MONETARY POLICY, STOCK MARKET AND SECTORAL COMOVEMENT

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Abstract

This paper evaluates the role that sectoral comovement plays in the propagation of monetary policy shocks on the stock market. In doing so, we introduce a factor-augmented vector autoregressive model with heterogeneous regime-switching factor loadings, denoted as MS2-FAVAR, that allows us to jointly assess (i) potential changes in the degree of comovement between each sector-specific stock return and the aggregate stock market as well as (ii) the propagation of monetary policy shocks taking into account such changes in comovement. We find that the efects of monetary policy shocks on stock returns are substantially amplied when industries experience a stronger degree of comovement, suggesting that a more interconnected stock market is more prone to the propagation of monetary policy shocks. The MS2-FAVAR model is also well-suited to perform a network analysis to characterize linkages in large datasets.

Keywords: stock market, monetary policy, markov-switching, factor model, network analysis.

JEL classification: E44, C32, G12.

Resumen

En este artículo se evalúa el papel que desempeña el movimiento conjunto sectorial en la propagación de choques de política monetaria hacia el mercado de valores. En particular, se propone un modelo de vectores autorregresivos aumentado con factores, el cual permite cambios heterogéneos de régimen en la carga de los factores. El modelo, denominado MS2-FAVAR, permite evaluar de manera conjunta dos aspectos. Primero, los cambios potenciales en el grado de movimiento común entre los retornos asociados a un sector económico específico y los retornos asociados a la bolsa de valores, de manera agregada. Segundo, la propagación de choques de política monetaria, una vez que se han tomado en cuenta dichos cambios en el grado de movimiento común. Los resultados muestran que el efecto de choques de política monetaria sobre los retornos de la bolsa de valores es amplificado sustancialmente cuando los sectores experimentan un mayor grado de movimiento común entre ellos. Esto sugiere que un mercado de valores en el cual los sectores económicos se encuentran altamente interconectados es más sensitivo a la propagación de choques de política monetaria.

Palabras clave: bolsa de valores, política monetaria, regímenes markovianos, modelo de factores, análisis de redes.

Códigos JEL: E44, C32, G12.

1 Introduction

The stock market represents an important element in the transmission mechanism of monetary policy to the real economy. Changes in asset returns influence economic decisions by firms and households that will ultimately affect inflation and output. Moreover, the degree of comovement in the stock market may significantly vary over time, representing a central feature in asset pricing. Changes in the comovement between asset prices from different sectors of the economy are thereby likely to affect the responses of the overall stock market to monetary policy shocks. Therefore, understanding the interactions between monetary policy, stock returns and sectoral comovement is likely to provide important insights about the propagation of monetary policy shocks throughout financial markets.

The conventional view is that unexpected monetary policy tightening episodes are associated with a negative response of share prices. For example, in a seminal paper, Bernanke and Kuttner (2005) using an event study estimate that a 100 basis point surprise increase in the policy rate is associated with a roughly 4 per cent decline in aggregate stock returns. Challenging this view, based on a VAR impulse response analysis, Galí and Gambetti (2015) find evidence in favor of protracted episodes in which stock prices respond positively to a surprise tightening in monetary policy, most notably since the 1980's.[1] However, the vast majority of the literature finds that a surprise tightening in monetary policy leads to declines in aggregate stock returns.

From a disaggregated perspective, the literature has documented a significant heterogeneity about the effects of U.S. monetary policy on stock returns across industries. For example, Ehrmann and Fratzscher (2004) find that stock returns associated with cyclical sectors, such as technology, communications and cyclical consumer goods react two to three times more to monetary policy shocks than less cyclical sectors (e.g., utilities and non-cyclical consumer goods sectors). Recently, Ozdagli and Weber (2016) study whether the sectoral linkages of the economy represent an important propagation mechanism of monetary policy shocks on stock market returns, finding that about two thirds of the overall reaction can be attributed to indirect effects, which are based on the structure of the production network.[2] Their analysis is based on constant sectoral linkages. In a financial

[1] Galí (2014) developed a general equilibrium model where increases in interest rates lead to an increase in the bubble component of stock prices. As a result, if the bubble component of stock prices is predominant relative to their fundamental component, observed stock prices can react positively to surprise increases in the policy rate.

[2] Acemoglu et al. (2012) also find that intersectoral relations are a conduit through which sector-level shocks transmit throughout the economy.

context, however, this is likely to be a too restrictive assumption. For example, Diebold and Yilmaz (2016) show that the comovement among asset returns varies substantially over time. The implications of changes in stock market comovement on the propagation of monetary policy shocks is something that has remained unexplored and this constitutes a focal point of our paper.

The first contribution of this paper is therefore to study whether changes in the interrelation between industry-specific stock returns affect the propagation mechanism of monetary policy shocks. In particular, we study the linkages between monetary policy and the stock market in periods when stock returns tend to move together and periods when stock returns follow more idiosyncratic dynamics. This is an important issue to investigate, since our analysis allows us to identify circumstances in which monetary policy decisions are the most potent on financial markets. A key aspect of our analysis is that we study the response of stock returns to monetary policy shocks at the level of an industry. The rationale for doing so is that industries with different expected dividends and perceived riskiness (i.e., risk premium) on stocks may well react differently to unanticipated changes in monetary policy. Hence, it is important to study the effects of monetary policy surprises on the stock market at a detailed industry-level, since it permits us to assess the sectors of the economy acting as main conduits in the propagation of monetary policy shocks throughout financial markets.

Our analysis is based on a novel econometric framework used to study the interactions between monetary policy, stock market and sectoral comovement. In particular, we summarize the cross-sectional information contained in monthly industry-specific stock returns using factor analysis and jointly relates that summarized information to macroeconomic fundamentals; that is, we estimate a factor-augmented vector autoregressive (FAVAR) model. To jointly evaluate the extent to which the responses to monetary policy shocks differ depending on the degree of comovement of a specific industry with the rest of the stock market, we endogenously model nonlinearities in the factor loadings, introducing a new model well-suited to our analysis.

The results indicate that changes in the degree of comovement is an important determinant of the stock market response to monetary policy shocks in that higher comovement is associated with a stronger response of stock returns to monetary policy shocks. Accordingly, when industry-specific stock returns switch from a regime of low comovement to a regime of high comovement, the effect of a monetary policy shock is about twice stronger, albeit there are differences across industries. Moreover, we find that there is a direct relation between how sensitive an industry is to monetary policy shocks and the ability of this industry to generate spillovers to the rest of industries. In particular, our results suggest that industries that are more central in the stock market network tend to react the most to monetary policy shocks and act as conduits through which monetary policy shocks transmit to the rest of the stock market.

The second contribution of this paper is methodological in nature in that we show how to easily estimate high-dimensional factor-augmented vector autoregressive models with heterogeneous regime-switching factor loadings. Here, heterogenous refers to the fact that we use a different Markov chain to model nonlinearities in each of the factor loadings. The literature on Markov-switching models has so far concentrated on the estimation of small-scale models, typically limited to vector autoregressive or factor models with less than ten variables. Notable examples include Sims and Zha (2006) and Hubrich and Tetlow (2015), who estimate Markov-switching VAR models to study, respectively, the changing transmission mechanism of monetary policy on the macroeconomic environment and the interaction between financial stress events, monetary policy and the macroeconomic environment. The techniques to estimate such models are outlined in Sims et al. (2008), but their implementation remains difficult from a computational point of view so that their use is not widely spread.[3]

Our methodological contribution consists in extending the Bernanke et al. (2005) FAVAR model to a setting where factor loadings can vary according to Markov processes. This is a novel contribution, since the literature on time-varying factor models has concentrated on time variation modelled through random walk type behaviours (see, e.g., Del Negro and Otrok (2008)). However, modelling time-variation through random walks implies gradual changes in the parameters, which is not appealing in our context since abrupt changes are a typical feature of financial variables. Moreover, as a by-product of our model, we show how to conduct a network analysis to analyse the synchronization of discrete regime shifts in a high-dimensional dataset.

The key advantage of our estimation method is that there is no need to assume – for computational simplicity – that a single or a limited number of Markov chains are driving the pattern of regime changes in the factor loadings. Instead, we allow for each factor loading to be driven by its own Markov chain, which helps to uncover and analyze the

[3]Bognanni and Herbst (2015) suggest to use the particle filter to facilitate inference on Bayesian Markov-switching VAR models. In a classical context, Guérin et al. (2016) extend the linear three-pass regression filter of Kelly and Pruitt (2015) to include Markov-switching parameters in high-dimensional factor models. They show that modelling time variation in the factor loadings through Markov-switching parameters is helpful to forecast bilateral exchange rates and key U.S. quarterly macroeconomic variables.

heterogeneity in their nonlinear dynamics. The computational burden of our estimation strategy is also limited compared with the case of the estimation of the Markov-switching Bayesian VARs outlined in Sims and Zha (2006). Accordingly, our framework is appealing in that it makes the estimation of FAVAR models with regime-switching factor loadings straightforward in a high-dimensional setting, which is highly relevant in the context of structural analyses of macroeconomic and financial dataset.

The paper is organized as follows. Section 2 presents the econometric model we introduce, a FAVAR model with regime-switching factor loadings, including the details of the estimation algorithm. This section also outlines how to analyse the network structure of high-dimensional datasets. Section 3 present our empirical results. Section 4 concludes.

2 Econometric Framework

Our information set is large, since it involves stock returns of 30 industries and a set of macroeconomic fundamentals. To tackle the high-dimensionality of this problem in a single econometric model, we estimate a FAVAR model that permits us to summarize the information from the industry-specific stock returns in a few factors at most. Note that it is important to include macroeconomic variables in the VAR system, since at a low frequency (monthly or quarterly), monetary policy explicitly reacts to fluctuations in the macroeconomic environment. Moreover, to endogenously account for changes in the interrelation between industry-level stock returns, we model time variation in the factor loadings through Markov processes, introducing a new model well-suited to our analysis. This allows us to perform our impulse response analysis conditional on high and low comovement regimes between industry-level stock returns and the aggregate stock market.

2.1 The MS2-FAVAR Model

We start by describing the Multi-State Markov-Switching Factor Augmented Vector Autoregressive model we use, which is denoted as MS2-FAVAR model. The estimation of such a model is a contribution in itself in that, to the best of our knowledge, this paper is the first one to describe and show how to estimate relatively easily a high-dimensional factor-augmented VAR model with Markov-switching factor loadings. Note that the majority of the empirical literature concentrates on the estimation of a linear FAVAR model as originally described in Bernanke et al. (2005). Time variation in FAVAR models has predominantly been introduced through random walk type behaviours (see, e.g., Korobilis (2013)), which implies gradual changes in the parameters of the model that are typically relevant for macroeconomic applications.[4] However, gradual changes in parameter estimates may not be relevant to model financial variables, since there is ample evidence suggesting that financial markets are subject to abrupt regime changes (see, e.g., Ang and Timmermann (2012)). Therefore, we use regime-switching dynamics to model time variation in the factor loadings. The model is described by the following measurement and transition equations

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} I & \mathbf{0} \\ \Lambda^Y & \Lambda^F_{S_t} \end{bmatrix} \begin{bmatrix} Y_t \\ F_t \end{bmatrix} + \begin{bmatrix} 0 \\ e^F_t \end{bmatrix}, \tag{1}$$

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \Phi_0 + \Phi(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \begin{bmatrix} u^Y_t \\ u^F_t \end{bmatrix}, \tag{2}$$

where Y_t collects n observed fundamentals, F_t is a vector of q unobserved components driving a large set of m variables X_t, $e^F_t \sim N(0,\Omega)$, with Ω being diagonal, and $u_t = (u^Y_t, u^F_t)'$ the VAR innovations such that $u_t \sim N(0,\Sigma)$. Equation (1) is the measurement equation (or factor equation) of the state-space system and equation (2) is its transition equation. For the case of one factor, $q = 1$, we define it as $f_t = F_t$. The matrices of factor loadings are given by $\Lambda^Y = (\lambda^Y_1, \lambda^Y_2, ..., \lambda^Y_m)'$ and $\Lambda^F_{S_t} = (\lambda^F_{1,S_{1,t}}, \lambda^F_{2,S_{2,t}}, ..., \lambda^F_{m,S_{m,t}})'$ and the dynamics of the loadings connecting the industry-level stock returns and the factor are given by

$$\lambda^F_{i,S_{i,t}} = \lambda^F_{i,0} + \lambda^F_{i,1} S_{i,t}, \tag{3}$$

for $i = 1, 2, ..., m$. Notice that each factor loading is a function of its own latent state variable, $S_{i,t}$ as opposed to assuming that a single Markov chain is driving regime changes for all m variables collected in X_t. This is important since this allows us to account for the potential heterogeneity in the regimes of comovement between industry-level stock returns and aggregate stock market.

