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A Markov switching factor-augmented VAR model for analyzing US business cycles and monetary policy

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Abstract

This paper develops a multivariate regime switching monetary policy model for the US economy. To exploit a large dataset we use a factor-augmented VAR with discrete regime shifts, capturing distinct business cycle phases. The transition probabilities are modelled as time-varying, depending on a broad set of indicators that influence business cycle movements. The model is used to investigate the relationship between business cycle phases and monetary policy. Our results indicate that the effects of monetary policy are stronger in recessions, whereas the responses are more muted in expansionary phases. Moreover, lagged prices serve as good predictors for business cycle transitions.

Keywords: Non-linear FAVAR, business cycles, monetary policy, structural model

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1 Introduction

The question on how monetary policy shocks affect economic conditions has received increasing attention in the recent literature on the analysis of business cycles. Policy makers at Central Banks strive for a better understanding of the underlying causal linkages between their policy actions and the business cycle. For instance, several researchers argue that while monetary policy can foster economic growth in the short-run, price adjustments render it effectively non-influential in the medium- and long-run, implying that the effect on business cycles is rather muted. Thus if the central bank aims to steer the economy towards a sustainable growth path, it is necessary to gain a better understanding of the underlying business cycle behavior.

In recent years increasing attention has been drawn to using large scale macroeconometric models to allow for a broad set of both macroeconomic and to some extent microeconomic variables to interact with business cycles. Sims (1992), and Leeper, Sims, and Zha (1996), among others, argued that most small scale models suffer from severe specification issues, leading to distorted inference. Thus several means of handling large information sets have emerged in the recent years. Among other alternatives, a combination of dynamic factor models with vector autoregressive (VAR) models overcomes problems associated with small information sets. These so-called factor-augmented VARs (FAVARs) aim to exploit a high dimensional information set while preserving the theoretical structure of the underlying model. While FAVARs are capable of exploiting large information sets, they are still linear models, unable to capture salient features of the time series used.

Several studies emphasized the usefulness of accounting for non-linearities in the study of business cycles and monetary policy. For instance, in a paper which is close in spirit to the present contribution, Kim and Nelson (1998) estimate a Markov switching factor model with time varying transition probabilities to investigate duration characteristics of different stages of the business cycle. Recently, researchers started to adopt non-linear models to analyze the transmission mechanism of monetary policy (Cogley and Sargent, 2002; Primiceri, 2005). Most studies find a moderate degree of time-variation in the autoregressive parameters, indicating only gradual adjustments of the underlying transmission channels. However, a broad consensus has formed with respect to the importance of allowing the error variances to vary over time (Sims and Zha, 2006; Koop, Leon-Gonzalez, and Strachan, 2009).

The majority of these contributions, however, use only small-scale models. This translates into a battery of so-called "puzzles", with the well-known "price-puzzle" being the most prominent one (Sims, 1992; Leeper, Sims, and Zha, 1996). To overcome such issues, researchers increasingly use methods that aim at reducing the dimensionality of the problem at hand. For instance, Bernanke, Boivin, and Eliasz (2005) investigate the effects of a US monetary policy shock on a broad set of variables within a FAVAR framework. Korobilis (2013) extends the work of Bernanke, Boivin, and Eliasz (2005) to the time-varying parameter framework. This approach combines the virtues of having a large dimensional model with drifting parameters and stochastic volatility, and in agreement with Primiceri (2005) reveals a moderate degree of time-variation in the parameters and the functions thereof.

The present paper develops a Markov switching factor-augmented vector autoregressive (MS-FAVAR) model with endogenous transition probabilities. The transition probabilities of the Markov chain employed follows a probit specification in the spirit of Amisano and Fagan (2013). Furthermore, we assume that the underlying hidden Markov chain that governs the state dynamics is driven by a large set of possible predictors, including the lagged factors of the FAVAR. Moreover, imposing the stochastic search variable selection prior put forward by George and McCulloch (1993) on the latent regression model allows us to unveil the relative importance of different factors on the behavior of the business cycle. While exploiting the information contained in a large dataset, the MS-FAVAR is prone to overfitting, leading to the "curse-of-dimensionality". Thus we impose the well-known Minnesota prior (Litterman, 1986; Sims and Zha, 1998) to shrink the system towards a stylized prior representation of the data. This model is then used to shed light on the dynamics of the transition probabilities and their dependence on different variables – in the context of US business cycles – by means of posterior inclusion probabilities. To investigate the complex relationship between US monetary policy and the economy within different business cycle regimes we perform a counter-factual analysis. Specifically we simulate a 50 basis points monetary policy shock and its effect on a panel of macroeconomic quantities in expansions and recessions.

The remainder of the paper is structured as follows. Section 2 presents the econometric framework employed and provides a concise overview on the priors and the estimation strategy. Section 3 presents the empirical application while the final section concludes.

2 A formal framework

We begin by laying out a formal framework for factor-augmented vector autoregression analysis put forward in Bernanke, Boivin, and Eliasz (2005). This framework is then extended by incorporating Markov switching with endogenous transition probabilities to allow for discrete regime changes. Finally, a Bayesian approach to estimation and inference is outlined.

2.1 The factor-augmented vector autoregressive model

The factor-augmented vector autoregressive model of the business cycle consists of two equations: a transition equation and a measurement equation. The transition equation describes the dynamics of observable economic variables and unobserved factors, while the factors and variables are related by an observation or measurement equation.

Let $\boldsymbol{x}_t$ be an $N \times 1$ vector of economic variables observable at time $t = 1, \dots, T$ that drive the dynamics of the economy. Following the standard approach in the monetary VAR literature $\boldsymbol{x}_t$ could contain observable measures of real activity and prices as well as some policy indicators, measuring the stance of monetary policy. The conventional approach involves estimating a VAR, a structural VAR or another multivariate time series model using data for $\boldsymbol{x}_t$ alone. But, in many applications, additional economic information, not fully captured by $\boldsymbol{x}_t$, may be relevant to modeling the evolution of the business cycles. Let us assume that this additional information can be summarized by a $K \times 1$ vector of unobserved factors $\boldsymbol{f}_t$ where K is small. We might think of unobserved factors as capturing fluctuations in unobserved potential output or reflecting theoretically motivated concepts such as price pressures or credit conditions that cannot easily be represented by one or two series, but are rather reflected in a wide range of economic variables (Bernanke, Boivin, and Eliasz, 2005).

Assume that the joint dynamics of $(\boldsymbol{f}'_t, \boldsymbol{x}'_t)'$ are given by the following transition equation

$$\begin{pmatrix} \boldsymbol{f}_t \\ \boldsymbol{x}_t \end{pmatrix} = \Phi(L) \begin{pmatrix} \boldsymbol{f}_{t-1} \\ \boldsymbol{x}_{t-1} \end{pmatrix} + \boldsymbol{u}_t \text{ for } t = 1, \dots, T \tag{2.1}$$

where $\Phi(L)$ is a polynomial in the lag operator L of finite order Q, and $\boldsymbol{u}_t$ are error terms with mean zero and variance-covariance matrix $\boldsymbol{\Sigma}_u$. Note that Eq. (2.1) is a VAR in $(\boldsymbol{f}'_t, \boldsymbol{x}'_t)'$ that reduces to a standard VAR in $\boldsymbol{x}_t$ if the terms of $\Phi(L)$ that relate $\boldsymbol{x}_t$ to $\boldsymbol{f}_{t-1}$ are all zero.

The unobserved factors are extracted by a large panel of M indicators, $\boldsymbol{y}_t$ which contain important information about the fundamentals of the economy. Note that M may be greater than T, the number of time periods, and much greater than the number of factors and observed variables in the VAR system ($M \gg K + N$). The factors and the variables in the panel are related by an observation equation of the form

$$\boldsymbol{y}_t = \boldsymbol{\Lambda}^f \boldsymbol{f}_t + \boldsymbol{\Lambda}^x \boldsymbol{x}_t + \boldsymbol{e}_t \tag{2.2}$$

with $\boldsymbol{\Lambda}^f$ and $\boldsymbol{\Lambda}^x$ representing $M \times K$ and $M \times N$ matrices of factor loadings, and $\boldsymbol{e}_t$ is an $M \times 1$ vector of normally distributed zero mean disturbances with a diagonal $K \times K$ variance-covariance matrix $\boldsymbol{\Sigma}_e$. Equation (2.2) captures the idea that both $\boldsymbol{f}_t$ and $\boldsymbol{x}_t$, which in general may be correlated, represent common forces that drive the dynamics of $\boldsymbol{y}_t$. Hence, conditional on $\boldsymbol{x}_t$, the $\boldsymbol{y}_t$ are noisy measures of the underlying unobserved factors $\boldsymbol{f}_t$. Note that the implication of Eq. (2.2) that $\boldsymbol{y}_t$ depends only on the current and not lagged values of the factors is not restrictive in practice, since $\boldsymbol{f}_t$ can be interpreted as including arbitrary lags of the fundamental factors.

2.2 A factor-augmented vector autoregressive model with Markov switching

The system given by Eqs. (2.1)- (2.2) is the FAVAR model proposed in Bernanke, Boivin, and Eliasz (2005). Our main innovation relative to them is the incorporation of regime switching with endogenous transition probabilities so that the extended model encompasses the two key features of the business cycle identified by Burns and Mitchell (1946), namely co-movement among economic variables through the cycle, and non-linearity in its evolution.

Let us assume that the R-dimensional vector $\boldsymbol{z}_t = (\boldsymbol{f}'_t, \boldsymbol{x}'_t)'$ with $R = K + N$ follows a Qth-order Markov switching VAR

$$\boldsymbol{z}_t = \sum_{q=1}^{Q} \boldsymbol{A}_{qS_t} \boldsymbol{z}_{t-q} + \boldsymbol{\varepsilon}_t \tag{2.3}$$

where the coefficient matrices $\boldsymbol{A}_{qS_t}$ $(q = 1, \ldots, Q)$ are regime-specific and of dimension $R \times R$, $\boldsymbol{\varepsilon}_t$ is a normally distributed zero mean error term with regime-specific variance-covariance matrix $\boldsymbol{\Sigma}_{\varepsilon S_t}$. The subscript S_t in $\boldsymbol{A}_{qS_t}$ and $\boldsymbol{\Sigma}_{\varepsilon S_t}$ indicates that all parameters are allowed to change across regimes. We assume that S_t is an unobserved binary Markov switching variable indicating whether the economy is in a expansionary $(S_t = 0)$ or recessionary $(S_t = 1)$ phase with transition probabilities given by

$$\boldsymbol{P}_t = \begin{pmatrix} p_{11,t} & p_{12,t} \\ p_{21,t} & p_{22,t} \end{pmatrix} \tag{2.4}$$

where $p_{ij,t} = Prob(S_t = j | S_{t-1} = i)$ with $\sum_{j=1}^{2} p_{ij,t} = 1$ for all i and t. This implies that the transition probabilities are allowed to vary over time. Note that the higher $p_{jj,t}$ is, the longer the process is expected to remain in state j.

