F^T) &= \int p(F^T, \Theta | X^T) d\Theta \\ p(\Theta) &= \int p(F^T, \Theta | X^T) dF^T\end{aligned}$$

The procedure applied to obtain the empirical approximation of the posterior distribution is the previously mentioned multi move version of the Gibbs sampling technique by Carter and Kohn [1994] and Frühwirth-Schnatter [1994]⁹.

A.1 Bayesian Inference

In this section we describe how to redefine the model in the respective state space form whenever required and how to draw the posterior quantities of interest.

A.2 Conditional density of the parameters θ given \tilde{X}_T and \tilde{F}_T

Sampling from the conditional distribution of the parameters $p(\theta | \tilde{X}_T, \tilde{F}_T)$ requires the blocking of the parameters into the two parts that refer to the observation equation and to the state equation respectively. The blocks can be sampled independently from each other conditional on the extracted factors and the data.

⁹For a survey and more details see Kim and Nelson [1999]

A.3 Conditional density of the factors: $p(F^T | X^T, \Theta^{State}, \Theta^{Obs})$

In this subsection we want to sample from $p(F^T | X^T, \Theta^{State}, \Theta^{Obs})$ assuming that the data and parameter space Θ are given, hence we describe Bayesian inference on the dynamic evolution of the factors F^T conditional on data X^T and Θ .

For the final state space we define the $[N \times KP]$ matrix $\tilde{\Lambda}_t = (\Lambda_t, \tilde{\Lambda}_{1,t}, \dots, \tilde{\Lambda}_{Q,t}, 0_{N \times K(P-1-Q)})$, the $[KP \times 1]$ vectors $\bar{F}_t = (F'_t, F'_{t-1}, \dots, F'_{t-p+1})'$ and $\bar{u}_t = (u'_t 0_{1 \times K(P-1)})'$. Furthermore, let B_t be a $[KP \times KP]$ matrix defined by

$$B_t = \begin{bmatrix} B_{1,t} & \cdots & \cdots & B_{p,t} \\ \mathcal{I}_K & 0_{K \times K} & \cdots & 0_{K \times K} \\ & \ddots & & \vdots \\ 0_{K \times K} & & \mathcal{I}_K & 0_{K \times K} \end{bmatrix}, \quad \bar{Q}_t = \begin{bmatrix} Q_t & 0_{K \times K(P-1)} \\ 0_{K(P-1) \times K} & 0_{K(P-1) \times K(P-1)} \end{bmatrix},$$

Hence the final state space to estimate the unobserved factors is

$$\tilde{X}_t = \tilde{\Lambda}_t \bar{F}_t + e_t \quad (\text{A.1})$$

$$\bar{F}_t = B_t \bar{F}_t + \bar{u}_t \quad (\text{A.2})$$

$$e_t \sim \mathcal{N}(0, R) \quad (\text{A.3})$$

$$\bar{u}_t \sim \mathcal{N}(0, \bar{Q}_t) \quad (\text{A.4})$$

The conditional distribution, from which the state vector is generated, can be expressed as the product of conditional distributions by exploiting the Markov property of state space models in the following way

$$p(\bar{F}^T | X^T, \Theta) = p(\bar{F}_T | X^T, \Theta) \prod_{t=1}^{T-1} p(\bar{F}_t | \bar{F}_{t+1}, X^T, \Theta)$$

The state space model is linear and Gaussian, hence we have according to Carter and Kohn (1994) and Frühwirth-Schnatter (1994):

$$\bar{F}_t | \bar{F}_{t+1}, \Theta \sim \mathcal{N}(\bar{F}_{t|t+1}, P_{t|t+1}^F) \quad (\text{A.5})$$

$$\bar{F}_{t|t+1} = E(\bar{F}_t | \bar{F}_{t+1}, X^T, \Theta) \quad (\text{A.6})$$

$$P_{t|t+1}^F = \text{Var}(\bar{F}_t | \bar{F}_{t+1}, X^T, \Theta) \quad (\text{A.7})$$

where (A.5) holds for the Kalman filter for $t = 1, \dots, T$ and (A.6) holds for the Kalman smoother for $t = T-1, T-2, \dots, 1$. Here $\bar{F}_{t|t}$ refers to the expectation of \bar{F}_t conditional on information dated t or earlier. We obtain $\bar{F}_{t|t}$ and $P_{t|t}$ for $t = 1, \dots, T$ by the forward Kalman Filter, conditional on Θ and the data X^{T10} .

¹⁰See Kim and Nelson (1994) for the derivation.

From the last iteration, we obtain $\bar{F}_{T|T}$ and $P_{T|T}$ and using those, we can draw \bar{F}_t . We can go backwards through the sample, deriving $\bar{F}_{T-1|T-1, \bar{F}_t}$ and $P_{T-1|T-1, \bar{F}_t}$ by Kalman smoother, drawing \bar{F}_{T-1} from (??), and so on for \bar{F}_t , $t = T-2, T-3, \dots, 1$. A modification of the Kalman filter procedure, as described in Kim and Nelson (1999), is necessary when the number of lags p in (??) is greater than 1.

A.4 Conditional density of : $p(\lambda, R \mid \tilde{\mathbf{X}}_T, \tilde{\mathbf{F}}_T)$

Prior Distribution

$$\begin{aligned} p_0(\lambda_n) &= \mathcal{N}(\lambda_{0,n}, R_{nn} V_{0,\lambda n}^{-1}) \\ p_0(R_{nn}) &= \mathcal{IG}\left(\frac{\nu_{0,n}}{2}, \frac{\delta_{0,n}}{2}\right) \end{aligned}$$

Posterior Distribution

$$\begin{aligned} p(\lambda_n \mid R_{nn}, X_T, F_T) &= \mathcal{N}(\lambda_{T,n}, R_{nn} \bar{V}_{\lambda,n}^{-1}) \\ p(R_{nn} \mid X_T, F_T) &= \mathcal{IG}\left(\frac{\bar{\nu}_n}{2}, \frac{\bar{\delta}_n}{2}\right) \end{aligned}$$

subject to the following updating

$$\begin{aligned} \Lambda_{T,n} &= \bar{V}_{\lambda,n}^{-1} \left(V_{0,\lambda n}^{-1} \lambda_{0,n} + (\tilde{F}'_n \tilde{F}_n) \hat{\lambda}_n \right) \\ \bar{V}_{\lambda,n} &= V_{0,\lambda n} + (\tilde{F}'_n \tilde{F}_n) \\ \bar{\nu}_n &= \nu_n + T - K \\ \bar{\delta}_n &= \delta_{0,n} + (T - K) S_n^2 + (\hat{\lambda}_n - \lambda_{0,n})' \left[V_{0,\lambda n}^{-1} + (\tilde{F}'_n \tilde{F}_n)^{-1} \right]^{-1} (\hat{\lambda}_n - \lambda_{0,n}) \end{aligned}$$

where

$$S_n^2 = \frac{1}{(T - K)} (\tilde{X}_n - \tilde{F} \hat{\lambda}_n)' (\tilde{X}_n - \tilde{F} \hat{\lambda}_n)$$

This part refers to observation equation of the state space model which, conditional on the estimated factors and the data, specifies the distribution of λ and R . The errors of the observation equation are mutually orthogonal hence R is diagonal. Therefore we can apply equation by equation OLS in order to obtain $\hat{\lambda}$ as the observation equation amounts to a set of independent regressions. I assume conjugate priors which according to Bayesian results conform to the following conditional posterior distribution where prio specification ($\delta_{0,n} = 1, \nu_{0,n} = 10^{-3}, \lambda_{0,n} = 0_{K \times 1}$), $V_{0,\lambda n} = I_K$ results in an uninformative prior. The regressors of the i -th equation are represented by \tilde{F}_T^i and the fitted errors of the i -th equation are represented by S_n^2 .