The information contained in the first factor, f_t, can be interpreted as summarizing the performance of the aggregate stock market. Therefore, in periods when the stock returns of a specific industry i tends to move in the same direction of the aggregate stock market, $S_{i,t} = 1$ and its degree of comovement is given by $(\lambda^F_{i,0} + \lambda^F_{i,1})$; whereas during periods when industry i follows a more independent pattern (i.e., $S_{i,t} = 0$), the degree of comovement is given by $\lambda^F_{i,0}$.

[4] Del Negro and Otrok (2008) being the early contribution for dynamic factor models – without a VAR setting – with time-varying parameters modelled through random walk type behaviours.

Each state variable follows the dynamics of a two-state first-order Markov chain. We assume that the transition probabilities governing each Markov chain are constant over time,

$$p(S_{i,t} = l_i | S_{i,t-1} = k_i) = p_{i,lk}, \tag{4}$$

for $i = 1, 2, ..., m$ and for $l, k = 0, 1$. For simplicity of the notation and in relation to our empirical application, we assume that the Markov chains can take only two regimes. However, the framework we present is general enough to accommodate more than two regimes.

We collect the set of transition probabilities in the matrix $P = (p_{1,lk}, p_{2,lk}, ..., p_{m,lk})'$. The state variables are assumed to be independent from each other, but note that this specification is nesting the case of correlated state variables. We proceed this way for computational tractability, but also because we want to impose as little structure as possible on the Markov chains. As a result, thanks to its generality, the MS2-FAVAR approach offers a flexible framework to model regime changes in high-dimensional settings.

A couple of additional comments are required. First, we only consider regime switching parameters in the factor loadings; the other parameters of the model are held constant. The reason for doing so is that we concentrate our impulse response analysis on the effects of monetary policy shocks on industry-level stock returns across different regimes of co-movement between industry-level stock returns and the aggregate stock market. Modelling regime changes in the VAR parameters (i.e., in equation (2)) would allow one to study changes in the transmission mechanism of monetary policy (if time variation is modelled in the autoregressive parameters of the VAR) or the changing nature of the shocks hitting the economy (if time variation is modelled in the elements of the variance-covariance matrix of the VAR innovations). This is not the focus of this paper, since we are interested in evaluating to what extent the effects of monetary policy on the stock market vary depending on the degree of comovement of the stock market.

Second, the MS2-FAVAR model assumes that the innovations Ω in equation (1) have a diagonal covariance matrix, which rules out the propagation of sector-specific shocks across industries. Foerster et al. (2011) perform a structural factor analysis, modelling intersectoral linkages using data from the Bureau of Economic Analysis' Input-Output table, which allows them to overcome the issue of zero off-diagonal elements in the innovation matrix of the measurement equation of the FAVAR model. However, assumptions about the functional form of the propagation mechanism of the intersectoral linkages need to be made. This is not appealing in our empirical application, since we want to impose as little structure as possible on the propagation mechanism of sectoral shocks. Instead, we are interested in using the information from the estimated factor loadings to provide an assessment about the propagation of shocks across sectors.

2.2 Estimation

Given that the measurement equation of the state-space representation (see equation (1)) depends on the configuration of the realizations of the vector $\mathbf{S}_t = (S_{1,t}, S_{2,t}, ..., S_{m,t})'$, and since there are two possible states for each i-th state variable, $S_{i,t} = \{0, 1\}$, there are 2^m possible states at time t of the measurement equation (1). Moreover, since the Kalman filter operates by relating information between time t and $t-1$, there will be a total of $2^{(2m)}$ possible states involved at every iteration. In our empirical application, we use the 30-industry portfolio of the Fama French database.[5] Therefore, with $m = 30$, there are 2^{60} possible states, which makes it infeasible to estimate the model by maximum likelihood. Therefore, we rely on Bayesian methods to estimate the proposed MS2-FAVAR model detailed previously.

The approach to estimate the vector of parameters, θ, along with the factors, F_t, relies on a multi-move Gibbs-sampling procedure. In this setting, (i) the parameters of the model $\theta = \{P, \Lambda^Y, \Lambda_0^F, \Lambda_1^F, \Omega, \Phi, \Sigma\}$, (ii) the Markov-switching variables $\tilde{S}_T = \{\mathbf{S}_t\}_1^T$, and (iii) the factors $\tilde{F}_T = \{F_t\}_1^T$, are treated as random variables given the data in $\tilde{y}_T = \{Y_t, X_t\}_1^T$. The purpose of this Markov chain Monte Carlo simulation method is to approximate the joint and marginal distributions of these random variables by sampling from conditional distributions.

2.2.1 Algorithm

The model is fully estimated in a Bayesian fashion using a Gibbs sampler estimation procedure, which is described by the following steps:

Step 1: Generate $\tilde{S}_T$ conditional on the data $\tilde{y}_T$, $\tilde{F}_T$ and θ.

Step 2: Generate P conditional on $\tilde{S}_T$.

Step 3: Generate Λ_0^F, Λ_1^F conditional on Λ^Y, Ω, $\tilde{S}_T$, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 4: Generate Λ^Y conditional on Λ_0^F, Λ_1^F, Ω, $\tilde{S}_T$, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 5: Generate Ω conditional on Λ^Y, Λ_0^F, Λ_1^F, $\tilde{S}_T$, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 6: Generate Φ conditional on Σ, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 7: Generate Σ conditional on Φ, $\tilde{F}_T$ and $\tilde{y}_T$.

Step 8: Generate $\tilde{F}_T$ conditional on $\theta, \tilde{S}_T$ and $\tilde{y}_T$.

[5]The 30-industry Fama French portfolio data are available online at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`.

Steps 1 through 8 can be iterated $L + M$ times, where L is large enough to ensure that the Gibbs sampler has converged. Thus, the marginal distributions of the state variables, synchronization variable and the parameters of the model can be approximated by the empirical distribution of the M simulated values. For our empirical application, we use a burn-in period of $L = 15000$ iterations to converge to the ergodic distribution, and run $M = 5000$ additional iterations. To assess convergence, we examine the recursive means of the retained draws. Recursive means are relatively constant, suggesting evidence in favor of convergence. Sequential runs of the algorithm led to similar results, providing additional evidence in favour of convergence.[6]

Notice that since the variance-covariance matrix of the transition equation of the state space representation, Ω, is assumed to be diagonal, steps 1 to 5 can be straightforwardly performed by sampling, equation by equation, draws of the parameters associated to univariate Markov-switching regressions following the approach of Kim and Nelson (1999), conditional on the information about the factors, $\tilde{F}_T$. This is a critical feature of the algorithm, since it greatly simplifies the estimation of the model by dealing with the proliferation of states in a straightforward manner.

Moreover, conditional on the factor, $\tilde{F}_T$, steps 6 and 7 can be performed using a standard Gibbs sampling approach to estimate small-scale linear VAR models. The challenge in the estimation of the MS2-FAVAR model lies in step 8, which is the estimation step of the factor $\tilde{F}_T$ that represents the element connecting the measurement equation with the transition equation. We present next the details for the last step of the algorithm.

2.2.2 Drawing the State Vector

For ease of exposition, we simplify notation and express compactly the model described in equations (1) and (2) as follows

$$\begin{aligned} Z_t &= H_{\mathbf{S}_t} W_t + v_t, \quad v_t \sim N(0, \Theta) && (5)\\ W_t &= G_0 + G W_{t-1} + u_t, \quad u_t \sim N(0, \Sigma), && (6) \end{aligned}$$

[6] Note also that to avoid label switching, we impose constraints on the draws to ensure that the second regime is a high comovement regime while the first regime is a low comovement regime. In practice, this is achieved by only retaining draws for which $\lambda^F_{i,1}$ is positive.

where $Z_t = (Y_t, X_t)'$, $W_t = (Y_t, F_t)'$, $\upsilon_t = (0, e_t^F)'$, and

$$G = \begin{bmatrix} \Phi_1 & \Phi_2 & \cdots & \Phi_{L-1} & \Phi_L \\ I_\kappa & 0 & \cdots & 0 & 0 \\ 0 & I_\kappa & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & I_\kappa & 0 \end{bmatrix}, \quad G_0 = \begin{bmatrix} \Phi_0 \\ 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

where $\kappa = n + q$. Notice that from step 1, at every iteration, the state variables contained in $\mathbf{S}_t$ are known, being interpreted as a set of observed dummy variables. Therefore, in the case of two regimes that is relevant for our empirical application, the measurement equation (5) can be expressed as

$$Z_t = (H_0 \odot (\mathbf{1} - \iota' \otimes S_t^*) + H_1 \odot (\iota' \otimes S_t^*)) \odot W_t + \upsilon_t, \tag{7}$$

where ι is a $(n + q)$ vector of ones, $S_t^* = (\mathbf{0}, \mathbf{S}_t)'$ with $\mathbf{0}$ being a $(n \times 1)$ zero vector, $\mathbf{1}$ is a $(n + m) \times (n + q)$ matrix of ones, and $\odot$ represents the Hadamard product, while $\otimes$ represents the Kronecker product. In our empirical application, we focus on the case of a one-factor model; i.e., $q = 1$, for ease of interpretation. Accordingly, the matrices of factor loadings for each regime can be defined as

$$H_0 = \begin{bmatrix} & & [I_n] & & \begin{matrix} 0 \\ \vdots \\ 0 \end{matrix} \\ \lambda_{1,1}^Y & \lambda_{1,2}^Y & \cdots & \lambda_{1,n}^Y & \lambda_{1,0}^F \\ \lambda_{2,1}^Y & \lambda_{2,2}^Y & \cdots & \lambda_{2,n}^Y & \lambda_{2,0}^F \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \lambda_{m,1}^Y & \lambda_{m,2}^Y & \cdots & \lambda_{m,n}^Y & \lambda_{m,0}^F \end{bmatrix}, \quad H_1 = \begin{bmatrix} & & [I_n] & & \begin{matrix} 0 \\ \vdots \\ 0 \end{matrix} \\ \lambda_{1,1}^Y & \lambda_{1,2}^Y & \cdots & \lambda_{1,n}^Y & (\lambda_{1,0}^F + \lambda_{1,1}^F) \\ \lambda_{2,1}^Y & \lambda_{2,2}^Y & \cdots & \lambda_{2,n}^Y & (\lambda_{2,0}^F + \lambda_{2,1}^F) \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \lambda_{m,1}^Y & \lambda_{m,2}^Y & \cdots & \lambda_{m,n}^Y & (\lambda_{m,0}^F + \lambda_{m,1}^F) \end{bmatrix}.$$

Therefore, conditional on the configuration of states the model becomes a linear state-space model and the Carter and Kohn (1994) algorithm can be readily applied to conduct inference on the state vector W_t, as shown in Kim and Nelson (1999).