A convenient parametrization for this mechanism is the probit specification (Amisano and Fagan, 2013)[1]

$$Prob(S_t = j | S_{t-1} = i, \boldsymbol{w}_{t-1}) = p_{ij,t} = \phi(\boldsymbol{\gamma}' \boldsymbol{w}_{t-1}) \tag{2.5}$$

with

$$\phi(\omega) = \int_{-\infty}^{\omega} \frac{1}{\sqrt{2\pi}} \exp\left\{ -\frac{1}{2}\omega^2 \right\} \, d\omega. \tag{2.6}$$

Hereby $\boldsymbol{w}_{t-1}$ is a K-dimensional vector including variables (both endogenous and exogenous) that may have statistical power to predict business cycle changes.

In this way the parameter γ_k, i.e. the kth element of $\boldsymbol{\gamma}$, measures the sensitivity of probability $p_{ij,t}$ with respect to w_{kt-1}, i.e. the kth element of $\boldsymbol{w}_{t-1}$. Note that Eq. (2.5) resembles a standard probit model with an underlying latent variable regression given by

$$r_t = \boldsymbol{\gamma}' \boldsymbol{w}_{t-1} + \epsilon_t \tag{2.7}$$

where $r_t \in \mathbb{R}$ is a continuous latent variable, $\boldsymbol{\gamma}$ is a K-dimensional parameter vector and ϵ_t denotes the error with variance normalized to unity for identification purposes.

[1] Another alternative would be to use a logit specification that provides advantages if the number of regimes is greater than two (see, for example, Kaufmann, 2015).

2.3 A Bayesian approach to estimation and inference

We pursuit a full Bayesian approach to inference in the model described in the previous subsection. The reasons for this are at least twofold. *First*, because the model in Eq. (2.3) suffers from severe overparametrization issues, we have to impose prior information to obtain reliable parameter estimates of $\boldsymbol{A}_{qS_t}(q = 1, \ldots, Q)$. *Second*, traditional methods rely on numerical optimization, which is daunting in the presence of irregular likelihood surfaces often encountered in the estimation of Markov switching models.

To simplify prior implementation let us rewrite the model as

$$\boldsymbol{z}_t = \boldsymbol{A}'_{S_t}\boldsymbol{d}_t + \boldsymbol{\varepsilon}_t \tag{2.8}$$

where $\boldsymbol{A}_{S_t} = (\boldsymbol{A}_{1S_t}, \ldots, \boldsymbol{A}_{QS_t})'$ is a $RQ \times R$ matrix of stacked coefficients, and $\boldsymbol{d}_t = (\boldsymbol{z}'_{t-1}, \ldots, \boldsymbol{z}'_{t-Q})'$ denotes a RQ-dimensional data vector. Note that conditional on S_t and $\boldsymbol{f}_t$ the model can be represented as a standard regression model, which implies that standard priors can be used (Zellner, 1973). Stacking the rows of $\boldsymbol{z}_t$ and $\boldsymbol{d}_t$ yields the corresponding $T_{S_t} \times R$ and $T_{S_t} \times RQ$ regime-specific full data matrices, denoted by $\boldsymbol{Z}_{S_t}$ and $\boldsymbol{D}_{S_t}$, where T_{S_t} is the number of observation related to the regime prevailing at time t.

Prior distributions for the state equation

We impose a set of conditionally conjugate priors given by

$$vec(\boldsymbol{A}_{s_t})|\boldsymbol{\Sigma}_{s_t} \sim \mathcal{N}(vec(\underline{\boldsymbol{A}}), \boldsymbol{\Sigma}_{\varepsilon S_t} \otimes \underline{\boldsymbol{V}}_A) \tag{2.9}$$

where $\underline{\boldsymbol{A}}$ denotes the $R \times RQ$ prior mean matrix and $\underline{\boldsymbol{V}}_A$ is a $RQ \times RQ$ prior variance-covariance matrix. The prior variance on the coefficients is governed by the Kronecker product $\boldsymbol{\Sigma}_{\varepsilon S_t} \otimes \underline{\boldsymbol{V}}_A$, which is a matrix of dimension $R^2Q \times R^2Q$.

The prior on the variance-covariance matrix is of inverted Wishart form given by

$$\boldsymbol{\Sigma}_{s_t} \sim \mathcal{IW}(\underline{\boldsymbol{C}}, \underline{v}) \tag{2.10}$$

with $\underline{\boldsymbol{C}}$ being a $R \times R$ prior scale matrix and $\underline{v}$ are the prior degrees of freedom. We specify the matrices $\underline{\boldsymbol{A}}$ and $\underline{\boldsymbol{V}}_A$ such that

$$\underline{\boldsymbol{A}} \text{ such that } E\{[\boldsymbol{A}_{qS_t}]_{ij}\} \quad = \begin{cases} \underline{a}_i & \text{for } q = 1 \text{ and } i = j \\ 0 & \text{for } q > 1 \text{ and } i \neq j \end{cases} \tag{2.11}$$

$$\underline{\boldsymbol{V}}_A \text{ such that } var\{[\boldsymbol{A}_{qS_t}]_{ij}\} = \frac{\theta^2}{q^2}\frac{\sigma_i}{\sigma_j} \tag{2.12}$$

for $q = 1, \ldots, Q$; $i = 1, \ldots, R$; $j = 1, \ldots, RQ$. The notation $[\boldsymbol{A}_{qS_t}]_{ij}$ selects the (i, j)th element of the matrix concerned. The prior mean associated with the first own lag of variable i is given by $\underline{a}_i$, whereas for higher lag orders and other lagged variables the prior mean is set equal to zero. The hyperparameter θ controls the tightness of the prior. σ_i and σ_j are standard deviations obtained by running a set of univariate autoregressions on $\boldsymbol{z}_t$[2]. They serve to account for the different variability of the data. This prior is a conjugate variant of the Minnesota prior put forward by Doan, Litterman, and Sims (1984) and Litterman (1986). The rationale behind the Minnesota prior is that a priori a random walk proves to be a good representation of the data. Thus it might be sensible to center the system on a (multivariate) random walk process. That would imply setting $\underline{a}_{ij} = 1$ for $i = j$. Between regimes we assume prior homogeneity, implying that the same set of priors is used for both regimes. This is not essential and can be relaxed quite easily. Note that assuming different regime-specific prior models could be useful in terms of shrinking the parameters towards selecting appropriate submodel specifications.

A convenient feature of the natural conjugate prior is the fact that it can be interpreted as data arising from a artificial dataset. Bańbura, Giannone, and Reichlin (2010) show how the moments of the Minnesota prior can be matched through so-called "dummy"-observations. This is achieved by concatenating the following matrices to $\boldsymbol{Z}$ and $\boldsymbol{D}$

$$\underline{\boldsymbol{Z}} = \begin{pmatrix} diag(\underline{a}_1\sigma_1, \ldots, \underline{a}_R\sigma_R)/\theta \\ \dots\dots\dots\dots\dots\dots \\ \mathbf{0}_{R(Q-1)\times R} \\ \dots\dots\dots\dots\dots\dots \\ diag(\sigma_1, \ldots, \sigma_R) \end{pmatrix} \tag{2.13}$$

$$\underline{\boldsymbol{D}} = \begin{pmatrix} \boldsymbol{J}_Q \otimes diag(\sigma_1, \ldots, \sigma_R)/\theta & \mathbf{0}_{RQ\times 1} \\ \dots\dots\dots\dots\dots\dots & \dots\dots \\ \mathbf{0}_{R\times RQ} & \mathbf{0}_{R\times 1} \end{pmatrix} \tag{2.14}$$

with $\boldsymbol{J}_Q = (1, \ldots, Q)'$. Loosely speaking, the first two blocks of the matrices in Eqs. (2.13) and (2.14) implement the prior on the coefficients associated with the lags of $\boldsymbol{z}_t$ and the final block the prior on $\boldsymbol{\Sigma}_{\varepsilon S_t}$.

Prior distributions for the probit model

We also have to specify priors on the latent regression model given by Eq. (2.7). Following George and McCulloch (1993) we impose a stochastic search variable selection (SSVS) prior on the elements of $\boldsymbol{\gamma}$. Specifically, the prior on the parameter associated with the kth factor in Eq. (2.7) is given by

$$\gamma_k|\delta_k \sim \mathcal{N}(0, \tau_0^2)\delta_k + \mathcal{N}(0, \tau_1^2)(1-\delta_k) \text{ for } k = 1, \ldots, K \tag{2.15}$$

where δ_k is a binary random variable controlling which normal prior to use for coefficient k. The prior variances τ_0^2 and τ_1^2 are set such that $\tau_0^2 \gg \tau_1^2$. Thus, if δ_k equals one,

[2] We obtain the standard deviations by running the autoregression using the principal components estimator for the latent factors.

the prior on the kth coefficient is effectively rendered non-influental. This captures the notion that no significant prior information for that parameter is available, centering the corresponding posterior distribution around the maximum likelihood estimate. If δ_k equals zero, we impose a dogmatic prior, shrinking γ_k towards zero. This case would lead to a posterior which is strongly centered around zero, implying that we can safely regard that coefficient being equal to zero. Let us introduce a scalar parameter h_k set such that

$$h_k = \begin{cases} \tau_0^2 \text{ if } \delta_k = 1 \\ \tau_1^2 \text{ if } \delta_k = 0. \end{cases} \tag{2.16}$$

Storing the h_ks in a $K \times K$ matrix $\boldsymbol{H} = diag(h_1, \ldots, h_K)$ permits to state the prior in terms of a multivariate normal distribution

$$\boldsymbol{\gamma}|\boldsymbol{H} \sim \mathcal{N}(\boldsymbol{\mu}_\gamma, \boldsymbol{H}\boldsymbol{H}) \tag{2.17}$$

with $\boldsymbol{\mu}_\gamma$ denoting the K-dimensional prior mean vector, assumed to equal zero.

We impose a Bernoulli prior on the elements of $\boldsymbol{\delta} = (\delta_1, \ldots, \delta_K)$,

$$\delta_k \sim Bernoulli\ (\underline{p}_k) \tag{2.18}$$

where $Prob(\delta_k = 1) = \underline{p}_k$ denotes the prior inclusion probability. In this specific application the SSVS prior allows us to investigate the relative importance of different factors on the evolution of the business cycle.