A.5 Block 3: Drawing $p(B^T, A^T, \Sigma^T, V^S \mid \tilde{X}_T, \tilde{F}_T)$

A.5.1 Sample $p(B^T \mid A^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T)$

The conditional distribution of the time-varying coefficients of the common factors $p(B^T \mid A^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T)$ can be factored as:

$$p(B^T \mid A^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T) = p(B^T \mid A^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T) \prod_{t=1}^{T-1} p(B_t \mid B_{t-1}, A^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T)$$

according to Carter and Kohn (1994) and Frhwirth-Schnatter (1994) where

$$B_t \mid B_{t+1}, A^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T \sim \mathcal{N}(B_{t|t+1}, P_{t|t+1}^B) \quad (\text{A.8})$$

$$B_{t|t+1} = E(B_t \mid B_{t+1}, \tilde{X}_T, \tilde{F}_T, A^T, \Sigma^T, V^S) \quad (\text{A.9})$$

$$P_{t|t+1}^B = \text{Var}(B_t \mid B_{t+1}, \tilde{X}_T, \tilde{F}_T, A^T, \Sigma^T, V^S). \quad (\text{A.10})$$

The prior for the coefficients in the FAVAR equation following a VAR(P) process are calibrated by estimating a fixed coefficient VAR model using data for the initial 5 years of the respective data set. For the first the training sample covers January 1919 - December 1924 and for the second data set the training sample covers January 1959 - December 1964 resulting in the following prior

$$B_0 \sim N(\hat{B}_{ols}, 12 \times \hat{V}_{B,ols}) \quad (\text{A.11})$$

with \hat{B}_{ols} and $\hat{V}_{B,ols}$ defining the respective maximum likelihood estimates for the training sample based on a fixed coefficient VAR model.

A.5.2 Sample $p(A^T \mid B^T, \Sigma^T, V^S, \tilde{X}_T, \tilde{F}_T)$

The state equation can be rewritten as:

$$A_t(F_t - \sum_{p=1}^P B_{p,t} F_{t-p}) = A_t \hat{F}_t \quad (\text{A.12})$$

$$A_t \hat{F}_t = \Sigma_t v_t \quad (\text{A.13})$$

The final state-space for contemporaneous covariance state is

$$\hat{F}_t = \check{F}_t \alpha_t + \Sigma_t v_t \quad (\text{A.14})$$

$$\alpha_t = \alpha_{t-1} + \omega_t^A \quad (\text{A.15})$$

The conditional distribution of the simultaneous covariance states can be factored similar to the previous step where (1x) and (3x) form the state space representation. Here:

$$\alpha_t \mid \alpha_{t+1}, B^T, \Sigma^T, V^s, \tilde{X}_T, \tilde{F}_T \sim \mathcal{N}(\alpha_{t|t+1}, P_{t|t+1}^\alpha) \quad (\text{A.16})$$

$$\alpha_{t|t+1} = E(\alpha_t \mid \alpha_{t+1}, B^T, \Sigma^T, V^s, \tilde{X}_T, \tilde{F}_T) \quad (\text{A.17})$$

$$P_{t|t+1}^\alpha = \text{Var}(\alpha_t \mid \alpha_{t+1}, B^T, \Sigma^T, V^s, \tilde{X}_T, \tilde{F}_T). \quad (\text{A.18})$$

Here the prior parameters are also taken from the fixed coefficient VAR model resulting in

$$\alpha_0 \sim N(\hat{\alpha}_{ols}, 12 \times \hat{V}_{\alpha,ols}). \quad (\text{A.19})$$

In order to set $\hat{\alpha}_{ols}$ I calculate the residual covariance matrix Σ_{OLS} , calculate the lower triangular Cholesky decomposition denoted by \tilde{C} so that $\tilde{C}\tilde{C}' = \Sigma_{OLS}$, after dividing each column of \tilde{C} by the corresponding element on the diagonal and denote this matrix by C . The corresponding lower triangular non-zero and non-one elements of C^{-1} are row-wise stacked in the vector $\hat{\alpha}_{ols}$. The covariance matrix $\hat{V}_{\alpha,ols}$ is assumed to be diagonal where its diagonal elements are multiplied by 12 the corresponding element in the vector $\hat{\alpha}_{ols}$.

A.5.3 Sample Volatility states: $p(\Sigma^T \mid B^T, A^T, V^s, \tilde{X}_T, \tilde{F}_T)$

We take as given, $B^T, A^T, V^s, \tilde{X}_T, \tilde{F}_T$ and rewrite the state equation:

$$A_t(F_t - \sum_{p=1}^P B_{p,t}F_{t-1}) = \Sigma_t v_t \quad (\text{A.20})$$

$$F_t^* = \Sigma_t v_t \quad (\text{A.21})$$

Note that according to Primiceri (2005) the above equation for F_t^* is linearized by taking logs of its square product. It follows:

$$F_{i,t}^{**} = \log[(F_{i,t}^*)^2 + \bar{c}] \quad (\text{A.22})$$

$$e_{i,t} = \log(v_{i,t}^2) \quad (\text{A.23})$$

$$h_{i,t} = \log(\sigma_{i,t}) \quad (\text{A.24})$$

$$F_t^{**} = 2 * h_t + v_t \quad (\text{A.25})$$

$$h_t = h_{t-1} + \eta_t \quad (\text{A.26})$$

Table 2: Selection of the mixing distribution to be $\chi^2(1)$.

ω	$q_j = Pr(\omega = j)$	m_j	v_j^2
1	0.00730	-10.12999	5.79596
2	0.10556	- 3.97281	2.61369
3	0.00002	-8.56686	5.17950
4	0.04395	2.777869	0.16735
5	0.32001	0.61942	0.64009
6	0.24566	1.79518	0.34023
7	0.25750	-1.08819	1.26261

Source: Kim, Shepard and Chip (1998).

Note that the above state-space is linear and non-Gaussian. The innovation e_t is a log $\chi^2(1)$ and the respective smoothing recursion is

$$h_t \mid h_{t+1}, B^T, A^T, \Sigma^T, V^s, s^T, \tilde{X}_T, \tilde{F}_T \sim \mathcal{N}(h_{t|t+1}, P_{t|t+1}^H) \quad (\text{A.27})$$

$$h_{t|t+1} = E(h_t \mid h_{t+1}, B^T, A^T, \Sigma^T, V^s, s^T, \tilde{X}_T, \tilde{F}_T) \quad (\text{A.28})$$

$$P_{t|t+1}^H = Var(h_t \mid h_{t+1}, B^T, A^T, \Sigma^T, V^s, s^T, \tilde{X}_T, \tilde{F}_T). \quad (\text{A.29})$$

where

$$Pr(s_{i,t} = j \mid y_{i,t}^{**}, h_{i,t}) \propto q_j f_N(y_{i,t}^{**} \mid 2h_{i,t} + m_j - 1.2704, v_j^2) \quad (\text{A.30})$$

B Marginal Data Density

In this section I discuss alternative estimators to simulate the marginal likelihood of large dimensional State Space models within the context of potentially non-Gaussianity and nonlinearity. Potential pitfalls of the popular modified harmonic mean estimator are discussed and an alternative method to overcome drawing based on Bridge sampling is proposed.

What's the purpose? In Bayesian Macroeconometrics do formal Model choice to compare models. In particular within the estimation framework that relies on posterior simulation this is a nontrivial task as there is no analytical solution to estimate the marginal data density.

So far parameter and model estimation is well developed, for (B)VAR,

TVP-BVAR, DFM, FAVAR, MS-VAR and DSGE estimation. However, the aspect of model selection in particular in a potentially nonlinear and non-Gaussian environment is not well understood and still subject to research. Sims, Wagoner and Zha (2008) first try to provide a solution to potential non-Gaussianity within the framework large multiple equation Markov-Switching models. They rely on the on the approach of Gewekes’s modified harmonic estimator (MHM) which goes back to a modification of the harmonic mean estimator proposed by Gelfand and Dey (1996). The authors choose a truncated elliptical distribution as a “weighting” function as opposed to the truncated Gaussian distribution to capture potential non-Gaussianity. The truncation is employed to ensure the overlap the support of the ratios oth the respective distributions.