2.2.3 Priors

We need to define the hyperparameters associated with each of the elements in the vector of parameter $\theta = \{P, \Lambda^Y, \Lambda_0^F, \Lambda_1^F, \Omega, \Phi, \Sigma\}$. For identification purposes about the changes in the degree of comovement, we set different mean hyperparameters for each regime; that is, for the regime-switching factor loadings, we use a Normal prior distribution, $\lambda_i^F \sim N(\underline{\lambda}^F, \underline{V}_{\lambda^F})$, with $\underline{\lambda}^F = (0, 1)'$, $\underline{V}_{\lambda^F} = 20 \times I_2$.[7] For the constant factor loadings, we also use a Normal prior distribution, $\lambda_i^Y \sim N(\underline{\lambda}^Y, \underline{V}_{\lambda^Y})$, with $\underline{\lambda}^Y = (0, ..., 0)'$, $\underline{V}_{\lambda^Y} = 20 \times I_n$.

We use an inverse Gamma distribution as prior for the variances in $\Omega = \text{diag}(\sigma_1, \sigma_2, ..., \sigma_m)$; i.e., $\sigma \sim IG(\underline{s}, \underline{v})$, with $\underline{s} = 0.01$ and $\underline{v} = 0.01$.

For the VAR coefficients matrix and variance-covariance matrix, Φ and Σ, the independent Normal-Wishart prior distribution is used

$$p(\Phi, \Sigma^{-1}) = p(\Phi)p(\Sigma^{-1}),$$

where $\Phi \sim N(\underline{\Phi}, \underline{V}_\Phi)$, with $\underline{\Phi} = \mathbf{0}$ and $\underline{V}_\Phi = I$, and $\Sigma^{-1} \sim W(\underline{S}^{-1}, \underline{v})$, with $\underline{S}^{-1} = I$ and $\underline{v} = 0$. For the case of constant transition probabilities associated to the i-th state variable, $p_{i,00}, p_{i,11}$, we use Beta distributions as conjugate priors

$$p_{i,00} \sim Be(u_{i,11}, u_{i,10}),\ p_{i,11} \sim Be(u_{i,00}, u_{i,01}),$$

where the hyperparameters are given by $u_{i,01} = 2$, $u_{i,00} = 8$, $u_{i,10} = 1$ and $u_{i,11} = 9$, for $i = 1, 2, ..., m$.

2.2.4 Empirical Issues

Data

The vector Y_t includes the following monthly variables: industrial production (first difference of the log-level), consumer price index (first difference of the log-level), real dividend series (first difference of the log-level), the World Bank (non-energy) commodity price index (first difference of the log-level), and the short-term interest rate (in level). The short-term interest rate is the Federal Funds rate until December 2008, but we use the Wu and Xia (2015) shadow interest rate from January 2009 onwards to circumvent the zero lower bound problem. Unlike the observed short-term interest rate, the shadow rate is not bounded below by 0 percent.[8] The choice of the variables included in Y_t directly derives from the modelling choice in Galí and Gambetti (2015). The variables in X_t consist of (monthly) industry-level stock returns for each of the 30 industries of the Fama French portfolio, the data are taken in real terms, as in Galí and Gambetti (2015) for the S&P 500 returns. A description of the industry portfolio data is reported in Table 1. We also standardize the industry-level stock returns prior the estimation of the model. The full sample size extends from January 1960 to December 2014.

[7] As a robustness check, we also estimated the model with equal mean hyperparameters for each regime. The results with such a specification were robust to our original conclusions.

[8] The shadow rate is assumed to be a linear function of three latent variables called factors of a Nelson-Siegel-Svensson yield curve. The latent factors and the shadow rate are estimated with an extended Kalman filter.

Number of Factors

We rely on Bai and Ng (2007) to determine the number of factors that are more suitable to explain the comovement among the 30 industry-specific returns. This approach allows us to estimate the number of dynamic factors without having to actually estimate them. The results indicate that one dynamic factor best summarizes the comovements among the 30 industries. Also, the use of a single factor is useful for ease of interpretation, since the factor estimate closely mimics the fluctuations in a broad stock market index (the S&P500 index).

Model selection

In Bayesian econometrics, calculating the marginal likelihood of a model is a standard way to perform model selection. We used the modified harmonic mean estimator of Geweke (1999) to evaluate the marginal likelihood. However, these marginal likelihood estimates were sensitive to outliers, which led to excessive variability of the estimator. This is not unusual in the context of non-linear large-scale models (see, e.g., Dahlhaus (2016)). Hence, we refrain from reporting estimates for the marginal likelihood across different model specifications. Our benchmark results are based on a model with three lags and two regimes, but the impulse response analysis is very much robust to the use of additional lags for the VAR. The rationale for choosing a model with two regimes is twofold. First, the use of two regimes eases the interpretation of the results in that we obtain a low comovement regime and a high comovement regime (as opposed to a model with a larger number of regimes that are not necessarily easily interpretable). Second, as mentioned previously, excessive variability in the marginal likelihood estimates prevented us from selecting the number of regimes based on marginal likelihood estimates. Moreover, for models with three or four regimes, we often encountered situations where regimes had zero occurrences, which makes estimation too challenging and suggests evidence in favor of a more parsimonious model in terms of number of regimes, see Droumaguet et al. (2016).

Normalization

It is important to specify the restrictions necessary to uniquely identify the factors and factor loadings so as to identify the factors against any rotations. In practice, this is done by restricting the upper $q \times q$ block of Λ^f to an identity matrix and the upper $q \times n$ block of Λ^y to zero. As such, these identification restrictions imply that the Y_t's do not affect contemporaneously the first q variables in X_t; hence, these variables do not react contemporaneously to innovations in Y_t. These restrictions are akin to those imposed by Bernanke et al. (2005).

Identification

Finally, the model is identified with a recursive (Cholesky) structure. We adopt the following ordering for the variables: industrial production, consumer price index, dividend series for the S&P 500, the World Bank commodity price index, the short-term interest rate and the factor extracted from industry-specific stock returns. This is consistent with an ordering from slow-moving to fast-moving (i.e., financial) variables, which is common in this type of application. As such, this identification structure rules out the possibility of a contemporaneous response of the monetary policy authorities to stock market fluctuations, a feature that is not necessarily undesirable from an empirical point of view (see, e.g., Furlanetto (2011) or Galí and Gambetti (2015)). Alternative identification schemes include the use of high-frequency data (see, e.g., Faust et al. (2004) and D'Amico and Farka (2011)) or the heteroskedastic feature of financial data (see, e.g., Rigobon and Sack (2003)) to allow for a simultaneous response of monetary policy to asset prices. However, based on a formal statistical analysis that allows for a contemporaneous response of monetary authorities to stock prices, Lütkepohl and Netsunajev (2014) find that the short-term interest rate does not respond significantly to stock returns shocks. As such, this supports our baseline (recursive) identification scheme in which the short-term interest rate does not react contemporaneously to changes in stock prices. Moreover, our analysis is conducted at a monthly frequency (as opposed to a quarterly frequency as it is usually done in the literature); and the higher the frequency, the less likely it is for monetary policy authorities to react contemporaneously to unexpected events in the stock market using interest changes. As a result, our baseline impulse response analysis that is conducted at a monthly frequency is less subject to the criticism of the strict time restrictions implied by the recursive identification scheme compared with VAR analyses performed at a quarterly frequency. However, as a robustness check to our baseline recursive identification scheme, we perform the impulse response analysis based on an identification scheme that allows for a contemporaneous response of monetary policy to stock market fluctuations.

2.3 Network analysis

Network-based measures have become increasingly popular to study interactions between economic agents, especially in financial markets following the 2008-2009 financial crisis. From a theoretical standpoint, Elliott et al. (2014) and Silva et al. (2017) study which network structure is the most sensitive to financial contagions, concentrating their analysis on the diversification and dependence of a network. Acemoglu et al. (2012) find that sectoral interconnections play an important role as a source of macroeconomic fluctuations. Also, Camacho and Leiva-Leon (2016) study the linkages that propagate industry-specific business cycle shocks throughout the economy, finding a sequential transmission of the sectoral shocks to the macroeconomic environment. Ahern (2014) investigates to what extent the degree of centrality matters for the cross section of stock returns. He finds that industries that are at the center of the network are characterized by higher industries' market "betas" (i.e., they covary more closely with market returns). He also estimates that the more central industries comove more closely with future consumption growth compared with less central industries.

Network metrics are often directly calculated from Input-Output tables as in Ozdagli and Weber (2016). One drawback of this approach is that Input-Output tables are only available at an annual frequency, which implies that network structures derived from Input-Output tables exhibit little time variation. As such, in our application with financial data, it does not seem to be an appropriate approach. Alternatively, Diebold and Yilmaz (2014) show that standard tools for VAR analysis (i.e., forecast error variance decomposition) can be used to calculate network metrics. In doing so, they estimate VAR models over rolling windows to obtain dynamic measures of connectedness.

Here, we show how to analyze the endogenous structure of the network of industry-specific stock returns derived from the proposed MS2-FAVAR model. In particular, we characterize the interactions among industry-specific stock returns using the information contained in the state variables driving the factor loadings; i.e., the $S_{i,t}$'s, (where $i = 1, 2, ..., m$), which indicate the degree of comovement (high or low) between each industry and the factor that summarizes the performance of the overall stock market. Accordingly, our goal is to measure the relationship between the state variables associated with any pair of industries, i,j $\forall i \neq j$ as opposed to analysing the network structure of the underlying continuous stock return series. In doing so, we use the quadratic probability score to construct the following statistic,

$$q_{i,j}^{(l)} = 1 - \frac{1}{T} \sum_{t=1}^{T} \left(S_{i,t}^{(l)} - S_{j,t}^{(l)} \right)^2, \tag{8}$$

where $S_{i,t}^{(l)}$ denotes the l-th draw of the Markovian latent variable associated to the i-th industry at time t. Next, $q_{i,j}$ is estimated by computing the median of the distribution of $q_{i,j}^{(l)}$.

Any pair of industries i and j that are highly interconnected should experience similar degrees of comovement with the factor, yielding a value of $q_{i,j}$ closer to 1. In contrast, if these two industries have distinct dynamics, one would expect $q_{i,j}$ yielding a value close to 0. All these pairwise relationships can be collected in an adjacency matrix,

$$Q = \begin{pmatrix} 0 & q_{1,2} & q_{1,3} & \cdots & q_{1,m} \\ q_{2,1} & 0 & q_{2,3} & \cdots & q_{2,m} \\ q_{3,1} & q_{3,2} & 0 & \cdots & q_{3,m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ q_{m,1} & q_{m,2} & q_{m,3} & \cdots & 0 \end{pmatrix}, \tag{9}$$

which summarizes the synchronization pattern between industry-specific stock returns. Notice that Q is symmetric, since $q_{i,j} = q_{j,i}$ for all $i, j = 1, 2, ..., m$.