Prior distributions for the observation equation

To complete the prior setup we also have to specify a suitable set of prior distributions on the factor loadings in Eq. (2.2). To simplify prior implementation let us collect $\boldsymbol{\Lambda}^f$ and $\boldsymbol{\Lambda}^x$ in a $M \times (K + N)$ matrix $\boldsymbol{\Lambda} = (\boldsymbol{\Lambda}^f, \boldsymbol{\Lambda}^x)$. Similar to the prior choice discussed above we impose a mixture Gaussian prior on the jth element of $\boldsymbol{\lambda} = vec(\boldsymbol{\Lambda})$

$$\boldsymbol{\lambda}_j|\iota_j \sim \mathcal{N}(0, \varrho_0^2)\iota_j + \mathcal{N}(0, \varrho_1^2)(1 - \iota_j) \text{ for } j = 1, \ldots, M(K + N). \tag{2.19}$$

Here, ι_j is again a binary random variable and ϱ_0, ϱ_1 are hyperparameters controlling the tightness of the prior. Conditional on $\boldsymbol{\iota} = (\iota_1, \ldots, \iota_{M(K+N)})$ we can again state this prior as a multivariate Gaussian prior on $\boldsymbol{\lambda}$

$$\boldsymbol{\lambda}|\boldsymbol{L} \sim \mathcal{N}(\underline{\boldsymbol{\mu}}_\Lambda, \boldsymbol{L}\boldsymbol{L}) \tag{2.20}$$

where $\boldsymbol{L} = diag(l_1, \ldots, l_{M(K+N)})$ and l_j is defined as

$$l_j = \begin{cases} \varrho_0^2 \text{ if } \iota_j = 1 \\ \varrho_1^2 \text{ if } \iota_j = 0. \end{cases} \tag{2.21}$$

Similar to the prior on $\boldsymbol{\delta}$, we impose a set of Bernoulli priors on the elements of $\boldsymbol{\iota} = (\iota_1, \ldots, \iota_{M(K+N)})$

$$\iota_j \sim Bernoulli(\underline{\rho}_j) \tag{2.22}$$

with $Prob(\iota_j = 1) = \underline{\rho}_j$ being the prior inclusion probability of a given variable in the observation equation.

Finally, the last ingredient missing is the prior on the innovation variances of the state equation, where we use inverted Gamma priors on the M diagonal elements of $\boldsymbol{\Sigma_e}$, denoted by ς_j $(j = 1, \ldots, M)$

$$\varsigma_j \sim \mathcal{IG}(\underline{\alpha}_j, \underline{\beta}_j). \tag{2.23}$$

$\underline{\alpha}_j$ is a prior shape parameter and $\underline{\beta}_j$ denotes a prior scale parameter.

The Markov chain Monte Carlo algorithm

Up to now we have remained silent on how to obtain estimates for $\boldsymbol{f}_t$. The literature suggests two routes. The first route to obtain consistent estimates of the latent factors (see, for example, Bernanke, Boivin, and Eliasz, 2005) involves using a two-step estimation approach in which the factors are estimated by principal components prior to estimation of the FAVAR. That is, one estimates the space spanned by the first K principal components of $\boldsymbol{y}_t$. This delivers consistent (in the large T, M case) estimates of the true space spanned by $\boldsymbol{f}_t$ and $\boldsymbol{x}_t$. Conditional on the principal components one can proceed as in the standard Markov switching VAR case.

This approach has the advantage to be computationally fast and easy to implement. One disadvantage, however, is that estimation based on principal components treats the factors $\boldsymbol{f}_t$ to be known, thus neglecting the noise surrounding $\hat{\boldsymbol{f}}_t$, the estimate of $\boldsymbol{f}_t$. The second route, which we are going to follow, accounts for this fact by using simulation based methods and simultaneously sampling all parameters of the model described above (see, for example, Kim and Nelson 1999). This can be implemented by using any of the well-known state-space algorithms, like the algorithms put forth in Carter and Kohn (1994), and Frühwirth-Schnatter (1994). However, while still straightforward to implement, this increases the computational burden considerably.

Conditional on the factors and the latent states in $\boldsymbol{s}$, the parameters of the transition equation (2.3) can be simulated using simple Gibbs steps, iteratively sampling from the (conditional) posterior distributions of the parameters in Eq. (2.3) (see Appendix A for details). In practice, under the conjugate prior this step is quite fast, implying that even if we increase the number of factors, computation does not become prohibitively slow. Sampling the latent states S_t is simplified by the fact that it is a numerical integration problem with discrete support. Several options are possible, however we employ the filter put forward by Kim and Nelson (1999) and Amisano and Fagan (2013). The implementation of these steps is described in detail in the appendix.

2.4 Identification of the factor-augmented vector autoregressive model

The model described above is econometrically unidentified and cannot be estimated. There are three different sets of restrictions that need to be imposed on the model. The first is a minimum set of normalization restrictions on the observation equation that are needed to be able to identify the latent factors and the corresponding loadings. The second is related to the label switching problem associated with the latent states controlling the prevailing phase of the business cycle. Finally, the identification of the structural shocks in the transition equation requires further restrictions.

Identification problems associated with the latent factors

Without restrictions the model given by Eqs. (2.2) and (2.3) is not identified. To see this note that Eq. (2.2) is observationally equivalent to

$$\boldsymbol{y}_t = \boldsymbol{\Lambda}^f \boldsymbol{M}\boldsymbol{M}'\boldsymbol{f}_t + \boldsymbol{\Lambda}^x \boldsymbol{x}_t + \boldsymbol{e}_t \tag{2.24}$$

where $\boldsymbol{M}$ is a $K \times K$ orthonormal matrix with $\boldsymbol{M}\boldsymbol{M}' = \boldsymbol{I}_K$. This implies that we have to impose a set of restrictions on $\boldsymbol{\Lambda}^f$ to identify the factors and the corresponding factor loadings.

We thus have to impose a normalization that rules out linear combinations of the form $\boldsymbol{f}_t^* = \boldsymbol{\mathcal{A}}\boldsymbol{f}_t - \boldsymbol{\mathcal{B}}\boldsymbol{x}_t$, where $\boldsymbol{\mathcal{A}}$ is $K \times K$ and non-singular, and $\boldsymbol{\mathcal{B}}$ is $K \times N$. Substituting for $\boldsymbol{f}_t$ in (2.24) we obtain $\boldsymbol{y}_t = \boldsymbol{\Lambda}^f \boldsymbol{\mathcal{A}}^{-1}\boldsymbol{f}_t^* + (\boldsymbol{\Lambda}^x + \boldsymbol{\Lambda}^f \boldsymbol{\mathcal{A}}^{-1}\boldsymbol{\mathcal{B}})\boldsymbol{x}_t + \boldsymbol{e}_t$. To induce $\boldsymbol{f}_t^* = \boldsymbol{f}_t$, that is $\boldsymbol{\mathcal{A}} = \boldsymbol{I}_K$ and $\boldsymbol{\mathcal{B}} = \boldsymbol{0}_{K\times N}$, it suffices to set the upper $K \times K$ block of $\boldsymbol{\Lambda}^f$ to an identity matrix and the upper $K \times N$ block of $\boldsymbol{\Lambda}^x$ to zero (Bernanke, Boivin, and Eliasz, 2005).

Label switching

Since the likelihood function of the model is invariant with respect to permutation of the labels of the states we have an identification problem. This problem, known as the label switching problem (Amisano and Fagan, 2013), poses no real problem for the estimation of the model, but for the economic interpretation of the estimation results. In the present application we analyze two regimes, a recessionary regime and an expansionary regime. To achieve identification we impose restrictions on the main diagonal elements of $\boldsymbol{\Sigma}_{\varepsilon S_t}$. More specifically we assume that the $S_t = 1$ marks a "recessionary" regime if

$$[\boldsymbol{\Sigma}_{\varepsilon S_t=1}]_{11} > [\boldsymbol{\Sigma}_{\varepsilon S_t=0}]_{11}. \tag{2.25}$$

Equation (2.25) implies that the errror variance of the first element of $\boldsymbol{z}_t$ is higher in the recessionary regime.

Structural identification

Finally, Eq. (2.3) presents the reduced form of the model. The (regime specific) structural form of the model is given by

$$\tilde{\boldsymbol{A}}_{0S_t}\boldsymbol{z}_t = \sum_{q=1}^{Q} \tilde{\boldsymbol{A}}_{qS_t}\boldsymbol{z}_{t-q} + \tilde{\boldsymbol{\varepsilon}}_t. \tag{2.26}$$

$\tilde{\boldsymbol{A}}_{0S_t}$ denotes a $R \times R$ matrix of impact coefficients, $\tilde{\boldsymbol{A}}_{qS_t}$ $(q = 1, \dots, Q)$ are $R \times R$ matrices of lagged structural coefficients and $\tilde{\boldsymbol{\varepsilon}}_t$ are standard normally distributed structural errors. Multiplying with $\tilde{\boldsymbol{A}}_{0S_t}^{-1}$ from the left yields again the reduced form of the model in Eq. (2.3). Note that the reduced form errors are given by $\tilde{\boldsymbol{A}}_{0S_t}^{-1}\tilde{\boldsymbol{\varepsilon}}_t$. This implies that the reduced form variance-covariance matrix $\boldsymbol{\Sigma}_{\varepsilon S_t}$ can be decomposed as $\tilde{\boldsymbol{A}}_{0S_t}^{-1}(\tilde{\boldsymbol{A}}_{0S_t}^{-1})'$. Thus obtaining the structural form of the model boils down to finding $\tilde{\boldsymbol{A}}_{0S_t}$. We follow Bernanke, Boivin, and Eliasz (2005) and identify the model by imposing zero impact restrictions. More specifically, we use a Cholesky factorization to obtain $\tilde{\boldsymbol{A}}_{0S_t}^{-1}$, which is a lower triangular matrix. Consistent with the literature we assume that all factors contained in $\boldsymbol{z}_t$ tend to react slower to monetary policy shocks.

3 An empirical application: US business cycles and monetary policy

So far we described the Markov switching factor-augmented vector autoregressive model in fairly general terms. In this section we apply the model to investigate the dynamic relationship between US monetary policy and the real economy in both stages of the business cycle. Subsection 3.1 briefly describes the data set and the model specification used for the specific application that focusses attention on two questions: first, which variables tend to drive US business cycles (see subsection 3.2), and then how monetary policy operates within expansionary phases and how these effects when the economy is in recession (see subsection 3.3).

3.1 Data and model specification

We conduct our analysis on quarterly data starting in 1971Q4 and ending in 2014Q2. For the present purpose we focus our attention on a broad panel of important indicators of real activity. These indicators can be divided into four subcategories, measuring movement in output, housing markets, labor markets and financial markets. Appendix B provides an overview of the variables included in $\boldsymbol{y}_t$ and $\boldsymbol{x}_t$. As observable variable we set $\boldsymbol{x}_t$ equal to the federal funds rate.

Since our final goal is to obtain a model capable of reproducing business cycle behavior we mainly include a wide range of real activity indicators in $\boldsymbol{y}_t$. More specifically we measure output through industrial production and the corresponding subcategories. In addition, to capture movements on the housing markets we include data on housing starts and new private housing units authorized. The demand side is represented by personal consumption expenditures for different categories of goods and services and personal income. We use information on the labor market by including data on average weekly hours in production and nonsupervisory employees and the civilian unemployment rate. Finally, the financial sector is represented by including the federal funds rate as observed variable in the FAVAR. Following Gilchrist, Yankov, and Zakrajšek (2009), who emphasize the usefulness of credit spreads to predict economic activity, we also include a measure of the credit spread, approximated through Moody's seasoned Baa corporate bond minus fed funds rate spread.

It is worth mentioning that a broader information set might dilute the regime allocation. For instance, the way how the Fed conducts monetary policy has changed dramatically in the beginning of the 1980s, indicating a serious regime shift with respect to monetary policy. Introducing more variables from the financial side would most likely lead to a regime allocation which does not necessarily represent distinct business cycle phases.