B.1 General Problem

Bridge sampling nests many different approaches to simulating normalizing constants and was introduced into statistics by Meng and Wong (1996) as a simulation based technique for computing ratios of normalizing constants. As in our application we focus on the problem to simulate the marginal data density as the key input to do model comparison via posterior odds ratio or Bayes factor.

B.2 Bridge Sampling: A nested Approach

The marginal data density (MDD) or marginal likelihood as it is sometimes referred to is defined by

$$p(Y^T) = \int (p(Y_1), \dots, p(Y_T) | \theta) p(\theta) d\theta \quad (\text{B.1})$$

where Y_t , is the time t observation, $Y^T = Y_1, \dots, Y_T$ is the history of data, $\theta \in \Theta$ is some unknown parameter vector taking values in the parameter space Θ . It is assumed that $p(\theta)$ is a proper prior density and the likelihood $p(Y^T | \theta)$ is available.

It follows from above that the MDD is equal to the normalizing constant of the posterior density

$$p(\theta | Y^T) = \frac{k(\theta | Y^T)}{p(Y^T)} \quad (\text{B.2})$$

where the posterior kernel is an unnormalized posterior density given by

$$k(\theta | Y^T) = p(Y^T | \theta) p(\theta) \quad (\text{B.3})$$

$$\propto p(\theta | Y^T) \quad (\text{B.4})$$

Let $q(\theta)$ denote a probability density function with known normalizing constant, as chosen to be some simple approximation to the posterior density. We will refer to $q(\theta)$ as an importance density. Furthermore let $\alpha(\theta)$ be any arbitrary function such that the following holds

$$C^\alpha = \int \alpha(\theta)k(\theta | Y^T)q(\theta)d\theta > 0 \quad (\text{B.5})$$

$$\int_{\Theta_p \cap \Theta_q} k(\theta | Y^T)q(\theta)d\theta > 0 \quad (\text{B.6})$$

$$0 < \left| \int_{\Theta_p \cap \Theta_q} \alpha(\theta)k(\theta | Y^T)q(\theta)d\theta \right| < \infty \quad (\text{B.7})$$

Bridge sampling is based on the following result

$$1 = \frac{\int \alpha(\theta)p(\theta | Y^T)q(\theta)d\theta}{\int \alpha(\theta)p(\theta | Y^T)q(\theta)d\theta} \quad (\text{B.8})$$

$$= \frac{E_q[\alpha(\theta)p(\theta | Y^T)]}{E_p[\alpha(\theta)q(\theta)]} \quad (\text{B.9})$$

where the expectation are taken with respect to the densities $p(\cdot)$ and $q(\cdot)$ respectively as denoted by the subscript. After substituting for the posterior density above we arrive at the following

$$p(Y) = \frac{E_q[\alpha(\theta)k(\theta | Y^T)]}{E_p[\alpha(\theta)q(\theta)]}. \quad (\text{B.10})$$

For estimating the MDD for a given function $\alpha(\theta)$ we rely on Monte Carlo integration, hence the expectations are substituted by sample averages of Markov chain Monte Carlo draws. The sequences $\{\theta^{(g)}\}_{g=1}^G$, $\{\tilde{\theta}^{(l)}\}_{l=1}^L$ denote draws from the posterior $p(\theta | Y^T)$ and i.i.d. draws from the importance density $q(\theta)$ resulting in the "general bridge-sampling" estimator.

$$\hat{p}(Y) = \frac{\hat{E}_q[\alpha(\theta)k(\theta | Y^T)]}{\hat{E}_p[\alpha(\theta)q(\theta)]} \quad (\text{B.11})$$

$$= \frac{L^{-1} \sum_{l=1}^L [\alpha(\tilde{\theta}^{(l)})k(\tilde{\theta}^{(l)} | Y^T)]}{G^{-1} \sum_{g=1}^G [\alpha(\tilde{\theta}^{(g)})k(\tilde{\theta}^{(g)} | Y^T)]} \quad (\text{B.12})$$

This approach nest many approaches to simulate ratios of normalizing constants as discussed in Meng and Wong (1996). The crucial part is the choice of the function $\alpha(\theta)$ that delivers the different estimators subsequently discussed.

B.3 Optimal Choice of $\alpha(\theta)$

The asymptotically optimal choice of the function $\alpha(\theta)$ that minimizes the expected relative error of the estimator of the MMD $\hat{p}(Y)$ for i.i.d. draws from both densities $p(\theta | Y^T)$ and $q(\theta)$ is discussed in Meng and Wong (1996) and results is

$$\alpha(\theta) \propto \frac{1}{Lq(\theta) + Gp(\theta | Y^T)}. \quad (\text{B.13})$$

Plugging the optimal choice for the function α in the general Bridge sampling formula delivers the bridge sampling estimator $\hat{p}_{BS}(Y^T)$. Note that for the optimal choice of $\alpha(\theta)$ depends on the *normalized* posterior. This led Meng and Wong (1996) to propose an iterative procedure to obtain the estimator where at each iteration step the normalized posterior $p(\theta | Y^T)$ is approximated by normalizing the posterior kernel with the bridge estimator of the previous step denoted by $p(\theta | Y^T) = \frac{k(\theta|Y^T)}{\hat{p}_{BS,t-1}(Y^T)}$. A new estimation of the bridge-sampling estimator leads to the following recursion:

$$\hat{p}_{BS,t}(Y^T) = \hat{p}_{BS,t-1}(Y^T) \frac{L^{-1} \sum_{l=1}^L \left[\frac{k(\tilde{\theta}^{(l)} | Y^T)}{Lq(\tilde{\theta}^{(l)}) + G\hat{p}(\tilde{\theta}^{(l)} | Y^T)} \right]}{G^{-1} \sum_{g=1}^G \left[\frac{q(\theta^{(g)})}{Lq(\theta^{(g)}) + G\hat{p}(\theta^{(g)} | Y^T)} \right]} \quad (\text{B.14})$$

B.4 Importance Estimator

In order to get the importance sampling estimator¹¹ $\hat{p}_{IS}(Y)$ we set

$$\alpha(\theta) = \frac{1}{q(\theta)} \quad (\text{B.15})$$

resulting in

$$p_{IS}(Y) = E_q \left[\frac{k(\theta | Y^T)}{q(\theta)} \right] \quad (\text{B.16})$$

$$\hat{p}_{IS}(Y) = \frac{1}{L} \sum_{l=1}^L \frac{k(\tilde{\theta}^{(l)} | Y^T)}{q(\tilde{\theta}^{(l)})} \quad (\text{B.17})$$

where the $p_{IS}(Y)$ estimator only depends on i.i.d. samples $\{\tilde{\theta}^{(l)}\}_{l=1}^L$ from the importance density $q(\theta)$.

¹¹See Frhwirth-Schnatter (1996).

B.5 Reciprocal Importance Sampling Estimator

In order to get the reciprocal importance sampling estimator¹² $\hat{p}_{RIS}(Y)$ we set

$$\alpha(\theta) = \frac{1}{k(\theta | Y^T)} \quad (\text{B.18})$$

resulting in

$$p_{RIS}(Y) = \left(E_p \left[\frac{q(\theta)}{k(\theta | Y^T)} \right] \right)^{-1} \quad (\text{B.19})$$

$$\hat{p}_{RIS}(Y) = \left(\frac{1}{G} \sum_{g=1}^G \frac{q(\tilde{\theta}^{(g)})}{k(\tilde{\theta}^{(g)} | Y^T)} \right)^{-1} \quad (\text{B.20})$$

where the $\hat{p}_{RIS}(Y)$ estimator only depends on the posterior MCMC draws $\theta^{(g)}$ _{$g=1$} ^{G} .