The adjacency matrix Q can be interpreted as a weighted network characterizing the interrelations between the comovement regimes of industry-specific stock returns with the aggregate stock market. To examine the structure of the network, we rely on measures of centrality and on multidimensional scaling (MDS) maps. The MDS technique consists in projecting the dissimilarities among the m industries, computed as $D = \mathbf{1} - \hat{Q}$, into a map in such a way that the Euclidean distances among the industries plotted in the plane approximate the dissimilarities in D.[9] In the resulting map, industries that exhibit large (small) dissimilarities have representations in the plane that are far (close) from each other. For further details about MDS maps, see Timm (2002).

Moreover, we examine the evolution of the degree of connectedness across industries and over time. In doing so, we compute the following dynamic statistic,

$$q_{i,j,t} = 1 - \frac{1}{L} \sum_{l=1}^{L} \left(S_{i,t}^{(l)} - S_{j,t}^{(l)} \right)^2 . \tag{10}$$

All these pairwise relationships can be collected in a time-varying adjacency matrix Q_t, as in equation (9). This can be used to assess changes in the importance, as measured by the degree of centrality, of each industry over time.

3 Monetary Policy Effects across Industries

There is a substantial literature on the effects of monetary policy surprises on the stock market based on VAR analyses (early references include Thorbecke (1997), Rigobon and Sack (2004) and Bjørnland and Leitemo (2009)). Our analysis contributes to this literature along several dimensions. First, we use industry-specific stock returns to provide a detailed picture of the effects of monetary policy on the stock market. In doing so, we use a factor-augmented VAR model to deal with parameter proliferation. Second, the use of the regime-switching parameter model detailed previously – the MS2-FAVAR – allows us to account for changes in the relation between industry-level stock returns and the aggregate stock market. Third, this feature allows us to characterize the network structure of the comovement of disaggregated stock returns in order to identify the industries acting as main conduits in the propagation of monetary policy shocks through the entire stock market.

3.1 Impulse response analysis

Figure 1 plots the estimated factor, which exhibits a correlation with the returns from the S&P500 index of approximately 0.7. Notice that the factor captures major stock market events, such as the flash crash of 1962 (or Kennedy slide), the "Black Monday" in 1987, the Lehman Brothers collapse in 2008, among others. This implies that the estimated factor can be interpreted as an indicator of the overall performance of the U.S. stock market.

[9] The term $\mathbf{1}$ denotes a $m \times m$ matrix of ones.

Also, note that the credible set for the estimated factor is very narrow, indicating that the underlying latent factor is well identified by the model.

Figure 2 shows the responses of macroeconomic and financial variables to a surprise 100 basis point increase in the policy rate obtained with the MS2-FAVAR model. First, the monetary policy shock temporarily increases the level of interest rates, which documents the persistence of the shock. Moreover, as expected, industrial production shows a prolonged negative response to a surprise monetary policy tightening. Inflation, as defined from the consumer price index, exhibits a positive hump-shaped response to a surprise monetary policy tightening, a phenomenon referred to as the "price puzzle." Dividends decline following a monetary policy shock, and the posterior credible sets exclude zero. This is consistent with the responses of output and interest rate in that a fall in output and higher cost of borrowing are expected to be associated with lower future dividends. Moreover, commodity prices do not react significantly to a monetary policy shock. Overall, these responses are very similar to those obtained from the linear model in Galí and Gambetti (2015).

We now turn our attention to the responses of industry-level stock returns to monetary policy shocks, reported in Figure 3. Given that the factor loadings are allowed to experience switches across regimes of comovement, we obtain for each industry, a regime-specific response to a monetary policy shock (i.e., a response in the high or low comovement regime). Again, the monetary policy shock is scaled to represent a surprise 100 basis point increase in the policy rate and the responses of equity returns are in standard deviation units. First, this figure shows that, for most industries, stock returns decline following a surprise tightening in monetary policy. This typically holds true for both the high and low comovement regimes. Second, there is a substantial degree of heterogeneity in the responses across industries. For example, the posterior credible sets for the responses to a monetary policy shock of specific industries (particularly energy-related industries), such as Petroleum and Natural Gas ("Oil"), Precious Metals, Non-Metallic, and Industrial Mining ("Mines"), Coal ("Coal") and Tobacco products ("Smoke") include zero in the low comovement regime. To the extent that commodity-sensitive stocks have predictive power for commodity prices, this suggests that the empirical relevance of models relating oil price fluctuations changes in U.S. interest rates remains rather elusive. Moreover, alimentary—Food Products ("Food") and Beer and Liquor ("Beer")—and utilities industries also tend to react relatively less to monetary policy shocks compared with the other industries. These industries have typically low market "betas," suggesting that industries that are less sensitive to monetary policy shocks tend to have returns less correlated with the aggregated market return. Third, it is important to note that for all industries, responses to monetary policy shocks in the high comovement regime are amplified compared with the responses in the low comovement regime, being roughly twice larger for most industries. However, this pattern is particularly true for Fabricated Products and Machinery ("Fabpr") and Electrical Equipment ("Elceq") industries where the credible sets for responses in both regimes do not overlap over the projection horizon. A similar pattern occurs for the following industries: Construction and Construction Materials ("Cnstr"), Aircraft, Ships and Railroad Equipment ("Carry"), Business Supplies and Shipping Containers ("Paper"), Wholesale ("Whlsl") and other industries ("Others"), where the most asymmetric responses are obtained. Finally, it is also interesting to note that, for most industries, the maximum impact of the monetary policy shock takes place on impact (i.e., for horizon $h = 1$) and that the effects of the shock die out relatively quickly.[10]

As a robustness check to our baseline identification scheme, we now consider the possibility that monetary policy can react contemporaneously to stock market shocks. As mentioned earlier, the evidence for a simultaneous response of central bank authorities to the stock market seems to be mixed and related to few specific events. However, Furlanetto (2011) suggests that the evidence for such a central bank response is apparent in the data only for the stock market crash of 1987. We follow Galí and Gambetti (2015) and calibrate the coefficient corresponding to the simultaneous response of the central bank to stock market shocks at 0.2, which implies that a one standard deviation unexpected increase in the stock market (as captured by the factor) leads to a 20 basis point increase in the short-term interest rate. The responses of the macroeconomic variables are little changed relative to the baseline case; hence, we do not report these results to conserve space. Figure A1 in the Appendix shows the industry-specific responses to the monetary policy shock. These results confirm our original conclusions. First, for all industries, the response in the high comovement regime is more negative compared with the response in the low comovement regime. Moreover, in many cases, the posterior credible sets do not overlap. Second, the industries that react the most to monetary policy shocks are very much similar with this alternative identification scheme relative to our baseline idenfication scheme. For example, Figure A1 shows that the Business Equipment ("Buseq") industry is the industry that reacts the most to a monetary policy shock in the high comovement regime, and this was also the case in our baseline identification scheme. Third, the peak response of the monetary policy shock no longer occurs on impact, but instead typically occurs at a 3-quarter horizon when allowing for a simultaneous response of the central bank to stock market shocks.

Next, we evaluate whether industries that experience longer periods in the high comovement regime tend to be more sensitive to monetary policy shocks. Accordingly, on the one hand, we compute the expected duration of the high comovement regime, $P^E_{i,1}$ and

[10]Our impulse response analysis is robust to including additional lags in the VAR system.

the expected duration of the low comovement regime, $P^E_{i,0}$, for industries $i = 1, 2, ..., m$ (where m is equal to 30, the total number of industries). The expected duration of regimes can be expressed as a function of the transition probabilities

$$P^E_{i,1} = \frac{1}{1 - p_{i,11}}, \quad P^E_{i,0} = \frac{1}{1 - p_{i,00}}.$$

On the other hand, we proxy the sensitivity of an industry to monetary policy shocks with the corresponding factor loadings, since they are mechanically linked to the estimated impulse responses. Formally, factor loadings capture the extent to which a specific industry is related to aggregate stock market fluctuations, but also the degree to which an industry reacts to a specific shock that hits the factor. Therefore, we interpret $(\lambda^F_{i,0} + \lambda^F_{i,1})$ as a measure of a high degree of responsiveness to monetary policy shocks and $\lambda^F_{i,0}$ as a measure for a low degree of responsiveness to monetary policy shocks for industries $i = 1, 2, ..., m$. Figure 4 reports scatter plots that relate the degrees of comovement and responsiveness to monetary policy shocks for each of the 30 industries. This shows that industries that experience longer periods in the high comovement regime tend to experience a stronger response to monetary policy shocks, whereas industries that experience longer periods in the low comovement regime tend to show a weaker response to monetary policy shocks. Overall, these results indicate that higher connectedness is associated with a stronger response to monetary policy shocks.

3.2 Characterizing the stock market network

When assessing the propagation of monetary policy shocks in a large system of economic and financial variables using FAVAR models, previous studies have typically focused on analyzing the responses of each variable to a specific or a few structural shocks. Beside the usual impulse response analysis, a key advantage of the proposed MS2-FAVAR model is to provide information about the degree of interdependence between industry-level stock returns using the information contained in the factor loadings.

Figure 5 shows the time-varying factor loadings. This provides evidence in favor of substantial time variation in the factor loadings, suggesting that the assumption of constant factor loadings is unlikely to be appropriate. Moreover, notice that most industries tend to remain in a high comovement regime for most of the time, and experience switches to a low comovement regime less frequently. However, there are some exceptions, such as the case of Textiles ("Txtls") for which the most common state is the low comovement regime, switching to a high comovement regime with few occurrences. This may represent valuable information from the point of view of financial market participants.

Figure 6 shows the structure of the network, as defined in Equation (9), for different strengths of the linkages between industries. In panels (a) and (b) of that figure, we plot significant relations among industries where the threshold for significance is such that $q_{i,j} > c$, where c is set to 0.5 and 0.9, respectively. This shows that the network of industry-level stock returns has a core-periphery structure, with a dense core composed by most of the industries and a sparse periphery composed by "Txtls," Automobiles and Trucks ("Autos"), Steel Works ("Steel"), Communication ("Tlcm") and Restaurants, Hotels, and Motels ("Meal") industries.

However, since the structure of the network is likely to change over time, we compute the time-varying centrality measures for each industry based on the information contained in Q_t and report the results in Figure 7. The estimates show substantial heterogeneity related to the importance (i.e., centrality) of each industry over time. In the sequel, we show that the time-varying centrality measures can be related to well-known economic and financial events.

For example, in Panel (a) of Figure 8, we plot the time-varying centrality of the Financial industry, which shows that its importance tends to increase sharply during most of the recessions defined by the NBER, including the Great Recession of 2008. This can be related to the strong linkages between financial and real sectors. Also, it rose sharply around October 1997; that is, during the Asian crisis that triggered a turmoil in global stock markets.

In Panel (b) of Figure 8, we show how the importance of the oil industry increased during the late 1960s and early 1980s, when oil shocks were key drivers of the business cycle. In particular, the centrality of the oil industry picked up during 1969 when the U.S. congress voted to reduce the percentage depletion allowance, leading to a significant decline in the value of oil stocks, as documented in Lyon (1989). The importance of the oil industry also increased substantially in 1980, when the United States enacted the Crude Oil Windfall Profit Tax as part of a compromise between the Carter Administration and the Congress over the decontrol of crude oil prices. The embargo on Libyan oil imports, imposed by the Reagan Administration in 1982, was also associated to an increase in the centrality of the oil industry. A similar situation occurred in 2011, due to political turmoil in oil exporting countries such as Libya and Egypt.