The literature on the determinants of business cycles in addition suggests other covariates which are assumed to be exogenous and do not enter Eq. (2.3) directly, but through the matrix $\boldsymbol{w}_t$ in the latent probit regression. These variables are assumed to be predictors of business cycle changes. In $\boldsymbol{w}_t$ we incorporate information from other variables which are not necessarily included in $\boldsymbol{y}_t$ for the specification of the transition probabilities. More specifically, we include a broad range of additional financial variables like information on the shape of the US treasury yield curve, commodity prices and exchange rates in the matrix $\boldsymbol{w}_t$ that may act as important predictors of US business cycles. Note that the variables contained in $\boldsymbol{w}_t$ only influence the regime allocation indirectly through the transition probabilities. Additional information can be found in Appendix B.

Before proceeding to the empirical results a brief word on the specification of the MS-FAVAR is necessary. We set the number of factors equal to four. This is based on comparing the marginal likelihood for K between one and five, where the marginal likelihood is approximated by the Bayesian information criterion (BIC). With regards to the prior specification, we set the tightness hyperparameter equal to $\theta = 0.5$. This is based on varying θ on a discrete grid of different values for $\theta \in \{0.001, 0.01, 0.1, 0.5, 2, 10^2\}$, where again the BIC approximation is used to discriminate between models. Finally, we set the lag length equal to two. This choice seems reasonable given the length of our data and the parameterization of the model. Since we standardize the variables in $\boldsymbol{w}_t$ we set the hyperparameters of the mixture normal priors equal to $\tau_0^2 = 1$ and $\tau_1^2 = 0.1$. The prior on the free elements of $\boldsymbol{\Lambda}$ is set equal to $\varrho_0^2 = 10$ and $\varrho_1^2 = 0.1$. Experimenting with different choices of ϱ_0 and ϱ_1 led to qualitatively the same results. Finally, we set $\underline{\alpha}_j = \underline{\beta}_j = 0.01$ to render this prior effectively non-influential.

3.2 What drives business cycles?

In this subsection we answer the question which variables exhibit significant effects on the probability of a change of the business cycle. The analysis is based on three pillars. First, we investigate the relationship between the latent factors contained in $\boldsymbol{z}_t$ and recessionary phases in the US. The second pillar is concerned with the question how well our model is able to discriminate between expansionary and recessionary phases. Finally, we look at the posterior inclusion probabilities (PIPs) of the variables in Eq. (2.7) and the corresponding marginal effects. This provides information on the relative importance of various indicators contained in $\boldsymbol{w}_t$ and the sensitivity of the transition probabilities with respect to changes of these indicators.

Figure 1 presents the posterior mean of the latent factors and the NBER reference recessions. Inspecting the correlation between the factors and the variables in $\boldsymbol{y}_t$ allows us to attach a certain degree of economic interpretation to the factors. More specifically, the business cycle risk factor in Fig. 1 exhibits a high, negative correlation with the industrial production components. These correlations are rather high, surpassing -0.95 for most components of industrial production. The second factor measures movements in labor markets, showing the highest correlation with the unemployment rate (around 0.99) and moderate negative correlation (around -0.65) for average weekly overtime hours of production. At a first glance, the third factor almost mirrors the first one, providing a gauge on business cycle conditions. Finally, the fourth factor is strongly correlated with housing market conditions. The correlations are around 0.8 to 0.95 for housing starts and new private housing units authorized.

[Fig. 1 about here.]

Inspection of Fig. 1 reveals that most factors tend to peak in the midst of a recession. However, some notable deviations from this pattern are worth emphasizing. First, glancing at the labor market factor reveals that labor market conditions tend to be worst in the end of a recession or shortly after a recession has ended. This holds true for all downturns encountered in our sample. Second, business cycle risk also shows a tendency to peak in the end of a recession. However, the twin recessions in the beginning of the eighties and the recession following the burst of the dot-com bubble mark important deviations from this pattern. This carries over to the business cycle conditions index, which exhibits a similar behavior as the business cycle risk factor. Finally, note that the housing market indicator tends to reach a bottom rather early in recessions, with the only notable exception being the recent financial crises. However, note that housing market conditions already started to decline around 2006, providing some sort of early warning mechanism for recessionary periods.

Figure 2 presents the posterior mean of the smoothed probabilities of being in a recession. The model manages to capture most recent recessions, beginning with the recession in 1973-1975. This recession was caused by sharp increases in government spending and energy prices, most notably the price of oil leading to a stagflationary period within the US. The recessions in the early 1980s were a consequence of the federal reserves pronounced regime shift, when chairman Paul Volcker started to fight inflation by increasing the policy rate dramatically. In 1990 the US experienced a relatively short period of negative growth caused by high oil prices, high debt levels and a low level of consumer confidence in the US. The period between the end of the 1990s recession and the recession following the burst of the dot-com bubble and the September 11th attacks was the longest period of sustained growth in US history. Note that the early 2000s recession is the only downturn our model was unable to capture. This can be explained by the fact that this recession was by far the mildest one, only resulting in an aggregate GDP loss of 0.3% from peak to through. Finally, the last recession in our sample is the recent financial crisis, which led to sustained losses in output. Again, the model captures this period rather well, allocating high probabilities of being in a recession for the given quarters.

[Fig. 2 about here.]

To answer the question which variables drive the transition between recessionary and expansionary regimes we investigate the corresponding posterior inclusion probabilities and the elasticities of transition probabilities at time $t = T$ computed from the MCMC output. Table 1 presents the posterior distribution of the elasticities (with the corresponding 16th and 84th percentiles) and the PIPs of the top 20 covariates included in Eq. (2.7).

[Table 1 about here.]

In what follows we only put our attention on covariates which obtain PIPs higher than 0.5, i.e. that are included in the majority of models sampled. First, the single most important determinant for predicting a change in the business cycle at time t is the number of employees in construction (USCONS) at time $t-1$. This variable is included in 74% of total models sampled. Taking a look at the elasticities reveals that a one percent increase in the number of employees in construction leads to a 2.5% lower probability of moving into a recession at time t. This finding suggests that companies tend to act in a forward looking manner, reducing employment if the economic outlook deteriorates. The next important predictor is consumer price inflation (CPIAUCSL) with a PIP of 0.65. The elasticities suggest that if inflation in the last period increases by one percent, the risk of dipping into a recession in the next period increases by roughly 1.8%. Employment in manufacturing (MANEMP) is the next determinant which is included in over 60% of the models sampled. Similar to employment in construction a one percent increase in employment in manufacturing at time $t-1$ translates into an 1.7% lower probability of being in a recession at time t. Next we find that the labor market factor (labor markets) is included in around 54 percent of the models. Note, however, that the corresponding elasticities are estimated rather imprecisely, rendering meaningful inference difficult. Finally, the (lagged) unemployment rate (UNRATE) and the real activity factor receive PIPs higher than 0.5. Our analysis suggests that if unemployment in $t-1$ increases by one percent, the probability of entering a recession in the following quarter also increases by around 1.2 percent.

To sum up we find that indicators summarizing labor market conditions and the hiring behaviour of companies may be important to predict changes of the business cycle. Moreover, we find that lagged prices tend to be of help to explain business cycle behaviour.

3.3 Monetary policy in different business cycle regimes

In this subsection we investigate how monetary policy operates within different regimes of the business cycle. For that purpose we simulate a 50 basis points monetary policy shock *conditional on the regime* and trace its effect on a subset of variables included in $\boldsymbol{y}_t$.

Since our dataset spans over 40 time series we focus only on eight series, representing different segments of the economy. More precisely, we focus on the responses of industrial production and consumer price inflation to capture the dynamic effects of monetary policy on real activity and prices. We investigate the behavior of labor markets by inspecting the responses of unemployment and the ISM Manufacturing: Employment index. Finally, housing markets are represented by looking at housing starts and new private housing units permitted, and financial markets are analyzed by investigating the response of the federal funds rate and the BAA-FFR spread.

Before proceeding to the results let us discuss the implications of our non-linear model in the context of the reaction function of the monetary policy authority. Because the model in Eq. (2.26) includes an equation that may be interpreted as a monetary policy reaction function (Bernanke and Blinder, 1992; Rudebusch, 1998), we can investigate how the Fed alters its policy behavior between recessions and expansions.

Throughout the rest of the paper we assume that the central bank is setting its policy instrument (in our case the federal funds rate) as follows

$$\mathfrak{p}_t = g_t(\Omega_t) + \eta_t \tag{3.1}$$

with $\mathfrak{p}_t$ being the policy rate, Ω_t denoting the information set available to the central bank and η_t is a monetary policy shock (in our case normalized to 50 basis points). Traditionally, $g_t(\Omega_t) = g(\Omega_t)$ for all t is assumed to be a linear function that relates $\mathfrak{p}_t$ to Ω_t (Christiano, Eichenbaum, and Evans, 1999). This is predicated by the fact that monetary policy in the US between the midst of the eighties and the beginning of the 2000s may be well described by a simple Taylor rule. However, Clarida, Gali, and Gertler (2000) emphasize that the way how the Fed conducts monetary policy has changed remarkably over time, suggesting a more flexible approach to describe the reaction function of the central bank.

Hence our model assumes that $g(\Omega_t)$ is a non-linear function given by

$$g_t(\Omega_t) = \begin{cases} \vartheta_0(\Omega_t) \text{ if } S_t = 0 \\ \vartheta_1(\Omega_t) \text{ if } S_t = 1 \end{cases} \tag{3.2}$$

where $\vartheta_j(\Omega_t)$ $(j = 0, 1)$ are again linear functions that relate $\mathfrak{p}_t$ to the information set Ω_t. Depending on the prevailing state of the economy the monetary authority thus changes its policy behaviour. In addition, Eq. (2.26) implies that the remaining variables are all modeled in a non-linear fashion, capturing the notion that economic agents tend to behave differently in distinct stages of the business cycle. Different reactions of macro quantities can thus be explained through a shift in the behavior of the central bank (i.e. whether their reaction function differs in recessions and expansions) or because of a change in the way how other sectors of the economy are responding to shocks.

Figures 3 and 4 present the dynamic responses of the macroeconomic aggregates discussed above in both phases of the business cycle. Figure 3(a) presents the responses of real activity, measured in terms of industrial production. As a reaction to a monetary tightening, output contracts in both business cycle stages. In expansionary phases, responses are statistically insignificant within the first three quarters, leading to persistent output contractions afterwards. In contrast, note that restrictive monetary policy triggers only temporary output contractions in recessions, peaking in the third quarter and petering out rather fast. The magnitudes of the responses are generally more pronounced within a recessionary period. This is in line with Feldkircher and Huber (2015), who find stronger reactions of US GDP to a monetary policy shocks in crises periods. This is owed to the fact that the volatility of macroeconomic quantities is higher in crises, leading to stronger reactions. With respect to the persistent nature of the shock, our findings corroborate findings in Beaudry and Koop (1993), who report rather persistent effects on output within expansionary phases and rather short-lived effects in crises periods.