B.6 Harmonic Rule

B.6.1 Harmonic Mean: Gelfand and Dey; Newton and Raftery (1994)

The harmonic mean is a special case of the reciprocal importance sampling estimator where the importance density is chosen to be equal to the prior density and it requires to set

$$\alpha(\theta) = \frac{1}{k(\theta | Y^T)}, \quad q(\theta) = p(\theta). \quad (\text{B.21})$$

B.6.2 Modified Harmonic Mean Estimator: Geweke

$$\hat{p}_{MHM,G}(Y) = \left(\frac{1}{G} \sum_{g=1}^G \frac{h(\theta)}{k(\tilde{\theta}^{(g)} | Y^T)} \right)^{-1} \quad (\text{B.22})$$

$$h(\theta) \sim \mathcal{N}(\bar{\theta}, \bar{\Sigma}) \times \mathcal{I} \left\{ \frac{(\theta^{(g)} - \bar{\theta})' \Sigma^{-1} (\theta^{(g)} - \bar{\theta})}{\chi_{(1-p)}^2(\nu)} \leq F_{\chi_{(1-p)}^2(\nu)} \right\} \quad (\text{B.23})$$

B.6.3 Modified Harmonic Mean Estimator: Sims, Waggoner and Zha (2008, JoE)

Sims, Waggoner and Zha (2008) follow the approach of Geweke's MHM estimator with the distinction that the "weighting" function $h(\theta)$ is not based on a

¹²See Gelfand and Dey (1994).

truncated Gaussian density but instead on a truncated elliptical distribution.

$$\hat{p}_{MHM,SWY}(Y) = \left(\frac{1}{G} \sum_{g=1}^g \frac{h(\tilde{\theta}^{(g)})}{k(\tilde{\theta}^{(g)} | Y^T)} \right)^{-1} \quad (\text{B.24})$$

with

$$h(\theta) = \frac{\chi_{\Theta_{\underline{L}}}(\theta)}{q_{\underline{L}}} g(\theta) \quad (\text{B.25})$$

where

$$g(\theta) = \frac{\Gamma(k/2) f(r)}{2\pi^{2/k} |\hat{S}| r^{k-1}} \quad (\text{B.26})$$

$$r = \sqrt{(\theta - \hat{\theta})' \hat{\Omega}^{-1} (\theta - \hat{\theta})} \quad (\text{B.27})$$

$$f(r) = \frac{vr^{v-1}}{b^v - a^v} \quad (\text{B.28})$$

$$\Theta_{\underline{L}} = \left\{ \theta : k(\theta | Y^T) \geq \underline{L} \right\} \quad (\text{B.29})$$

C Data

Data are downloaded from the St. Louis FRED database in monthly frequency. The abbreviation TC stand for transformation code where the entry 1 refers to no transformation and 5 refers the first difference in logarithms. Slow moving variables are denoted by the SC code set to 1 and 0 in case of financial market data. All the variables are transformed to induce stationarity. The transformation code is abbreviated TC and refer to: 1: no transformation, 2: first difference, 3: second differences, 4: logarithm, 5: first difference of logarithms and 6: second difference of logarithms following the convention of Stock and Watson. The first data set covers the period of January 1919 to August 2009. The second larger data set covers the period January 1959 to August 2009.

C.1 Long-run Data Set: 01:1919 - 08:2009

Pos.	Mnemonic	Description	TC	SC
1	PAYEMS	Total Nonfarm Payrolls: All Employees	5	1
2	DSPIC96	Real Disposable Personal Income	5	1
3	NAPM	ISM Manufacturing: PMI Composite Index	1	1
4	UNRATE	Civilian Unemployment Rate	1	1
5	INDPRO	Industrial Production Index	5	1
6	PCEC96	Real Personal Consumption Expenditures	5	1
7	CPIAUCSL	Consumer Price Index For All Urban Consumers: All Items	5	1
8	PCEPI	Personal Consumption Expenditures: Chain-type Price Index	5	1
9	PPIACO	Producer Price Index: All Commodities	5	1
10	FEDFUNDS	Effective Federal Funds Rate	1	0
11	Credit Spread: MOIAD	Moody's A Industrial Bond Yield	1	0
12	Credit Spread: MOIAAD	Moody's AA Industrial Bond Yield	1	0
13	Credit Spread: MOIBAAD	Moody's BAA Industrial Bond Yield	1	0
14	Credit Spread: MOUAD	Moody's A Utility Bonds Yield	1	0
15	Credit Spread: MOUAAD	Moody's AA Utility Bond Yield	1	0
16	Credit Spread: MOUBAAD	Moody's BAA Utility Bond Yield	1	0
17	Credit Spread: MOCORPD	Moody's Corporate Bond Composite Yield	1	0
18	Credit Spread: MOCAAAD	Moody's Corporate AAA Yield	1	0
19	Credit Spread: MOCAAD	Moody's Corporate AA Yield	1	0
20	Credit Spread: MOCAD	Moody's Corporate A Yield	1	0
21	Credit Spread: MOCBAAD	Moody's Corporate BAA Yield	1	0
22	Credit Spread: MOINDUD	Moody's Industrial Bond Yield	1	0
23	Credit Spread: MOUTILD	Moody's Utility Bond Yield	1	0
24	Credit Spread: INUSADJD	Dow Jones Corporate Bond Yield	1	0

C.2 Post-WW II Data Set: 01:1959 - 08:2009

Pos.	Mnemonic	Description	TC	SC
1	DSPIC96	Real Disposable Personal Income	5	1

Pos.	Mnemonic	Description	TC	SC
2	NAPM	ISM Manufacturing: PMI Composite Index	1	1
3	PCEC96	Real Personal Consumption Expenditures	5	1
4	USIPBUSEQM	Industrial Production: Business Equipment (Index 2002=100: SA)	5	1
5	USIPCONGDM	Industrial Production: Consumer Goods (Index 2002=100: SA)	5	1
6	USIPDCONGDM	Industrial Production: Durable Consumer Goods (Index 2002=100: SA)	5	1
7	USIPDMATM	Industrial Production: Durable Materials (Index 2002=100: SA)	5	1
8	USINDPROM	Industrial Production Index (Index 2002=100: SA)	5	1
9	USIPFINALM	Industrial Production: Final Products (Market Group) (Index 2002=100: SA)	5	1
10	USIPMATM	Industrial Production: Materials (Index 2002=100: SA)	5	1
11	USIPNCONGDM	Industrial Production: Nondurable Consumer Goods (Index 2002=100: SA)	5	1
12	USCOMPNFBQ	Nonfarm Business Sector: Compensation Per Hour (Index 1992=100: SA)	5	1
13	USHOANBSQ	Nonfarm Business Sector: Hours of All Persons (Index 1992=100: SA)	5	1
14	USIPDNBSQ	Nonfarm Business Sector: Implicit Price Deflator (Index 1992=100: SA)	5	1
15	USOUTNFBQ	Nonfarm Business Sector: Output (Index 1992=100: SA)	5	1
16	USOPHNFBQ	Nonfarm Business Sector: Output Per Hour of All Persons (Index 1992=100: SA)	5	1
17	USCOMPRNFBQ	Nonfarm Business Sector: Real Compensation Per Hour (Index 1992=100: SA)	5	1
18	USULCNFBQ	Nonfarm Business Sector: Unit Labor Cost (Index 1992=100: SA)	5	1
19	USUNLPNBSQ	Nonfarm Business Sector: Unit Nonlabor Payments (Index 1992=100: SA)	5	1
20	USPAYEMSM	Total Nonfarm Payrolls: All Employees (Thous.: SA)	5	1
21	USUNEMPLOYM	Unemployed (Thous.: SA)	5	1
22	USHCOMPBSQ	Business Sector: Compensation Per Hour (Index 1992=100: SA)	5	1
23	USHOABSQ	Business Sector: Hours of All Persons (Index 1992=100: SA)	5	1
24	USIPDBSQ	Business Sector: Implicit Price Deflator (Index 1992=100: SA)	5	1
25	USOUTBSQ	Business Sector: Output (Index 1992=100: SA)	5	1
26	USOPHPBSQ	Business Sector: Output Per Hour of All Persons (Index 1992=100: SA)	5	1
27	USRCPHBSQ	Business Sector: Real Compensation Per Hour (Index 1992=100: SA)	5	1
28	USULCBSQ	Business Sector: Unit Labor Cost (Index 1992=100: SA)	5	1
29	USUNLPBSQ	Business Sector: Unit Nonlabor Payments (Index 1992=100: SA)	5	1
30	USCE16OVM	Civilian Employment (Thous.: SA)	5	1
31	USEMRATIOM	Civilian Employment-Population Ratio (%: SA)	1	1
32	USCLF16OVM	Civilian Labor Force (Thous.: SA)	5	1
33	USCIVPARTM	Civilian Participation Rate (%: SA)	1	1
34	USUEMP5TO14M	Civilian Unemployed for 5-14 Weeks (Thous.: SA)	5	1
35	USUEMP15OVM	Civilians Unemployed - 15 Weeks & Over (Thous.: SA)	5	1
36	USUEMPLT5M	Civilians Unemployed - Less Than 5 Weeks (Thous.: SA)	5	1
37	USUEMP15T26M	Civilians Unemployed for 15-26 Weeks (Thous.: SA)	5	1
38	USUEMP27OVM	Civilians Unemployed for 27 Weeks and Over (Thous.: SA)	5	1
39	USMANEMPM	Employees on Nonfarm Payrolls: Manufacturing (Thous.: SA)	5	1
40	UNUSAM	United States Unemployment Rate	1	1
41	USCONSM	All Employees: Construction (Thous.: SA)	5	1
42	USDMANEMPM	All Employees: Durable Goods Manufacturing (Thous.: SA)	5	1
43	USEHSM	All Employees: Education & Health Services (Thous.: SA)	5	1
44	USFIREM	All Employees: Financial Activities (Thous.: SA)	5	1
45	USGOODM	All Employees: Goods-Producing Industries (Thous.: SA)	5	1
46	USGOVTM	All Employees: Government (Thous.: SA)	5	1
47	USINFOM	All Employees: Information Services (Thous.: SA)	5	1
48	USLAHM	All Employees: Leisure & Hospitality (Thous.: SA)	5	1