Regarding the importance of the communication industry, Panel (a) of Figure 8 shows that the largest increase in the centrality of communication industry occurred in the early 1990s, when the internet started to be publicly commercialized. Other episode of high importance in the communication industry as captured by the time-varying centrality occurred during the dot-com bubble, in the early 2000's, and in the wake of the merger between AT&T and BellSouth, in December 2006, one of the largest communication mergers in history.

Another interesting example is the case of the "Steel" industry, for which its importance in the stock market network remained at relatively low levels until the late 1990s, when steel prices started to increased. In particular, the steel industry experienced its highest level of centrality during March 2002, when President Bush announced that the United States was imposing three-year tariffs on imported steel ranging from 8% to 30%. Also, the centrality of the "Steel" industry was subject to significant changes around the late 2000s, period that coincides with the end of the a so-called commodity super cycle.

The above examples show that, in general, the time-varying centrality measures experience dynamics that line up well with important industry-specific events. This information can be useful for policy makers and financial market participants in order to perform a timely assessment about the industries playing a key role in the stock market network.

4 Conclusions

This paper investigates the interactions between monetary policy and the stock market, concentrating on the extent to which this relation is affected by the degree of comovement – or connectedness – of the stock market. In doing so, our analysis uses industry-level stock return data so as to provide a comprehensive assessment of the effects of monetary policy on the stock market. Our impulse response analysis suggests that whenever an industry is more related to the aggregate stock market, this industry tends to react relatively more to monetary policy shocks. As such, our results provide evidence in favor of an important role for the connectedness of the stock market in propagating monetary policy shocks. Moreover, our analysis identifies the industries that react the most to monetary policy shocks and thereby act as conduits through which monetary policy shocks transmit to the rest of the stock market.

A key contribution of this paper is also methodological in that we show how to estimate a large-scale factor-augmented vector autoregressive model with Markov-switching factor loadings. This new framework denoted as MS2-FAVAR is well-suited to perform a network analysis of large dimensional datasets to analyze the comovement of discrete regime shifts in high-dimensional datasets. Moreover, it is straightforward to implement and can be easily adapted to many applications in macroeconomics and finance when one is interested in modelling regime switching dynamics in factor-augmented vector autoregressive models.

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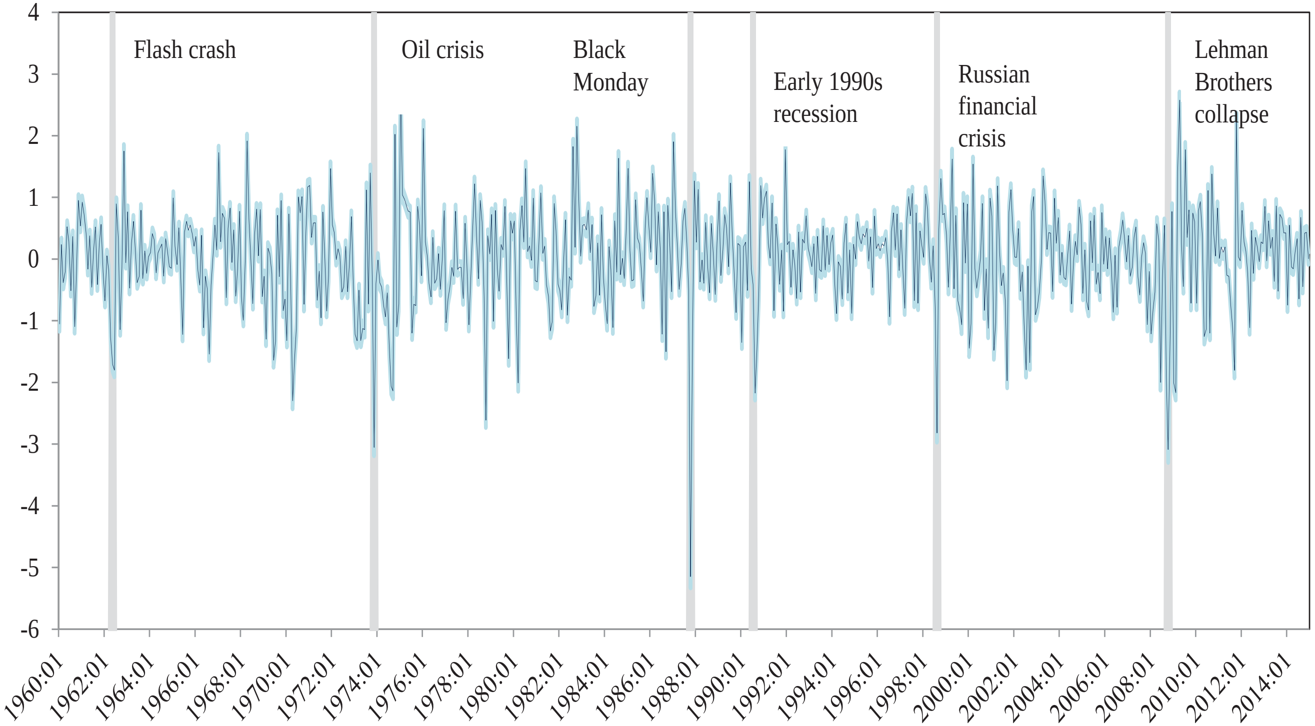
Table 1: Industry portfolio

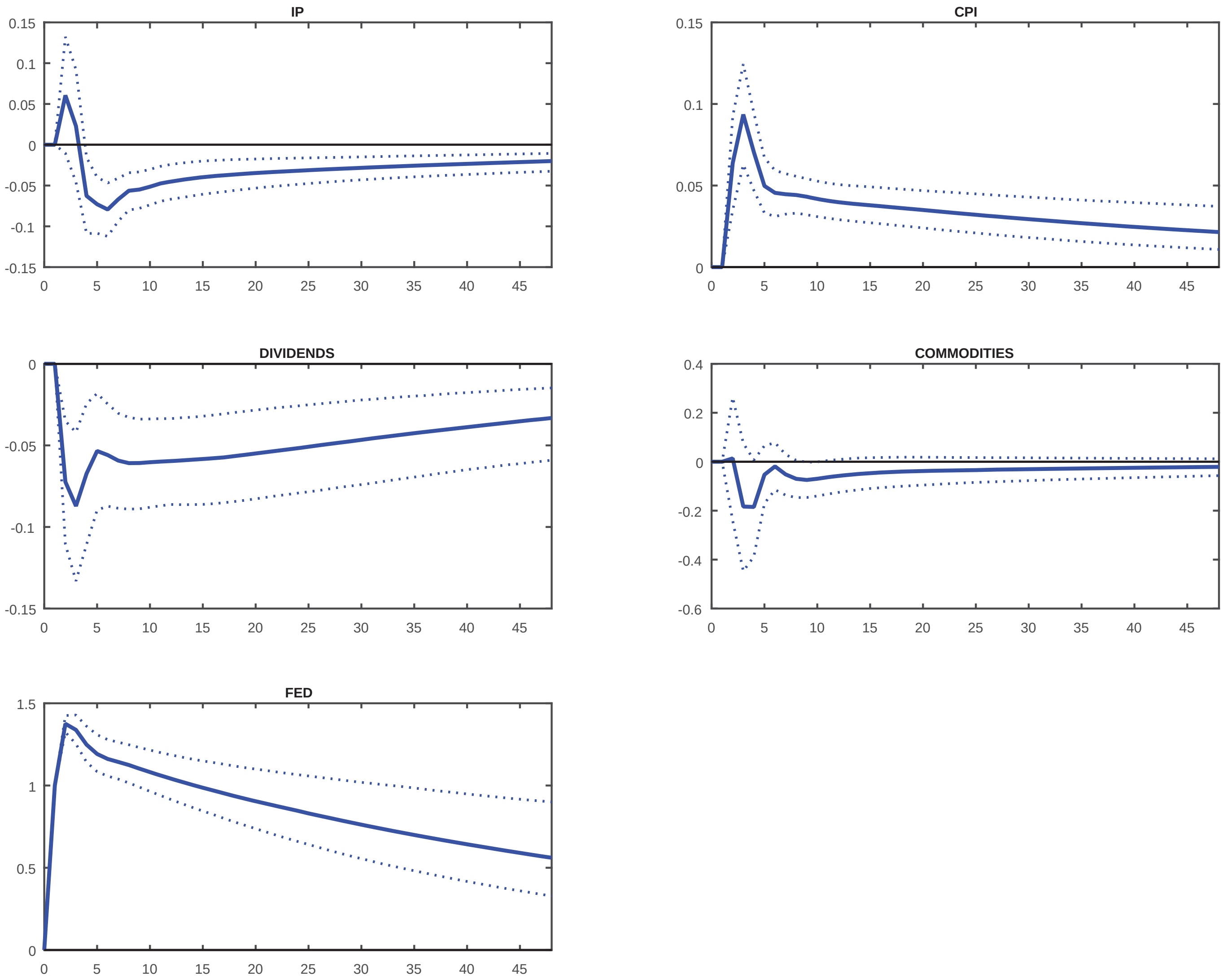
Abbreviation	Description
Food	Food Products
Beer	Beer and Liquor
Smoke	Tobacco products
Games	Recreation
Books	Printing and publishing
Hshld	Consumer goods
Clths	Apparel
Hlth	Healthcare, Medical Equipment, and Pharmaceutical Products
Chems	Chemicals
Txtls	Textiles
Cnstr	Construction and Construction Materials
Steel	Steel Works Etc.
Fabpr	Fabricated Products and Machinery
Elceq	Electrical Equipment
Autos	Automobiles and Trucks
Carry	Aircraft, Ships, and Railroad Equipment
Mines	Precious Metals, Non-Metallic, and Industrial Metal Mining
Coal	Coal
Oil	Petroleum and Natural Gas
Util	Utilities
Tlcm	Communication
Servs	Personal and Business Services
Buseq	Business Equipment
Paper	Business Supplies and Shipping Containers
Trans	Transportation
Whlshl	Wholesale
Rtail	Retail
Meals	Restaurants, Hotels, and Motels
Fin	Banking, Insurance, Real Estate, and Trading
Other	Everything Else