Figure 3(b) depicts the reaction of prices to a monetary policy shock. Prices tend to decrease after one quarter providing evidence that the large information set used alleviates the price puzzle, i.e. the common finding that prices increase in response to a restrictive monetary policy shock. Moreover, we find a rather persistent decline of inflation in expansionary periods, becoming significant within the first quarter. Similar to the responses of output, prices react stronger in recessions, albeit in a statistically insignificant fashion for the first five quarters. Afterwards, prices tend to increase marginally before turning insignificant after around twelve quarters.

[Fig. 3 about here.]

The responses of the unemployment rate are depicted in Fig. 3(c). Note that the unemployment rate is rising slowly in both business cycle phases, again being more persistent in the expansionary regime. The magnitudes of the responses are quite similar, producing only marginally stronger responses in recessions. The sign of the responses is consistent with standard New Keynesian dynamic stochastic general equilibrium models (Christiano, Eichenbaum, and Evans, 1999) which predict falling employment and rising unemployment as a direct consequence of the contraction of output. To measure corporate sector expectations with respect to labour markets we also include the response of the ISM manufacturing: Employment index (NAPMEI), see Fig. 3(b). Note that consistent with the rise of the unemployment rate, the employment index also falls in response to a monetary policy shock. Interestingly, the employment index reacts faster, significantly falling after around two quarters. The decrease of the employment index is much more persistent in expansions, whereas it is again only of transitory nature in recessionary phases.

[Fig. 4 about here.]

Figure 4(a) presents the responses of housing starts in both regimes. We find significant reactions of housing markets after around one quarter, leading to persistent decreases in housing starts as a response to a monetary policy shock. In addition, Fig. 4(b) presents the responses of new private housing units permitted (PERMIT) that exhibits similar reactions as housing starts. This is caused by rising short-term interest rates that serve as a rough gauge of mortgage costs. Note that both, housing starts and new housing permitted, is reacting stronger in recessions, albeit not in a statistically significant manner.

Finally, Figs. 4(c) and 4(d) present the responses of the policy rate and the BAA-FFM spread, which serves as a measure of the risk spread (i.e. the yield difference between corporate credit and the US federal funds rate). Contrasting the responses of the Fed funds rate in the expansionary regime with the recessionary regime yields insights on the way how the Fed is adjusting their policy behavior over time. Note that similar to most cases outlined above, responses are more persistent in expansions, where the policy instrument is falling slowly as compared to the recession regime. Here the Fed funds rate reacts much faster, turning insignificant after around twelve quarters. The BAA-FFM spread, shown in Fig. 4(d), increases after four to five quarters. This implies that the yield on corporate credit is reacting stronger as the federal funds rate, signaling increased costs of corporate credit. While the increases of the risk spread seems to be rather small and only barely significant in the recessionary regime, they appear to be persistent within expansions.

4 Closing remarks

In the present paper we developed a dynamic macroeconometric model for the US economy that is able to discriminate between business cycle phases. We allow for time-varying transition probabilities of the underlying Markov chain that controls the current regime. The model was then used to shed further light on the dynamic relationship between US monetary policy and the transition mechanism between distinct business cycle regimes. Using a variant of the SSVS prior allows us to unveil the importance of different variables on the probability of moving into a recession. The results reveal that, among others, the share of workers in construction and inflation at time $t-1$ are important predictors of business cycle turning points.

To investigate the effects of US monetary policy in expansions and recessions we simulate how a US monetary policy shock affects the economy in both business cycle phases. The results clearly suggest strong differences between expansions and recessions, producing more persistent responses in the former, while being only of transitory nature in the latter. In addition, the model produces responses which are fully consistent with a broad set of recent theoretical macroeconomic models, avoiding prominent puzzles that commonly surface in the presence of small-scale linear time series models.

Possible avenues for further research include extensions of the model described in Section 2 to allow for more general patterns of regime-switching behaviour in two directions. First, introducing additional latent variables that would allow different sectors of the economy to be in different states, and second, allow for more than two regimes, could improve the empirical fit of the model and provide a more detailed picture on the underlying transmission channels.

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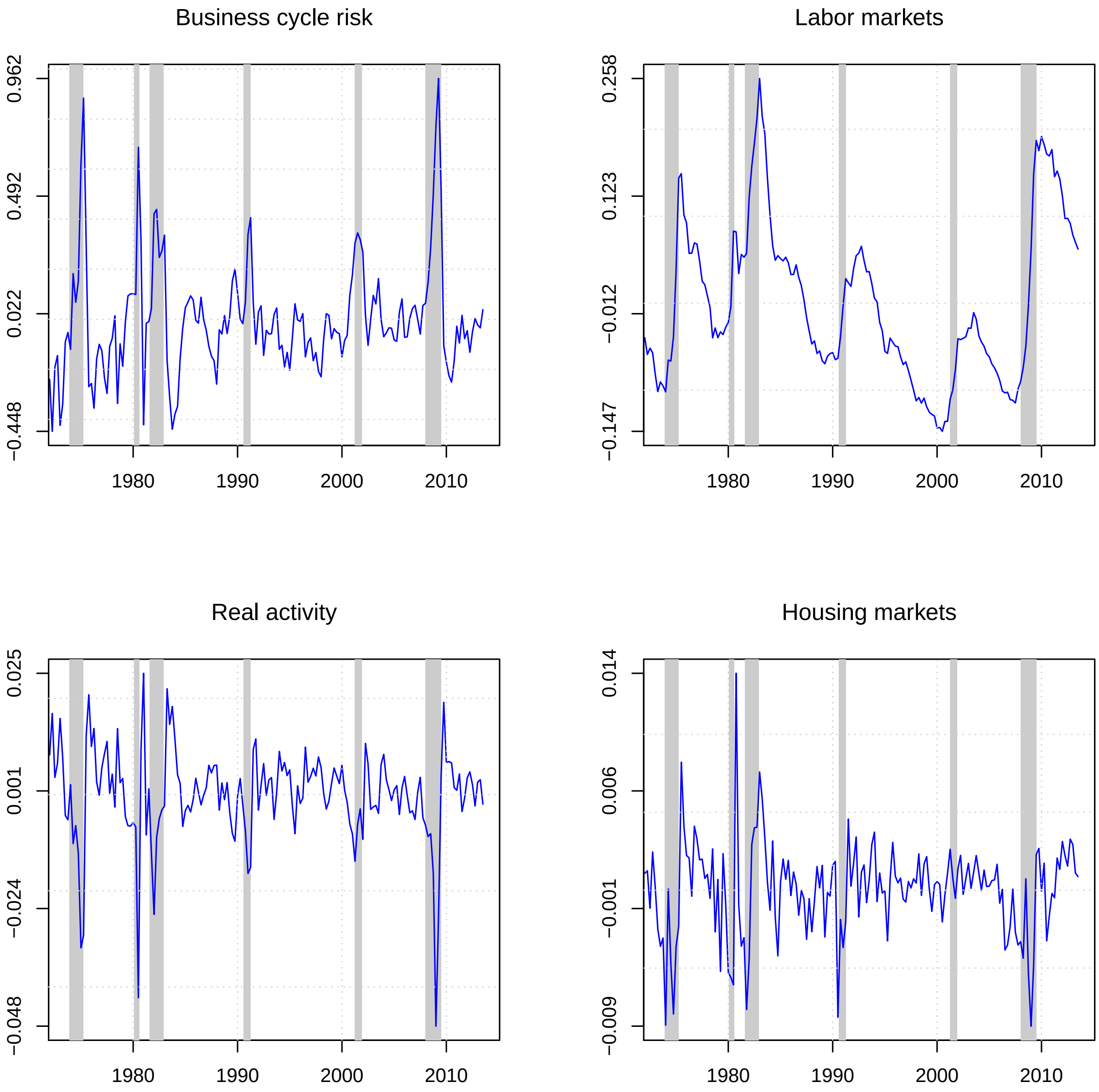
Table 1: Posterior distribution of elasticities along with posterior inclusion probabilities

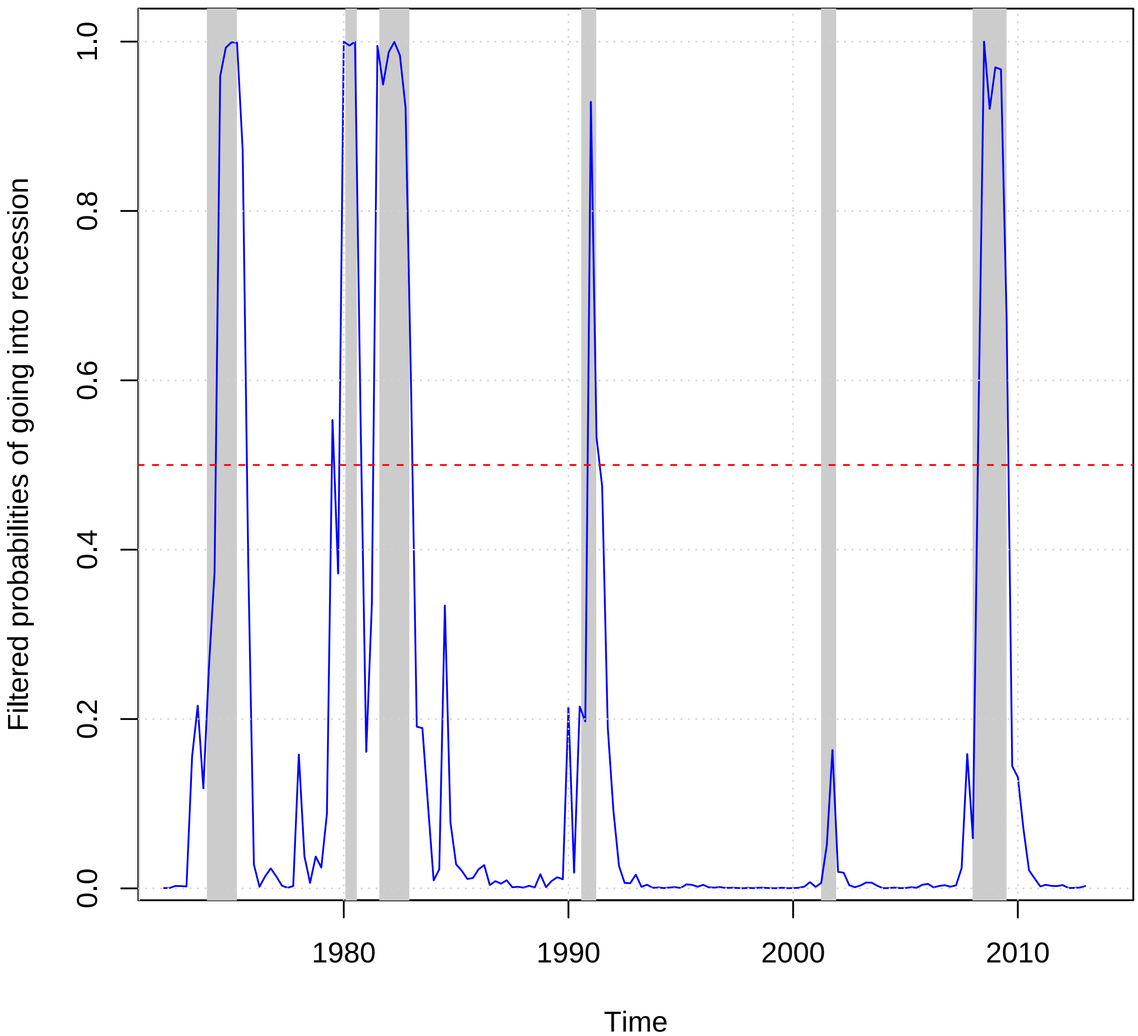
Elasticities	$\text{Low}_{0.16}$	Mean	$\text{High}_{0.84}$	PIP
USCONS	-5.221	-2.552	-0.137	0.740
CPIAUCSL	0.060	1.795	3.780	0.654
MANEMP	-3.830	-1.735	0.044	0.604
Labor markets	-1.148	0.283	2.197	0.544
UNRATE	-0.083	1.255	2.900	0.542
Real activity	-1.558	0.039	1.621	0.529
Housing markets	-1.308	0.022	1.350	0.499
Business cycle risk	-0.709	0.478	2.056	0.486
TB6MS	-0.316	0.921	2.633	0.480
FEDFUNDS	-0.614	0.297	1.360	0.450
AAAFFM	-0.630	0.267	1.195	0.429
GS10	-0.389	0.553	1.621	0.424
INDPRO	-1.742	-0.639	0.222	0.415
TB3MS	-0.587	0.185	1.066	0.414
T10YFFM	-0.439	0.405	1.230	0.400
CE16OV	-1.425	-0.556	0.268	0.400
BUSLOANS	-0.179	0.623	1.479	0.398
PPICMM	-1.334	-0.531	0.152	0.378
W875RX1	-0.637	-0.068	0.405	0.327