Pos.	Mnemonic	Description	TC	SC
49	USMINEM	All Employees: Natural Resources & Mining (Thous.: SA)	5	1
50	USNDMANEMPM	All Employees: Nondurable Goods Manufacturing (Thous.: SA)	5	1
51	USSERVM	All Employees: Other Services (Thous.: SA)	5	1
52	USPBSM	All Employees: Professional & Business Services (Thous.: SA)	5	1
53	USTRADEM	All Employees: Retail Trade (Thous.: SA)	5	1
54	USSRVPRDM	All Employees: Service-Providing Industries (Thous.: SA)	5	1
55	USPRIVM	All Employees: Total Private Industries (Thous.: SA)	5	1
56	USTPUM	All Employees: Trade: Transportation & Utilities (Thous.: SA)	5	1
57	USWTRADEM	All Employees: Wholesale Trade (Thous.: SA)	5	1
58	USUEMPMEANM	Average (Mean) Duration of Unemployment (Weeks: SA)	5	1
59	USAHECONSM	Average Hourly Earnings: Construction (\$ per Hour: NSA)	5	1
60	USAHEMANM	Average Hourly Earnings: Manufacturing (\$ per Hour: NSA)	5	1
61	USAWHMANM	Average Weekly Hours: Manufacturing (Hours: SA)	5	1
62	WPUSAM	USA Producer Price Index-All Commodities	5	1
63	WPUSAICM	USA Producer Price Index-Industrial Commodities	5	1
64	USPPICPEM	Producer Price Index Finished Goods: Capital Equipment (Index 1982=100: SA)	5	1
65	USPPICRMM	Producer Price Index: Crude Materials for Further Processing (Index 1982=100: SA)	5	1
66	USPPIFCFM	Producer Price Index: Finished Consumer Foods (Index 1982=100: SA)	5	1
67	USPPIFCGM	Producer Price Index: Finished Consumer Goods (Index 1982=100: SA)	5	1
68	USPFCGEFM	Producer Price Index: Finished Consumer Goods Excluding Foods (Index 1982=100: SA)	5	1
69	USPPIFGSM	Producer Price Index: Finished Goods (Index 1982=100: SA)	5	1
70	USPPIENGM	Producer Price Index: Fuels & Related Products & Power (Index 1982=100: NSA)	5	1
71	USPPIITMM	Producer Price Index: Intermediate Materials: Supplies & Components (Index 1982=100: SA)	5	1
72	USCPIAUCSLM	Consumer Price Index For All Urban Consumers: All Items (Index 1982-84=100: SA)	5	1
73	USCPILEGNSM	Consumer Price Index for All Urban Consumers: All Items Less Energy (Index 1982-84=100: NSA)	5	1
74	USCPILEGSLM	Consumer Price Index for All Urban Consumers: All Items Less Energy (Index 1982-84=100: SA)	5	1
75	USCPIULFNSM	Consumer Price Index for All Urban Consumers: All Items Less Food (Index 1982-84=100: NSA)	5	1
76	USCPIULFSLM	Consumer Price Index for All Urban Consumers: All Items Less Food (Index 1982-84=100: SA)	5	1
77	USCPILFNSM	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy (Index 1982-84=100: NSA)	5	1
78	USCPILFESLM	Consumer Price Index for All Urban Consumers: All Items Less Food & Energy (Index 1982-84=100: SA)	5	1
79	USCPIENGNSM	Consumer Price Index for All Urban Consumers: Energy (Index 1982-84=100: NSA)	5	1
80	USCPIENGSLM	Consumer Price Index for All Urban Consumers: Energy (Index 1982-84=100: SA)	5	1
81	USCPIUFDNSM	Consumer Price Index for All Urban Consumers: Food (Index 1982-84=100: NSA)	5	1
82	USCPIUFDSLM	Consumer Price Index for All Urban Consumers: Food (Index 1982-84=100: SA)	5	1
83	CS: MOIAD	Moody's A Industrial Bond Yield	1	0
84	CS: MOIAAD	Moody's AA Industrial Bond Yield	1	0
85	CS: MOIBAAD	Moody's BAA Industrial Bond Yield	1	0
86	CS: MOUAD	Moody's A Utility Bonds Yield	1	0
87	CS: MOUAAD	Moody's AA Utility Bond Yield	1	0
88	CS: MOUBAAD	Moody's BAA Utility Bond Yield	1	0
89	CS: MOCORPD	Moody's Corporate Bond Composite Yield	1	0

Pos.	Mnemonic	Description	TC	SC
90	CS: MOCAAAD	Moody's Corporate AAA Yield	1	0
91	CS: MOCAAD	Moody's Corporate AA Yield	1	0
92	CS: MOCAD	Moody's Corporate A Yield	1	0
93	CS: MOCBAAD	Moody's Corporate BAA Yield	1	0
94	CS: MOINDUD	Moody's Industrial Bond Yield	1	0
95	CS: MOUTILD	Moody's Utility Bond Yield	1	0
96	CS: INUSADJD	Dow Jones Corporate Bond Yield	1	0