Figure 1: Factor extracted from the 30 industry Fama-French portfolio



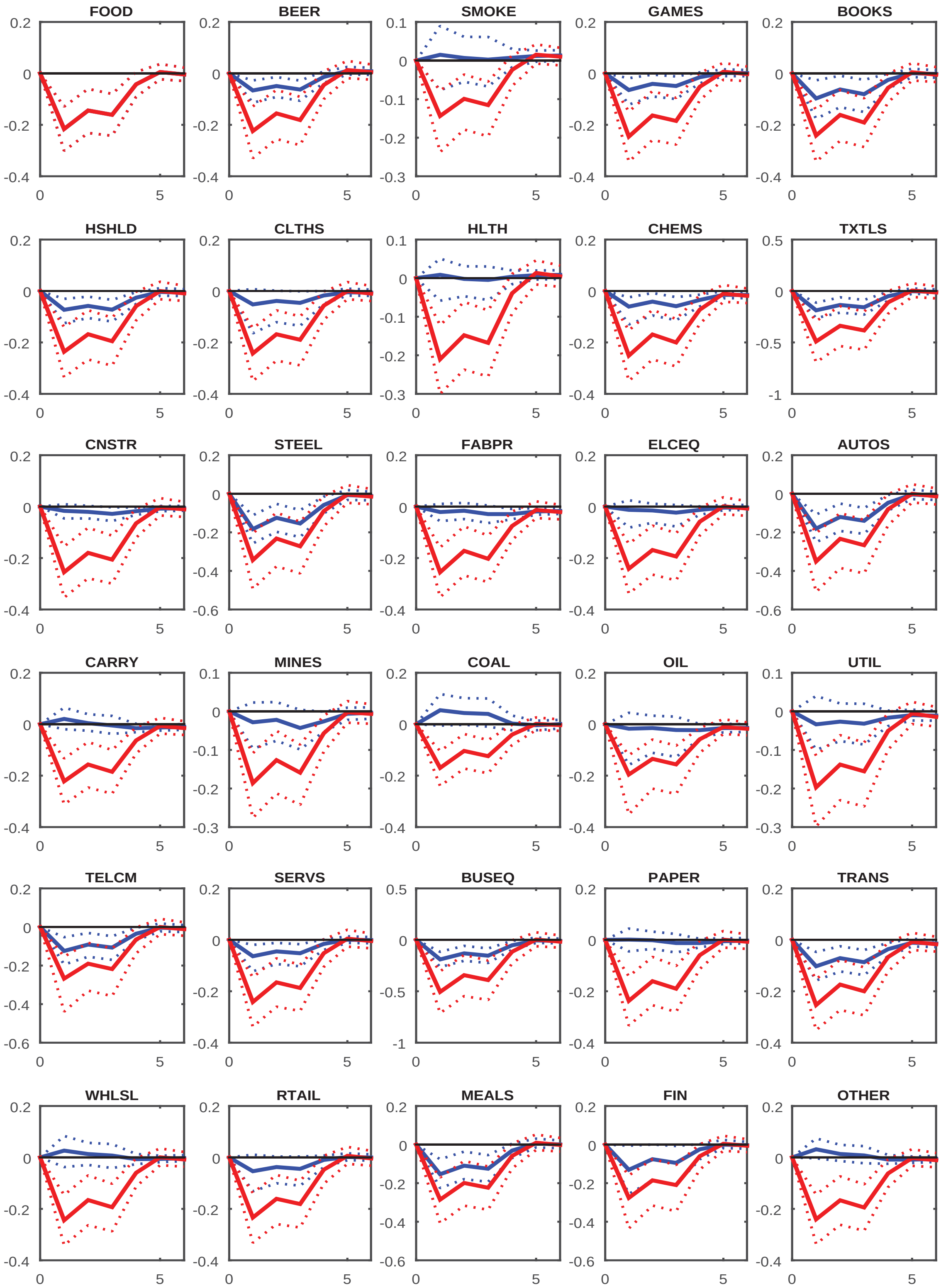
Note: This figure plots the dynamic factor extracted from the 30 industry-specific stock returns. The sample covers 1960:1-2014:12. Bands represent the 16 and 84 percentile estimates of the posterior distribution. Shaded bars indicate selected financial crash episodes.

Figure 2: Estimated responses of macroeconomic variables to a monetary policy shock from the MS2-FAVAR model



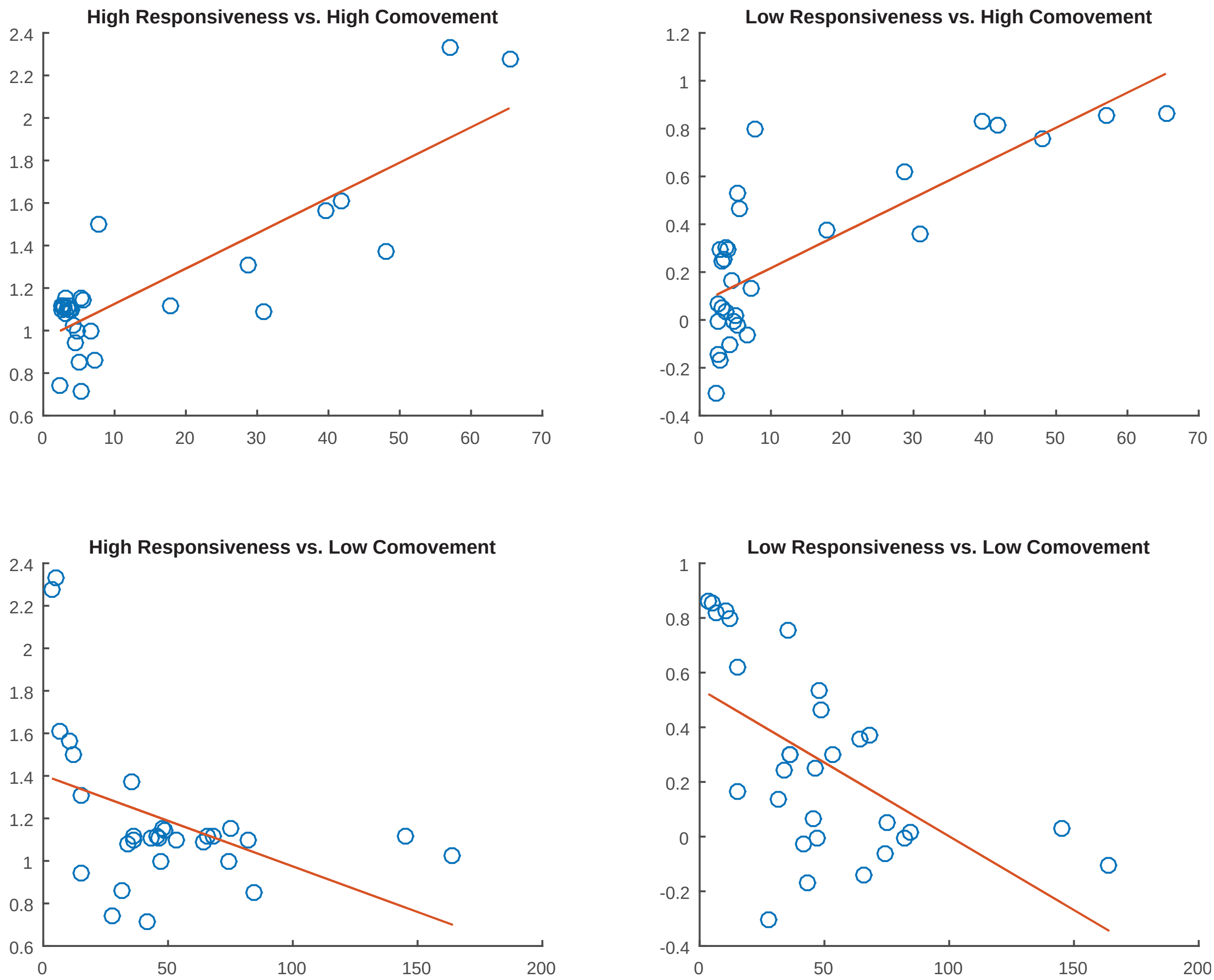
Note: This figure plots the impulse responses to an unexpected 100 basis point increase in the policy rate obtained from the MS2-FAVAR. The shock takes place in period 1. The solid line represents the median estimates of the posterior distribution, the dotted lines represent the 10- and 90- percentile estimates of the posterior distribution.

Figure 3: Estimated responses of industry-specific stock returns to a monetary policy shock from a MS2-FAVAR model



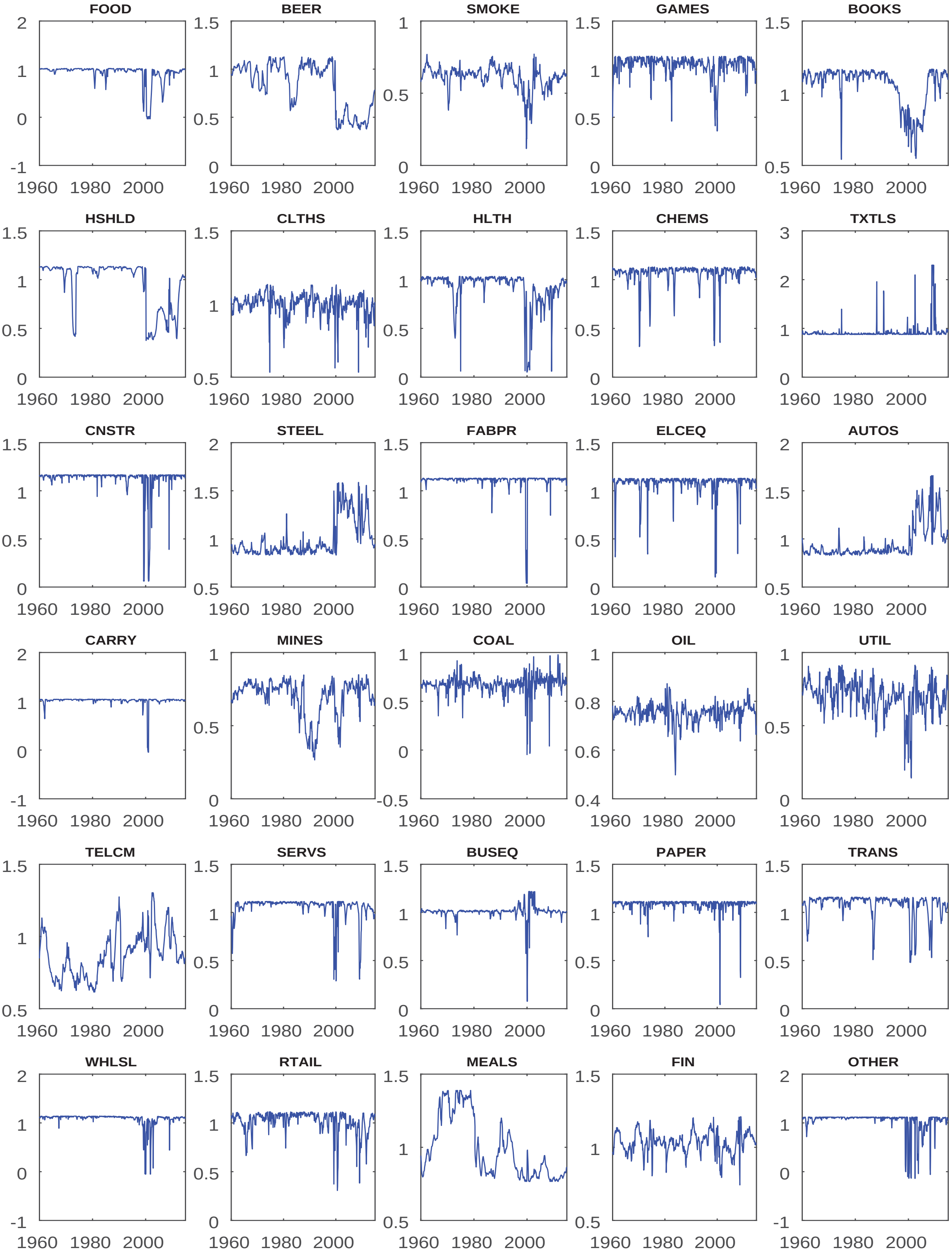
Note: Blue (red) lines plot the impulse responses to an unexpected 100 basis point increase in the policy rate during regimes of low (high) comovement. The shock takes place in period 1. The solid line represents the median estimates of the posterior distribution, the dotted lines represent the 10- and 90-percentile estimates of the posterior distribution. There is no response for the "Food" industry in the low comovement regime, since the factor loading in that case is restricted to be zero to identify the factor.