Notes: The table presents the posterior mean of the elasticities originating from the probit model along with the 16th and 84th percentiles. In addition, the final column presents the posterior inclusion probabilities (PIP) for each variable under scrutiny. The first column provides the mnemonics, where detailed information can be found in Appendix B. The bold elements refer to the lagged factors.



Notes: Posterior mean of the latent factors. Grey shades refer to recessions that are dated by the Business Cycle Dating Committee of the National Bureau of Economic Research (`www.nber.org`). Results based on 5,000 posterior draws.

Fig. 1: Posterior mean of latent factors contained in $\boldsymbol{f}_t$

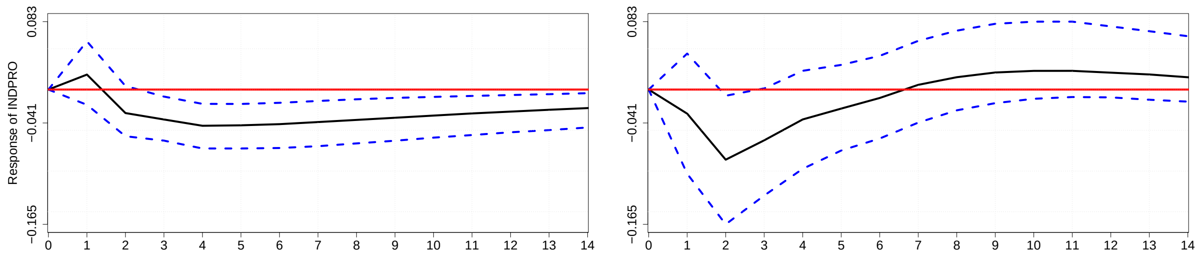


Notes: Posterior mean of the filtered probabilities to move into a recession. Grey shades refer to recessions that are dated by the Business Cycle Dating Committee of the National Bureau of Economic Research (www.nber.org). Results based on 5,000 posterior draws.

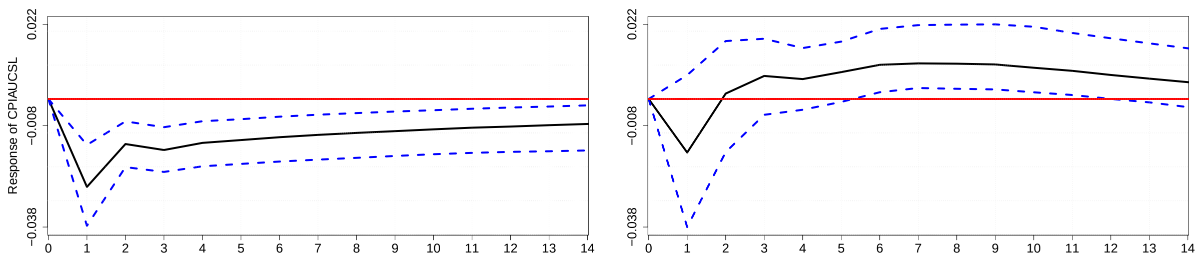
Fig. 2: Posterior mean of smoothed recession probabilities

Response in ’expansionary phase’ **Response in ’recessionary phase’**

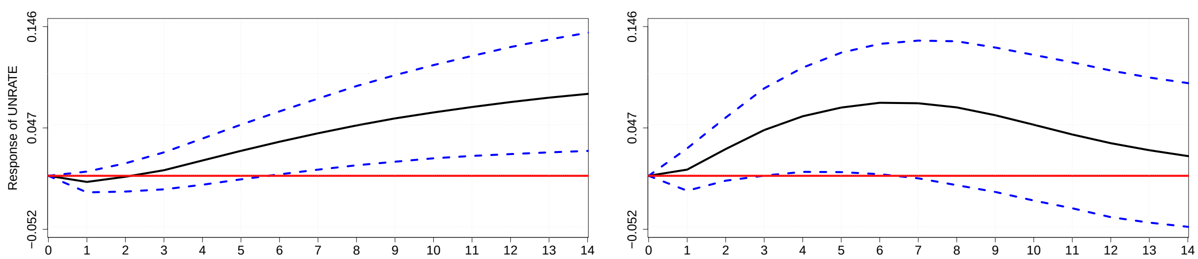
(a) Industrial production (INDPRO)



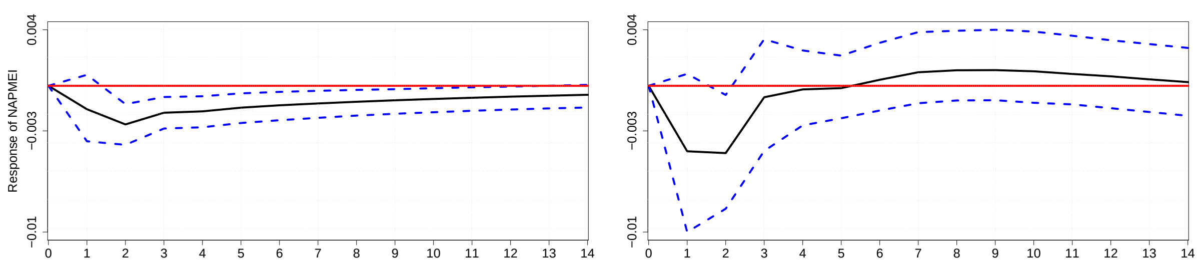
(b) Consumer price inflation (CPIAUCSL)



(c) Unemployment rate (UNRATE)



(d) ISM Manufacturing: Employment Index (NAPMEI)

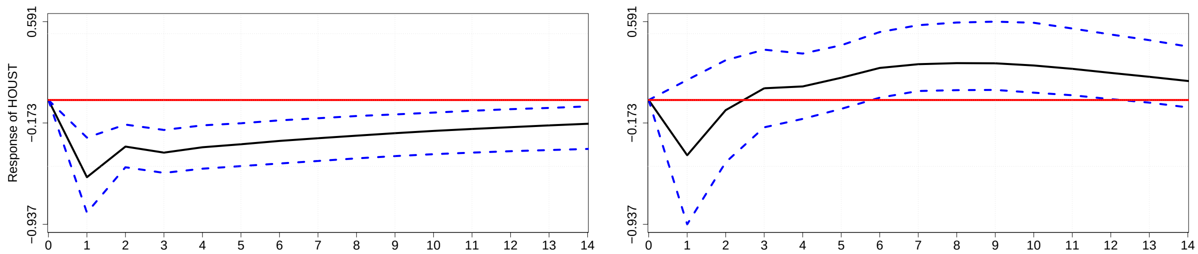


Notes: Posterior distribution of impulse responses. Median in black. Dashed blue lines correspond to 16th and 84th percentiles in dark blue. Results based on 5,000 posterior draws.

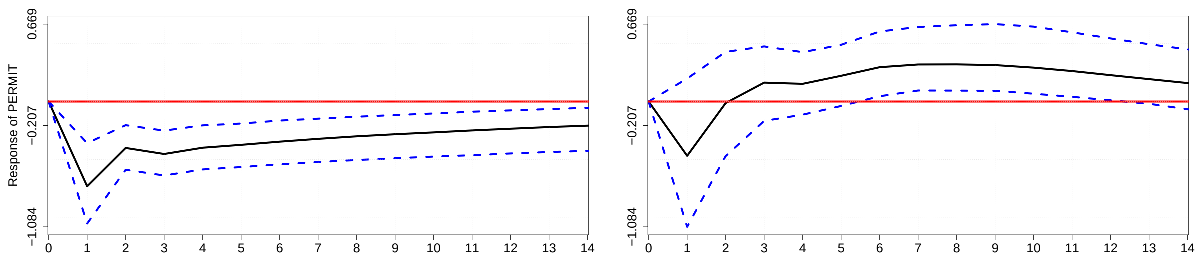
Fig. 3: Dynamic responses of real activity and labor market indicators to a 50 basis point (bp) monetary policy shock

Response in 'expansionary phase' **Response in 'recessionary phase'**

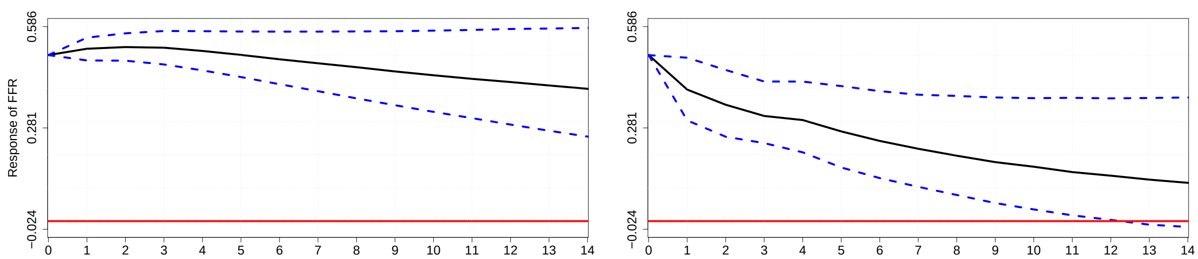
(a) Housing starts (HOUST)



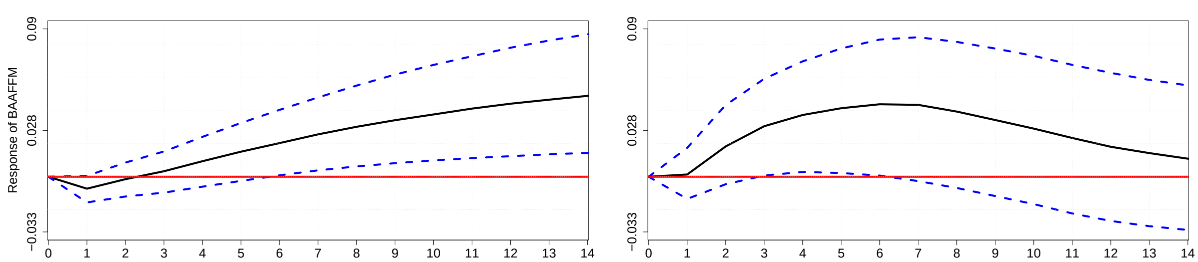
(b) New private housing units permitted (PERMIT)



(c) Fed funds rate (FEDFUNDS)



(d) BAA-FFR spread (BAAFFM)



Notes: Posterior distribution of impulse responses. Median in black. Dashed blue lines correspond to 16th and 84th percentiles in dark blue. Results based on 5,000 posterior draws.