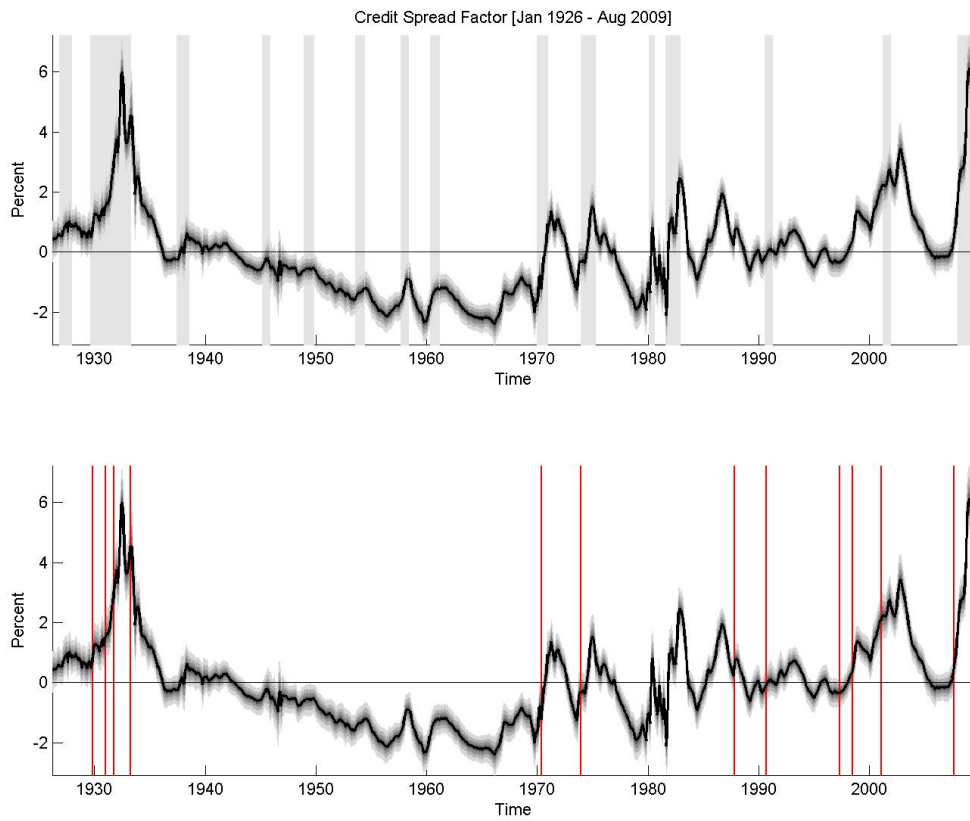


Figure 1: Credit Spread Factor

The credit spread factor sampled from the bond spread data of major groups represents the common component of credit spreads. Areas shaded in grey mark recessions according to the NBER chronology. The red vertical lines in the lower panel mark specific events associated financial disruptions or institutional changes. In chronological order the red lines refer to periods of financial turmoil: Stock market crash October 1929, first banking panic December 1930, German debt and reparations moratorium July 1931, Britain's departure from the Gold Standard, Roosevelt's bank closure March 1933, Penn central commercial paper crisis May 1970, Oil shock November 1973, Stock market crash October 1987, Iraq invasion August 1990, Asian Crisis April 1997, LTCM crisis July 1997, New economy bubble 2001, Subprime mortgage crisis August 2008. Almost all NBER recession periods and financial market disruptions either coincide or are led by a widening in the credit spread factor.

D Figures

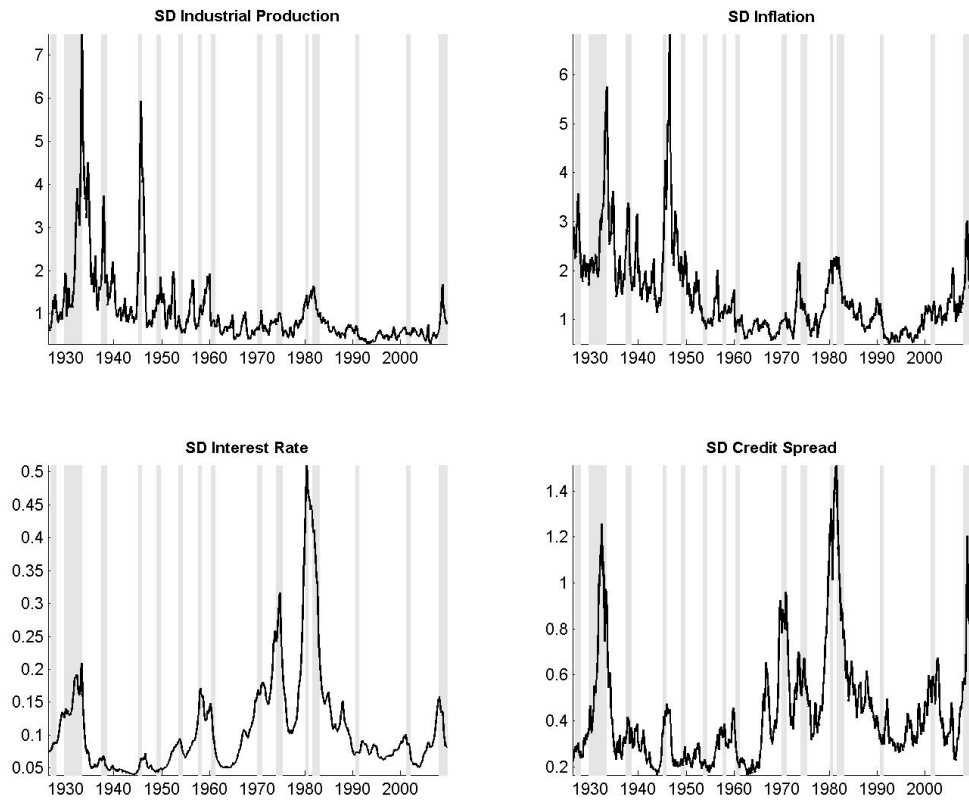


Figure 2: Posterior median innovation volatility of industrial production, inflation, interest rate and the credit spread factor.

These plots show the posterior median of the U.S. innovation volatility of industrial production, inflation, interest rate and the credit spread factor from 1926-2009. The Gray shaded are refer to NBER recession dates. The figures show a very high volatility of all innovations during the period of the great depression. For industrial production and inflation the difference between the subsequent periods and recession is substantially lower. The short term interest rate and the credit spread factor however show an even higher volatility during the event of the 80s which coincides with the disinflationary policy of Paul Volcker to combat high inflation. Interestingly the credit spread factor surges during the current crises in magnitude almost as strong as during the Great Depression.

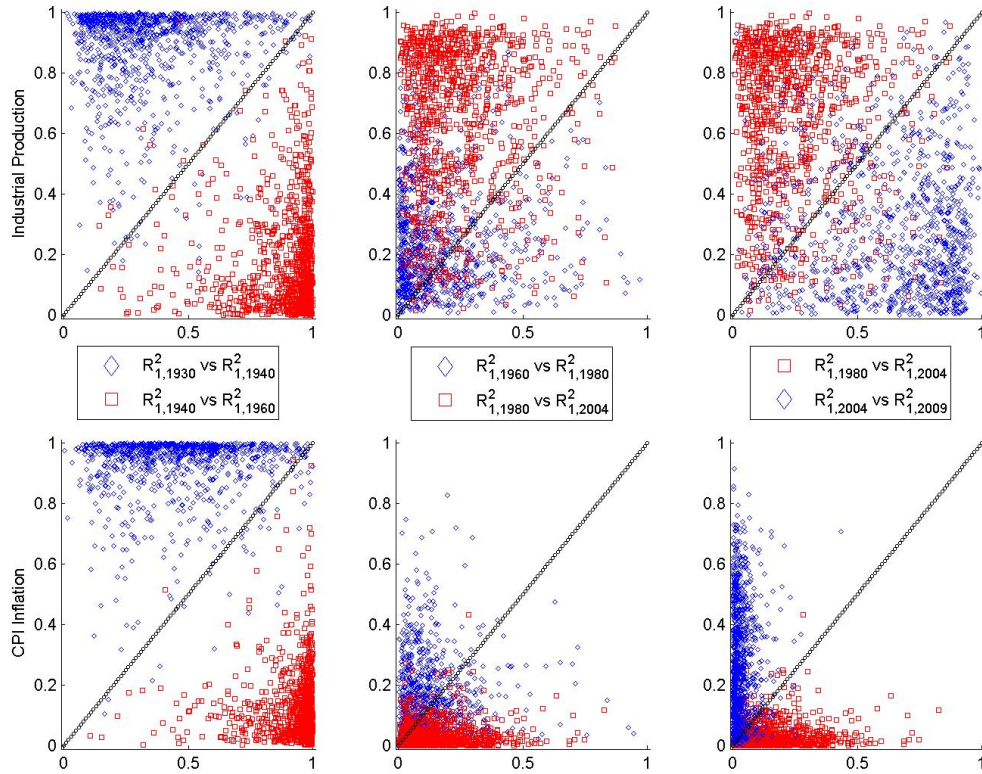


Figure 3: **Scatter plot of the joint distribution of $R^2_{1,1930}$, $R^2_{1,1940}$, $R^2_{1,1960}$, $R^2_{1,1980}$, $R^2_{1,2000}$, $R^2_{1,2004}$ and $R^2_{1,2009}$, probability of changes in the persistence of industrial production and inflation for selected pairs of time periods.**