Figure 4: Stock returns comovement and monetary policy responsiveness



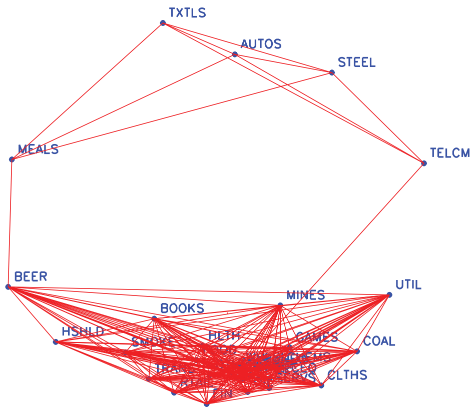
Note: The top left panel plots the high degree of responsiveness to monetary policy shocks, $(\lambda^F_{m,0} + \lambda^F_{m,1})$ against the expected duration of being in the high comovement regime, $P^E_{m,1}$. The top right chart plots low degrees of responsiveness to monetary policy shocks, $\lambda^F_{m,0}$ against the expected duration of being in the high comovement regime, $P^E_{m,1}$. The bottom left chart plots the high degree of responsiveness to monetary policy shocks, $(\lambda^F_{m,0} + \lambda^F_{m,1})$ versus the expected duration of being in the low comovement regime, $P^E_{m,0}$. The bottom right chart plots the low degrees of responsiveness to monetary policy shocks, $\lambda^F_{m,0}$ against the expected duration of being in the low comovement regime, $P^E_{m,0}$. For each chart, the Y-axis measures the factor loading, whereas the X-axis represents the expected duration of being in a given regime in months.

Figure 5: Time-varying factor loadings

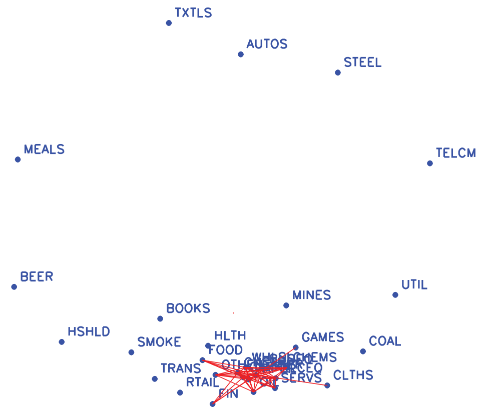


Note: This figure shows the time-varying factor loadings obtained from the MS2-FAVAR for all 30 industries.

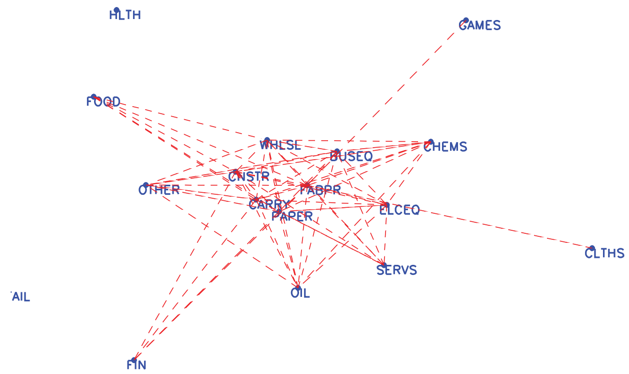
Figure 6: Network of industry-specific stock returns



(a) Bilateral relations with $q_{i,j} > 0.5$



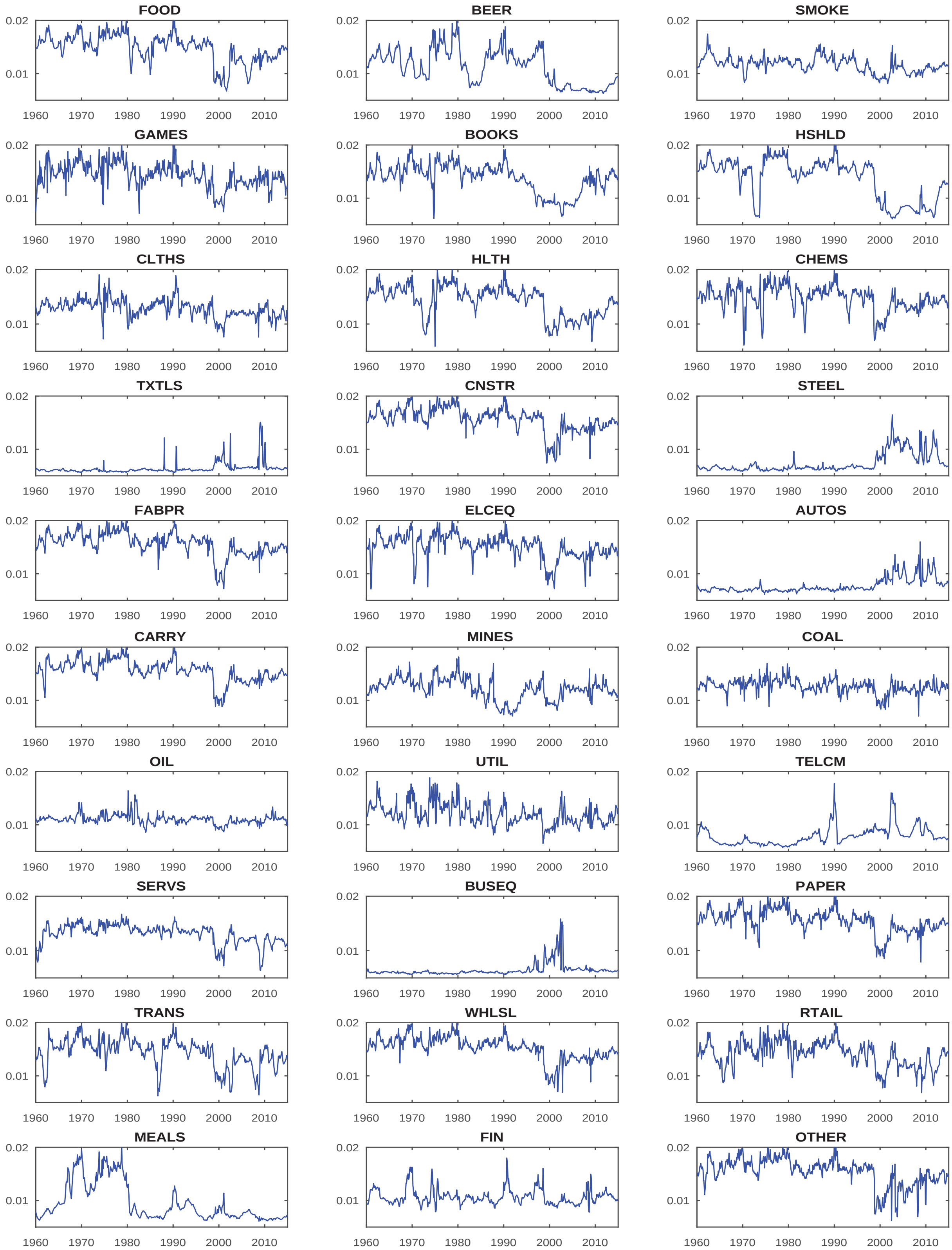
(b) Bilateral relations with $q_{i,j} > 0.9$



(c) Zoom of bilateral relations with $q_{i,j} > 0.9$

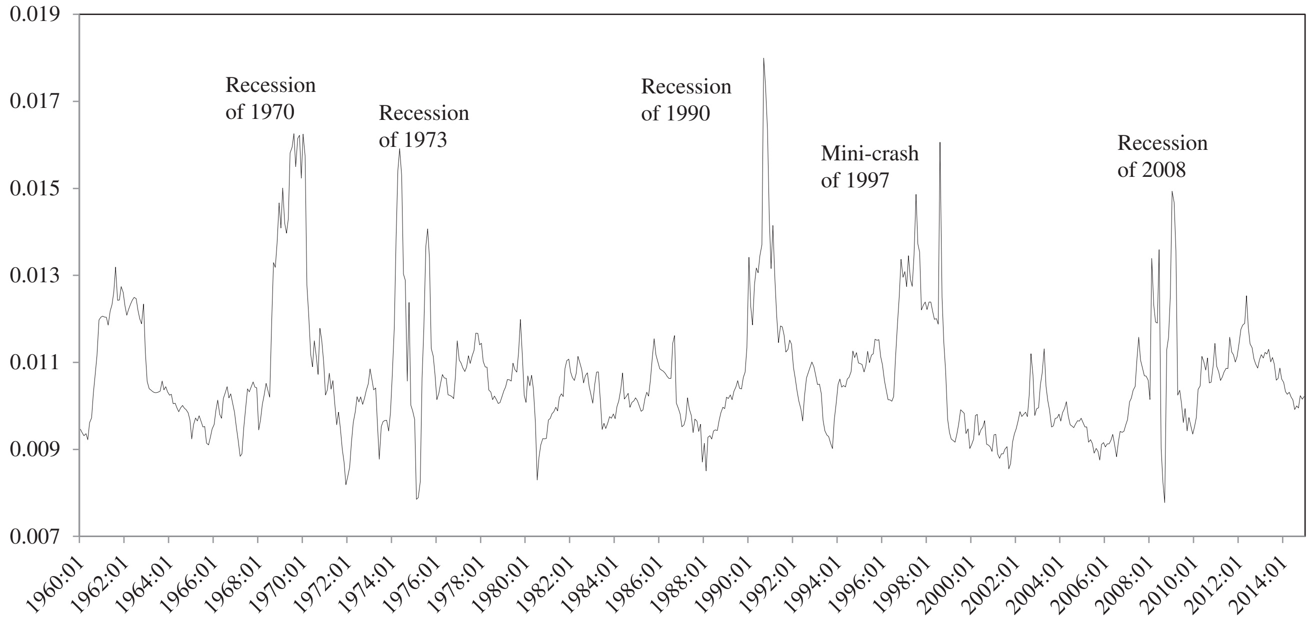
Note: The figure plots the bilateral relationships in terms of synchronization between the industry stock market returns. Each node represents an industry i, and each line represents the link between two industries i and j.