Fig. 4: Dynamic responses of housing and financial market indicators to a 50 basis point (bp) monetary policy shock

Appendix A Posterior distributions

In this section we provide exact details on the corresponding posterior distributions and how to simulate them. Before proceeding, a brief word on notation. Let

$$\boldsymbol{\pi}^t = (\boldsymbol{\pi}_1', \dots, \boldsymbol{\pi}_t')' \tag{A.1}$$

denote the history of a generic vector $\boldsymbol{\pi}$ up to time t, and

$$\boldsymbol{\Pi}^t = (vec(\boldsymbol{\Pi}_1)', \dots, vec(\boldsymbol{\Pi}_T)')' \tag{A.2}$$

the history of a generic matrix $\boldsymbol{\Pi}$ up to time t. In addition, let us use the following notation to indicate estimates of some random quantity χ based on information available at time t

$$\chi_{t|t} = E(\chi_t|\mathcal{I}_t) \tag{A.3}$$

with $\mathcal{I}_t$ denoting a generic information set. Accordingly, we denote a forecast of χ by

$$\chi_{t+1|t} = E(\chi_{t+1}|\mathcal{I}_t). \tag{A.4}$$

Conditional posterior distributions for the state equation

The (conditional) posterior distributions of the parameters in Eq. (2.3) take a particularly simple form,

$$vec(\boldsymbol{A}_{S_t})|\boldsymbol{\Xi}^T, \mathcal{D}^T \sim \mathcal{N}(vec(\overline{\boldsymbol{A}}_{S_t}), \boldsymbol{\Sigma}_{S_t} \otimes \overline{\boldsymbol{V}}_{AS_t}) \tag{A.5}$$

$$\boldsymbol{\Sigma}_{\varepsilon S_t}|\boldsymbol{\Xi}^T, \mathcal{D}^T \sim \mathcal{IW}(\overline{\boldsymbol{C}}_{S_t}, \overline{v}_{S_t}) \tag{A.6}$$

where $\boldsymbol{\Xi}^T$ stores the remaining parameters, regime indicators and latent factors and $\mathcal{D}^T$ denotes the available data up to time T.

The posterior moments for $\boldsymbol{A}_{S_t}$ are given by

$$\overline{\boldsymbol{A}}_{S_t} = (\overline{\boldsymbol{D}}_{S_t}'\overline{\boldsymbol{D}}_{S_t})^{-1}\overline{\boldsymbol{D}}_{S_t}'\overline{\boldsymbol{Z}}_{S_t} \tag{A.7}$$

$$\overline{\boldsymbol{V}}_{s_t} = (\overline{\boldsymbol{D}}_{S_t}'\overline{\boldsymbol{D}}_{S_t})^{-1} \tag{A.8}$$

with $\overline{\boldsymbol{D}}_{S_t} = (\boldsymbol{D}_{S_t}', \underline{\boldsymbol{D}}_{S_t}')'$ and $\overline{\boldsymbol{Z}}_{S_t} = (\boldsymbol{Z}_{S_t}', \underline{\boldsymbol{Z}}_{S_t}')'$. The posterior scale matrix of $\boldsymbol{\Sigma}_{\varepsilon S_t}$, $\overline{\boldsymbol{C}}_{S_t}$ is given by

$$\overline{\boldsymbol{C}}_{S_t} = (\overline{\boldsymbol{Z}}_{S_t} - \boldsymbol{D}_{S_t}'\overline{\boldsymbol{A}}_{S_t})'(\overline{\boldsymbol{Z}}_{S_t} - \boldsymbol{D}_{S_t}'\overline{\boldsymbol{A}}_{S_t}). \tag{A.9}$$

Conditional posterior distributions for the probit model

The parameters of the latent regression model obey posterior distributions which are of a well-known form (George and McCulloch, 1993), namely a normal distribution for

$\boldsymbol{\gamma}$ and a Bernoulli distribution for each δ_k.

$$\boldsymbol{\gamma}|\boldsymbol{\Xi}^T, \mathcal{D}^T \sim \mathcal{N}(\overline{\gamma}, \overline{\boldsymbol{V}}_{\gamma}) \tag{A.10}$$

where

$$\overline{\boldsymbol{V}_{\gamma}} = (\boldsymbol{w}'\boldsymbol{w} + \boldsymbol{H}'\boldsymbol{H})^{-1} \tag{A.11}$$

$$\overline{\gamma} = \overline{\boldsymbol{V}_{\gamma}}(\boldsymbol{w}'\boldsymbol{r}). \tag{A.12}$$

Consistent with the notation used above $\boldsymbol{w}$ and $\boldsymbol{r}$ are the corresponding full-data counterparts of $\boldsymbol{w}_t$ and $\boldsymbol{r}_t$.

The posterior of δ_k follows a Bernoulli distribution

$$\delta_k \sim \textit{Bernoulli}\ (\overline{p}_k) \tag{A.13}$$

with the corresponding posterior probability given by

$$\overline{p}_k = \frac{\frac{1}{\tau_0} \exp\left(-\frac{1}{2}(\frac{\gamma_k}{\tau_0})^2\right) \underline{p}_k}{\frac{1}{\tau_0} \exp\left(-\frac{1}{2}(\frac{\gamma_k}{\tau_0})^2\right) \underline{p}_k + \frac{1}{\tau_1} \exp\left(-\frac{1}{2}(\frac{\gamma_k}{\tau_1})^2\right) (1 - \underline{p}_k)}. \tag{A.14}$$

The posterior of r_t takes a particularly simple distributional form, namely a truncated standard normal distribution as described in Albert and Chib (1993).

Conditional posterior distributions for the observation equation

Since we assume that the variance-covariance matrix associated with the innovations in Eq. (2.2) is diagonal and in light of the restrictions described in Section 2.4, the conditional posterior for $\boldsymbol{\Lambda}$ is described exclusively in terms of the remaining $M - K$ rows of $\boldsymbol{\Lambda}$,

$$\boldsymbol{\Lambda}_{j\bullet}|\boldsymbol{\Xi}^T, \mathcal{D}^T \sim \mathcal{N}(\overline{\boldsymbol{\Lambda}}_{j\bullet}, \overline{\boldsymbol{V}}_{\boldsymbol{\Lambda}_{j\bullet}}) \tag{A.15}$$

where $\boldsymbol{\Lambda}_{j\bullet}$ selects the jth row of $\boldsymbol{\Lambda}$ for $K < j \leq M$. The corresponding posterior moments are given by

$$\overline{\boldsymbol{V}}_{\boldsymbol{\Lambda}_{j\bullet}} = (\varsigma_j^{-1}\boldsymbol{f}'\boldsymbol{f} + \boldsymbol{L}_j'\boldsymbol{L}_j)^{-1} \tag{A.16}$$

$$\overline{\boldsymbol{\Lambda}}_{j\bullet} = \overline{\boldsymbol{V}}_{\boldsymbol{\Lambda}_{j\bullet}}(\varsigma_j^{-1}\boldsymbol{f}'\boldsymbol{Y}_{\bullet j}). \tag{A.17}$$

Here, $\boldsymbol{f} = (\boldsymbol{f}_1, \ldots, \boldsymbol{f}_T)'$, $\boldsymbol{L}_j$ denotes the block of $\boldsymbol{L}_j$ associated with the coefficients of the jth row in Eq. (2.2) and $\boldsymbol{Y}_{\bullet j}$ selects the jth column of a $T \times M$ matrix $\boldsymbol{Y}_t = (\boldsymbol{y}_1, \ldots, \boldsymbol{y}_T)'$.

The posterior of ι_k is Bernoulli distributed with the corresponding posterior probability $\overline{\rho}_k$ given by

$$\overline{\rho}_k = \frac{\frac{1}{\varrho_0}\exp\left(-\frac{1}{2}(\frac{\iota_k}{\varrho_0})^2\right)\overline{\rho}_k}{\frac{1}{\varrho_0}\exp\left(-\frac{1}{2}(\frac{\iota_k}{\varrho_0})^2\right)\overline{\rho}_k + \frac{1}{\varrho_1}\exp\left(-\frac{1}{2}(\frac{\iota_k}{\varrho_1})^2\right)(1-\overline{\rho}_k)}. \tag{A.18}$$

For all other quantities like the discrete states $\boldsymbol{s}$ the conditional posteriors require more complex forward filtering-backward sampling algorithms (FFBS). Fortunately, several convenient and efficient algorithms are available to obtain posterior estimates.