The scatter plot refers to the probability of a change in the persistence of either industrial production (upper panels) or CPI inflation (lower panels). The legends between the panels refer to both the panel directly below and above. Both the blue diamonds and the red squares refer to the pair of years considered as indicated by the subscript of the legend. Note that the first mentioned refers to the x -axis and the second refers to the y -axis. Scatters concentrated above the 45 degree line indicate a higher probability of change in the persistence for the pair of years under consideration.

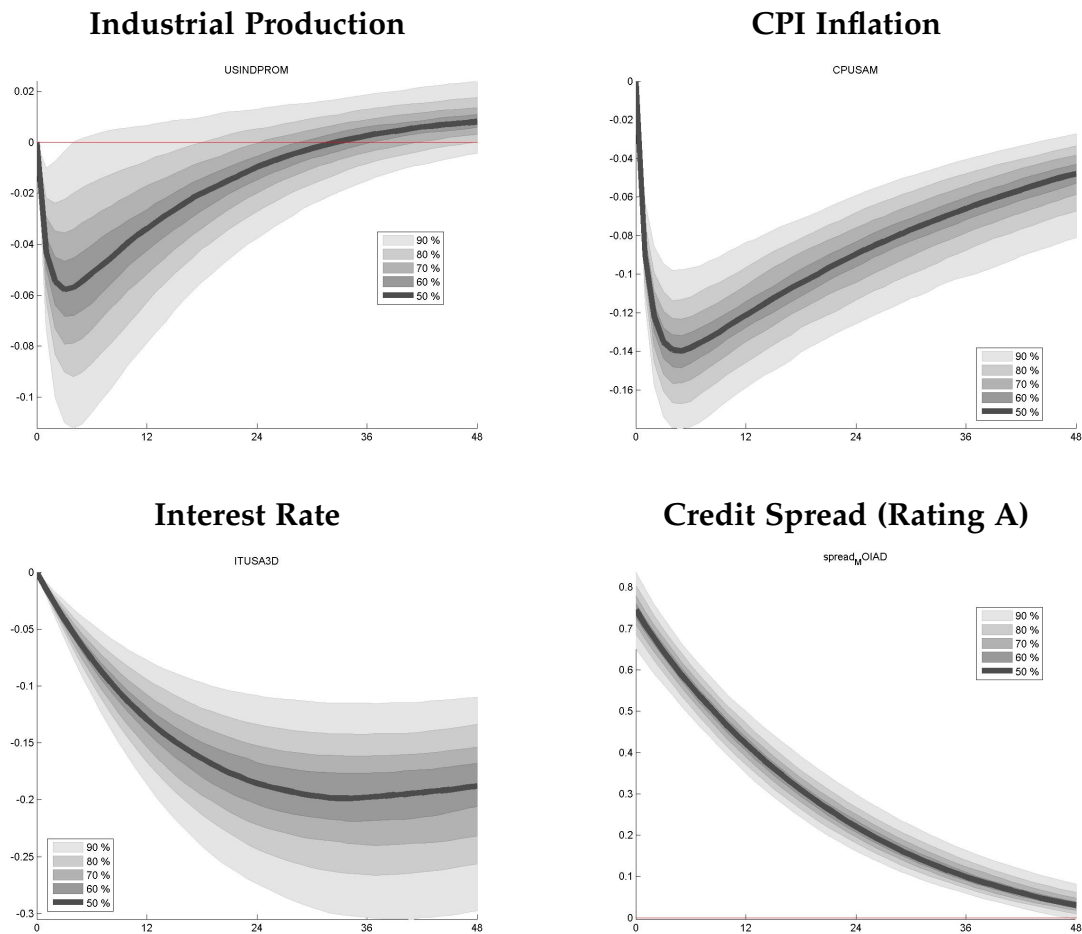


Figure 4: Impulse response functions to a positive credit spread shock in the constant parameter FAVAR covering the period 1926-2009

This figure reports impulse response function of industrial production, CPI, short term interest rate and a corporate bond spread rated A according to Moody's to a positive credit spread shock 100 basis points in size. Results are based on U.S. data covering the period 1926-2009. The gray line reports the posterior median responses with the equal tail error bands covering the 9 deciles. The lightest gray shaded area covers the 80% equal tail posterior distribution and the darkest shaded area covers the 50% equal tail posterior distribution and the dark grey line refers to the posterior median. Following a positive credit spread shock industrial production contracts, CPI declines and interest rates decline. The response of output is rather short lived whereas the remaining responses are more persistent.

Unemployment

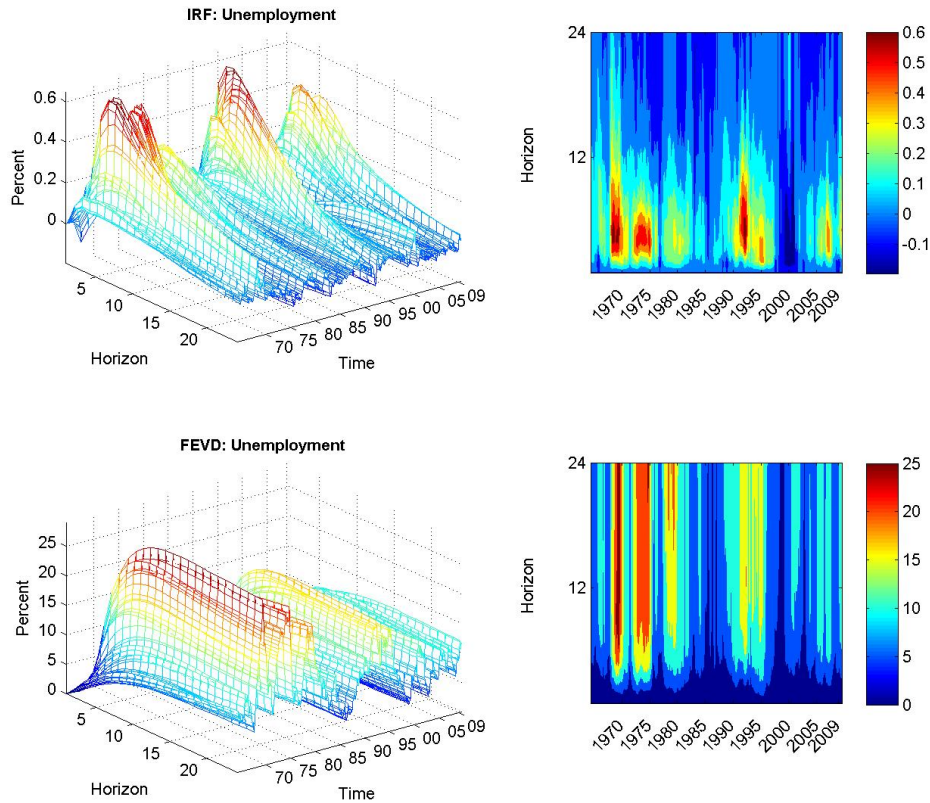


Figure 5: Posterior mean impulse response and forecast error variance decomposition to a positive credit spread shock of unemployment.