Figure 7: Time-varying centrality of industries in the stock market network

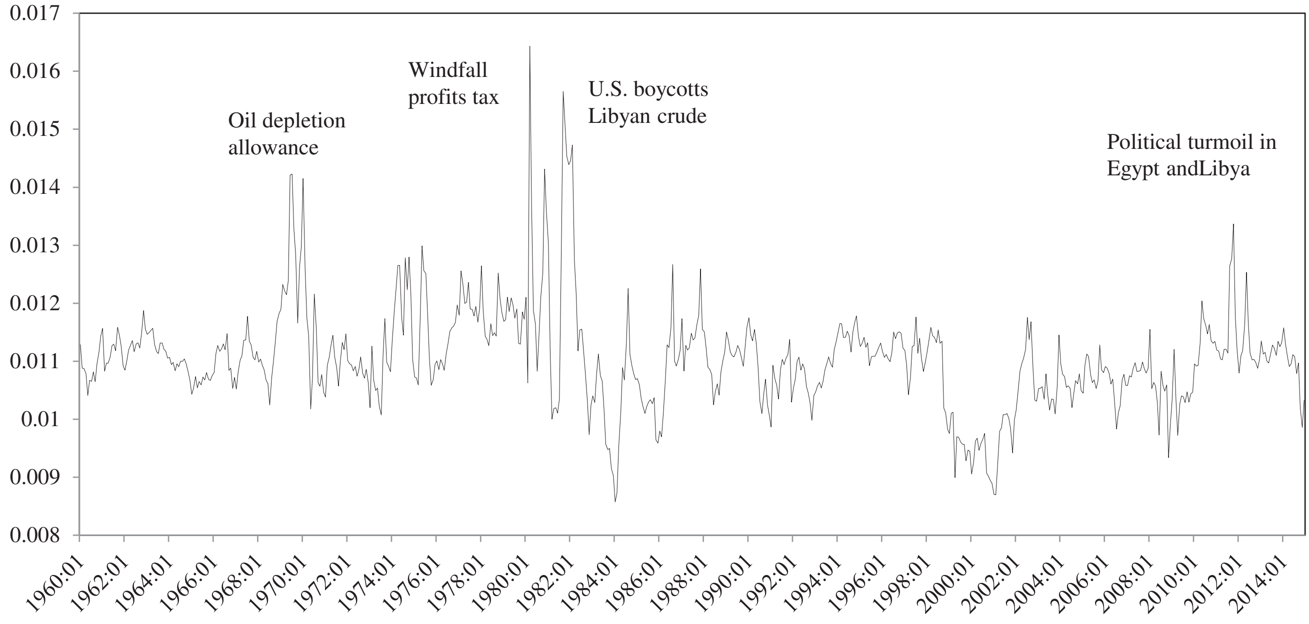


Note: This shows the time-varying centrality for all industries.

Figure 8: Time-varying centrality of selected industry-level stock markets



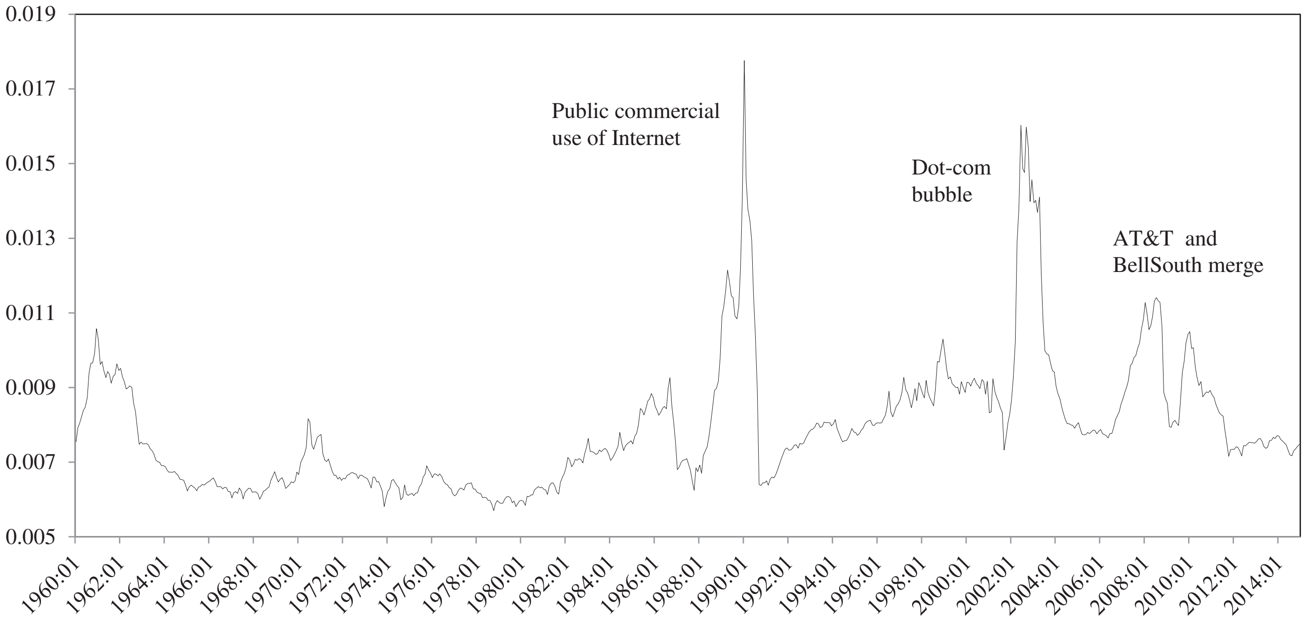
(a) Financial Industry



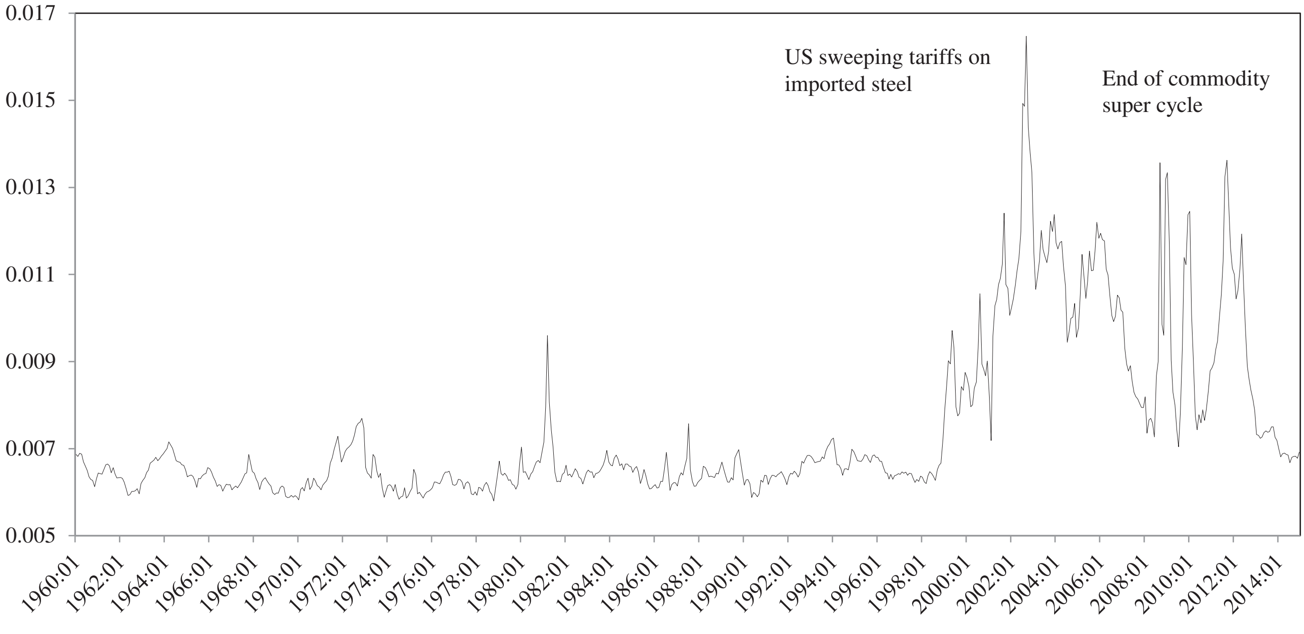
(b) Oil industry

Note: This shows the time-varying centrality for the selected industries along with specific events of relevance.

Figure 9: Time-varying centrality of selected industry-level stock markets



(a) Communication industry

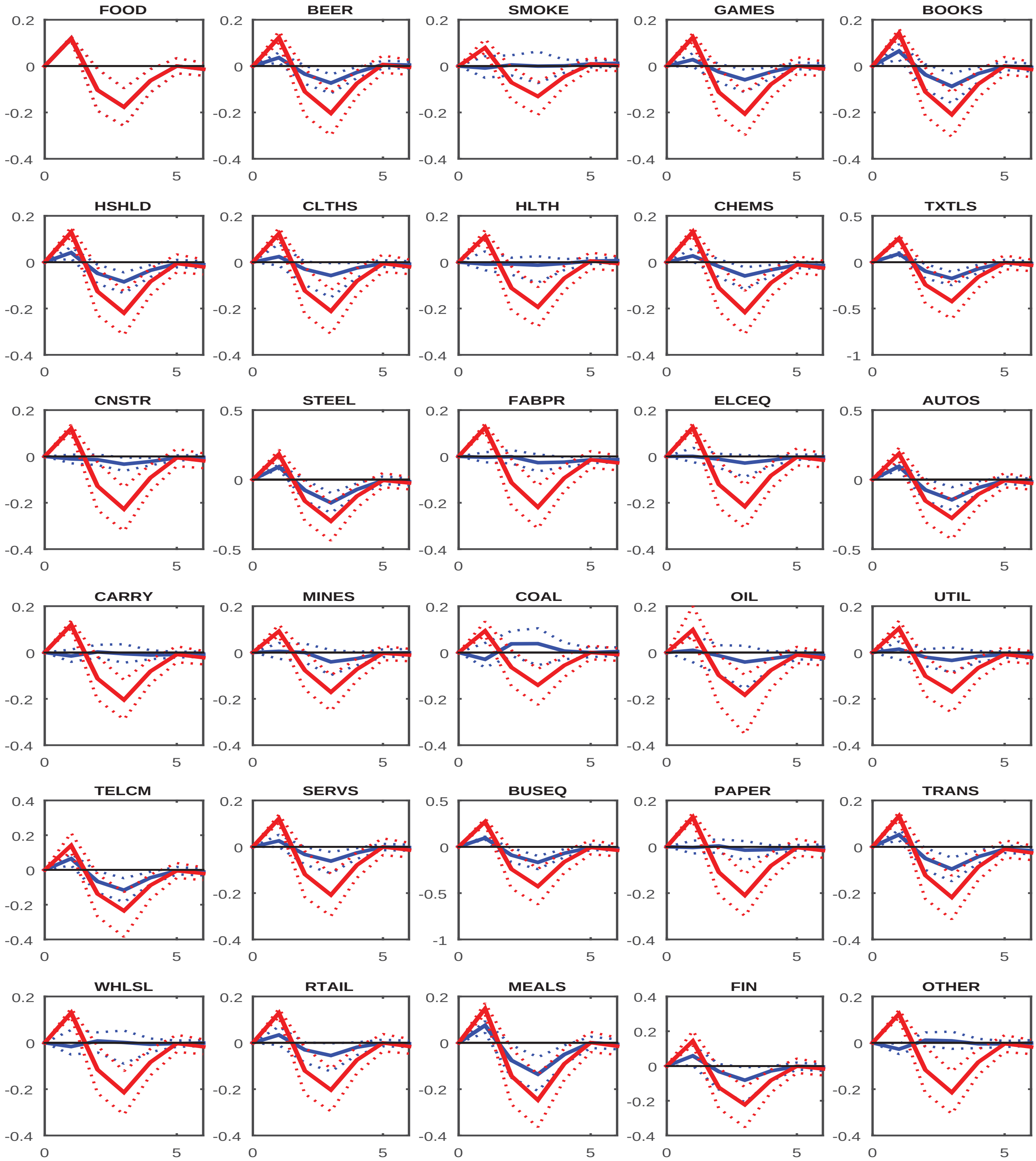


(b) Steel industry

Note: This shows the time-varying centrality for the selected industries along with specific events of relevance.

Appendix

Figure A1. Estimated responses of industry-specific stock returns to a monetary policy shock from a MS2-FAVAR model – Alternative identification scheme



Note: Blue (red) lines plot the impulse responses to an unexpected 100 basis point increase in the policy rate during regimes of low (high) comovement. The solid line represents the median estimates of the posterior distribution, the dotted lines represent the 10- and 90-percentile estimates of the posterior distribution. The identification scheme allows for a simultaneous response of monetary policy to stock market shocks.

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