Sampling the latent factors $\boldsymbol{f}_t$

The latent factors are obtained by using the well-known algorithm put forth in Carter and Kohn (1994), and Frühwirth-Schnatter (1994). The density of $\boldsymbol{f}_t$ can be factored as

$$p(\boldsymbol{f}^T|\boldsymbol{\Xi}^T, \mathcal{D}^T) = p(\boldsymbol{f}_T|\boldsymbol{\Xi}^T, \mathcal{D}^T)\prod_{t=1}^{T-1} p(\boldsymbol{f}_t|\boldsymbol{f}_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T)$$

where the moments are given by

$$\begin{aligned}
\boldsymbol{f}_t|\boldsymbol{f}_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T &\sim \mathcal{N}(\boldsymbol{f}_{t|t+1}, \boldsymbol{\Omega}_{t|t+1}) \\
\boldsymbol{f}_{t|t+1} &= E(\boldsymbol{f}_t|\boldsymbol{f}_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T) \\
\boldsymbol{\Omega}_{t|t+1} &= var(\boldsymbol{f}_t|\boldsymbol{f}_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T).
\end{aligned}$$

If $\boldsymbol{f}_{t|t+1}$ and $\boldsymbol{\Omega}_{t|t+1}$ is available, the full history of the latent factors can be sampled in a straightforward fashion from $\mathcal{N}(\boldsymbol{f}_{t|t+1}, \boldsymbol{\Omega}_{t|t+1})$. $\boldsymbol{f}_{t|t+1}$ and $\boldsymbol{\Omega}_{t|t+1}$ are obtained using Kalman filtering and the corresponding backward recursions. More specifically, let us assume without loss of generality that Q equals one and no observable quantities are included. Then Eq. (2.3) can be rewritten as

$$\boldsymbol{f}_t = \boldsymbol{A}_{1S_t}\boldsymbol{f}_{t-1} + \boldsymbol{\varepsilon}_t. \tag{A.19}$$

In addition, the observation Eq. (2.2) can be written more compactly as

$$\boldsymbol{y}_t = \boldsymbol{\Lambda}^f\boldsymbol{f}_t + \boldsymbol{e}_t. \tag{A.20}$$

Conditional on $\boldsymbol{f}_{0|0}$ and $\boldsymbol{\Omega}_{0|0}$, the Kalman filter produces

$$
\begin{aligned}
\boldsymbol{f}_{t|t-1} &= \boldsymbol{A}_{1S_t}\boldsymbol{f}_{t-1|t-1} \\
\boldsymbol{\Omega}_{t|t-1} &= \boldsymbol{A}_{1S_t}\boldsymbol{\Omega}_{t-1|t-1}\boldsymbol{A}'_{1S_t} + \boldsymbol{\Sigma}_{\varepsilon t} \\
\boldsymbol{K}_t &= \boldsymbol{\Omega}_{t|t-1}\boldsymbol{\Lambda}^{f'}(\boldsymbol{\Lambda}^f\boldsymbol{\Omega}_{t|t-1}\boldsymbol{\Lambda}^{f'} + \boldsymbol{\Sigma}_{\boldsymbol{e}})^{-1} \\
\boldsymbol{f}_{t|t} &= \boldsymbol{f}_{t|t-1} + \boldsymbol{K}_t(\boldsymbol{y}_t - \boldsymbol{\Lambda}^f\boldsymbol{f}_{t|t-1}) \\
\boldsymbol{\Omega}_{t|t} &= \boldsymbol{\Omega}_{t|t-1} - \boldsymbol{K}_t\boldsymbol{\Lambda}^f\boldsymbol{K}'_t\boldsymbol{\Omega}_{t|t-1}.
\end{aligned}
$$

Note that at time $t = T$ we obtain $\boldsymbol{f}_{T|T}$ and $\boldsymbol{\Omega}_{T|T}$, which permits us to sample $\boldsymbol{f}_T$. This draw of $\boldsymbol{f}_T$, in conjunction with $\boldsymbol{f}_{T|T}$ and $\boldsymbol{\Omega}_{T|T}$ is then used to obtain $\boldsymbol{f}_{t|t+1}$ and $\boldsymbol{\Omega}_{t|t+1}$ until time $t = 0$ is reached. The corresponding recursions are given by

$$
\begin{aligned}
\boldsymbol{f}_{t|t+1} &= \boldsymbol{f}_{t|t} + \boldsymbol{\Omega}_{t|t}\boldsymbol{A}'_{1S_t}\boldsymbol{\Omega}^{-1}_{t+1|t}(\boldsymbol{f}_{t+1} - \boldsymbol{A}_{1S_t}\boldsymbol{f}_{t|t}) \\
\boldsymbol{\Omega}_{t|t+1} &= \boldsymbol{\Omega}_{t|t} - \boldsymbol{\Omega}_{t|t}\boldsymbol{A}'_{1S_t}\boldsymbol{\Omega}^{-1}_{t+1|t}\boldsymbol{A}'_{1S_t}\boldsymbol{\Omega}^{-1}_{t|t}.
\end{aligned}
$$

Sampling the regime indicators s_t

Following Kim and Nelson (1999), and Amisano and Fagan (2013) we obtain the filtered and predicted probabilities, $\hat{p}_{jt|t} = Prob(S_t = j|\boldsymbol{\Xi}^t, \mathcal{D}^t)$ and $\hat{p}_{it+1|t} = Prob(S_t = i|\boldsymbol{\Xi}^t, \mathcal{D}^t)$ through a standard filter (Kim and Nelson, 1999). The prediction and updating probabilities are given by

$$
\begin{aligned}
\hat{p}_{jt+1|t} &= \sum_{i=1}^{2} p_{ij,t|t}\hat{p}_{jt|t} \\
\hat{p}_{jt+1|t+1} &= \frac{\hat{p}_{jt+1|t}\,p(\boldsymbol{z}_{t+1}|\boldsymbol{A}_{1S_{t+1}=j}, \boldsymbol{\Sigma}_{\varepsilon S_{t+1}=j})}{\sum_{h=1}^{2}\hat{p}_{ht+1|t}\,p(\boldsymbol{z}_{t+1}|\boldsymbol{A}_{1S_{t+1}=h}, \boldsymbol{\Sigma}_{\varepsilon S_{t+1}=h})}
\end{aligned}
$$

The filtered probabilities are then used in the next step to sample the full history of regime indicators $\boldsymbol{s}^T$. Similar to the decomposition of the joint conditional density of the latent factors, it is possible to use the following factorization

$$
p(\boldsymbol{s}^T|\boldsymbol{\Xi}^T, \mathcal{D}^T) = p(S_T|\boldsymbol{\Xi}^T, \mathcal{D}^T)\prod_{t=1}^{T-1} p(S_t|S_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T)
$$

where $p(S_T|\boldsymbol{f}^T, \boldsymbol{\Xi}^T, \mathcal{D}^T)$ is obtained from the final iteration of the Hamilton (1989) filter. S_t conditional on S_{t+1} and the remaining parameters can be obtained in a straightforward fashion by noting that

$$
p(S_t|S_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T) \propto p(S_{t+1}|S_t)p(S_t|\boldsymbol{\Xi}^T, \mathcal{D}^T).
$$

The first term on the right hand side refers to the transition probability and the second term is obtained from the Hamilton filter. Thus $p(S_t|S_{t+1}, \boldsymbol{\Xi}^T, \mathcal{D}^T)$ can be obtained by iterating backwards until time $t = 0$ is reached. To be more precise, let

$$Prob(S_t = i | S_{t+1} = j, \mathbf{\Xi}^T, \mathcal{D}^T) = \frac{\hat{p}_{jt|t} p_{ij,t+1}}{\sum_{h=1}^{2} \hat{p}_{ht|t} p_{hj,t+1}}.$$

Finally, the corresponding transition probabilities $p_{ij,t}$ are obtained straightforwardly through Eq. (2.5).

Appendix B

Table: Data overview

Name	Mnemonic	$\boldsymbol{y}_t$	$\boldsymbol{x}_t$	$\boldsymbol{w}_t$
10-Year Treasury Constant Maturity Minus Federal Funds Rate	T10YFFM			X
10-Year Treasury Constant Maturity Rate	GS10			X
3-Month Treasury Bill: Secondary Market Rate	TB3MS			X
6-Month Treasury Bill: Secondary Market Rate	TB6MS			X
All Employees: Construction	USCONS			X
All Employees: Durable goods	DMANEMP			
All Employees: Manufacturing	MANEMP			X
Average Weekly Hours of Production and Nonsupervisory Employees: Manufacturing	AWHMAN	X		
Average Weekly Hours of Production and Nonsupervisory Employees: Goods-Producing	CES0600000007			X
Average Weekly Overtime Hours of Production and Nonsupervisory	AWOTMAN	X		
Canada / U.S. Foreign Exchange Rate	EXCAUS			X
Civilian Employment	CE16OV			X
Civilian Unemployment Rate	UNRATE	X		X
Commercial and Industrial Loans, All Commercial Banks	BUSLOANS	X		X
Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	X		X
Effective Federal Funds Rate	FEDFUNDS		X	X
Housing Starts in Midwest Census Region	HOUSTMW	X		
Housing Starts in Northeast Census Region	HOUSTNE	X		
Housing Starts in South Census Region	HOUSTS	X		
Housing Starts in West Census Region	HOUSTW	X		
Housing Starts: Total: New Privately Owned Housing Units Started	HOUST	X		X
Industrial Production Index	INDPRO	X		X
Industrial Production: Business Equipment	IPBUSEQ	X		
Industrial Production: Consumer Goods	IPCONGD	X		
Industrial Production: Durable Consumer Goods	IPDCONGD	X		
Industrial Production: Durable Materials	IPDMAT	X		
Industrial Production: Final Products (Market Group)	IPFINAL	X		
Industrial Production: Final Products and Nonindustrial Supplies	IPFPNSS	X		
Industrial Production: Fuels	IPFUELS	X		
Industrial Production: Manufacturing (SIC)	IPMANSICS	X		
Industrial Production: Materials	IPMAT	X		
Industrial Production: Nondurable Consumer Goods	IPNCONGD	X		
Industrial Production: nondurable Materials	IPNMAT	X		
ISM Manufacturing: Employment Index	NAPMEI	X		
ISM Manufacturing: Inventories Index	NAPMII	X		
ISM Manufacturing: New Orders Index	NAPMNOI	X		
ISM Manufacturing: PMI Composite Index	NAPM	X		
ISM Manufacturing: Prices Index	NAPMPRI	X		
ISM Manufacturing: Production Index	NAPMPI	X		
ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	X		
Japan / U.S. Foreign Exchange Rate	EXJPUS			X
M2 Money Stock	M2SL			X
Moody's Seasoned Aaa Corporate Bond Minus Federal Funds Rate	AAAFFM			X
Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate	BAAFFM	X		
New Private Housing Units Authorized by Building Permits	PERMIT	X		X
New Private Housing Units Authorized by Building Permits in the Mid West	PERMITMW	X		
New Private Housing Units Authorized by Building Permits in the North East	PERMITNE	X		
New Private Housing Units Authorized by Building Permits in the South	PERMITS	X		
New Private Housing Units Authorized by Building Permits in the West	PERMITW	X		
Personal Consumption Expenditures: Chain-type Price Index	PCEPI	X		
Personal consumption expenditures: Durable goods (chain-type price	DDURRG3M086SBEA	X		
Personal consumption expenditures: Nondurable goods (chain-type price	DNDGRG3M086SBEA	X		
Personal consumption expenditures: Services (chain-type price index)	DSERRG3M086SBEA	X		
Personal Income	PI	X		
Producer Price Index: Commodities: Metals and metal products: Primary	PPICMM			X
Real Estate Loans, All Commercial Banks	REALLN			X
Real Manufacturing and Trade Industries Sales	CMRMTSPL	X		
Real personal consumption expenditures (chain-type quantity index)	DPCERA3M086SBEA	X		X
Real Personal Income	RPI	X		X
Real personal income excluding current transfer receipts	W875RX1	X		X
Reserves Of Depository Institutions, Nonborrowed	NONBORRES			X
Spot Oil Price: West Texas Intermediate	OILPRICE			X
St. Louis Adjusted Monetary Base	AMBSL			X
Switzerland / U.S. Foreign Exchange Rate	EXSZUS			X
Total Reserves of Depository Institutions	TOTRESNS			X
U.S. / U.K. Foreign Exchange Rate	EXUSUK			X

Notes: This table presents the dataset used in this study. Mnemonics refer to codes used to obtain the time series from the US FRED database. The final three columns indicate whether a variable is included in $\boldsymbol{y}_t$,$\boldsymbol{x}_t$, $\boldsymbol{w}_t$ or in all of them.