This figure reports on the upper left panel the posterior mean impulse response to a positive credit spread factor shock, at each point in time 100 basis points in size, to unemployment identified via a Cholesky decomposition over the entire time period covering 1964-2009. The upper right panel shows the respective contour plot improving the visual inspections regarding timing and the degree of persistence of the amplified and propagated shocks. According to the mean estimates during the decade of the 70s unemployment increases much stronger than on average to a credit spread shock. During the beginning 90s and the current financial crisis unemployment responses show on average amplified responses though not as strong as during the high volatility periods of the 70s but still very strong. Compared to the average along time, the contour plot on the upper right panel shows that the unemployment response has a higher persistence during the mid and end 70s and again during the current recession indicating a change in the propagation of the credit spread transmission mechanism. The lower left panel show the posterior mean of fraction of the h -step ahead forecast revision explained by a the respective credit spread shock at each point in time. The horizon considered is $h = 24$. The lower right panel, again refers to the contour plot of the lower left panel. The fraction of variance explained is substantially higher on average those periods of amplified and propagated responses. Note that that are periods that coincide with an overall higher volatility.

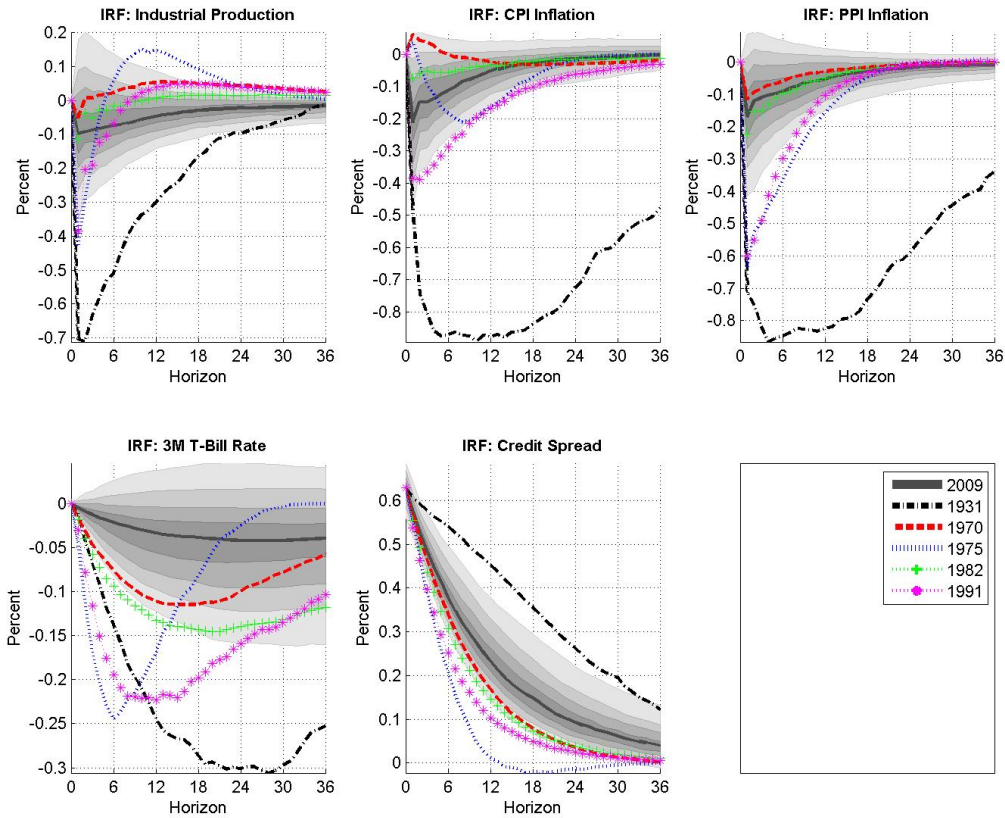


Figure 6: Impulse responses to a positive credit spread shock during selected recession periods.

This figure reports impulse responses to a positive credit spread shock, identified via a Cholesky decomposition at different selected recession periods to selected series of interest. Results are based on U.S. data covering the period 1926-2009. The gray line reports the posterior median responses in 2009 with the equal tail error bands covering the 9 deciles. The gray line reports the posterior median responses with the equal tail error bands covering the 9 deciles. The lightest gray shaded area covers the 80% equal tail posterior distribution and the darkest shaded area covers the 50% equal tail posterior distribution. Most strikingly the responses during the Great Depression are incomparably stronger than during other recession periods. Also the persistence of the responses are on average higher.

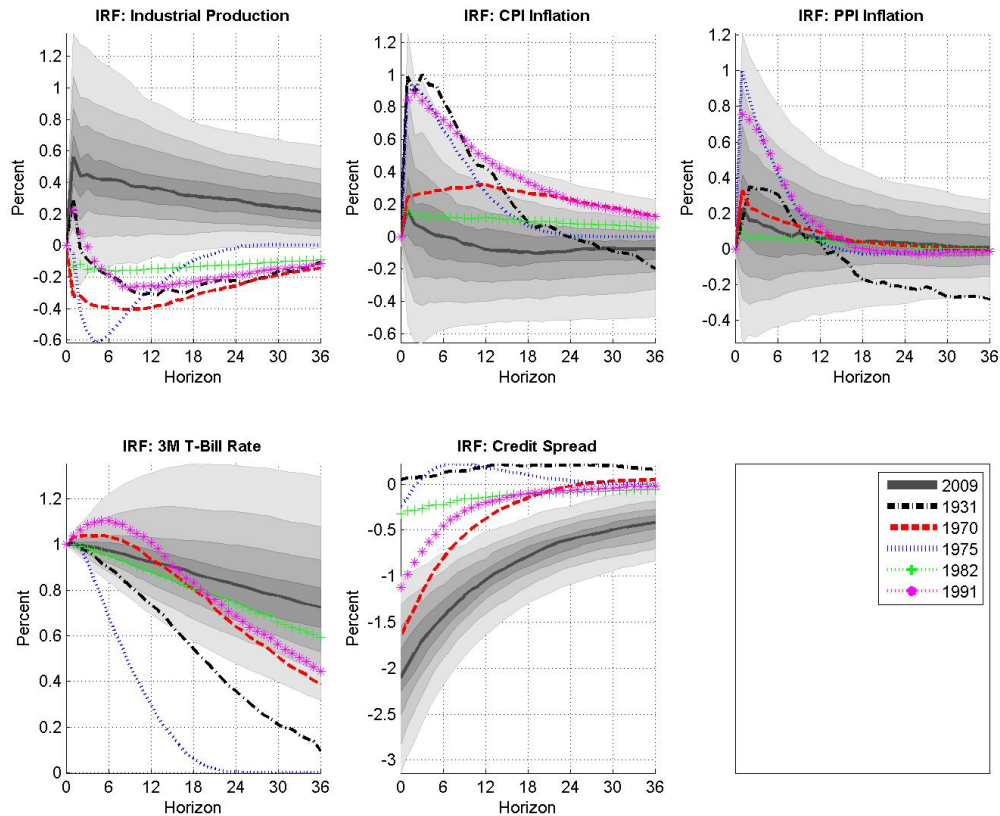


Figure 7: Impulse responses to a contractionary monetary policy shock during selected recession periods.

This figure reports impulse responses to a contractionary monetary policy shock of 100 basis points in size, identified via a Cholesky decomposition at different selected recession periods to selected series of interest. Results are based on U.S. data covering the period 1926-2009. The gray line reports the posterior median responses in 2009 with the equal tail error bands covering the 9 deciles. The gray line reports the posterior median responses with the equal tail error bands covering the 9 deciles. The lightest gray shaded area covers the 80% equal tail posterior distribution and the darkest shaded area covers the 50% equal tail posterior distribution. The figure shows periods of selected series to a monetary policy shock comparing different episodes of recessions and high overall volatility covering the period 1926-2009