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Bayesian State-Space Modeling for Analyzing Heterogeneous Network Effects of US Monetary Policy*

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Abstract

We extend the econometric literature on the role of production networks in the propagation of monetary policy shocks along two dimensions. First, we allow for time-varying industry-specific responses, reflecting non-linearities and heterogeneity in direct transmission channels. Second, we allow for time-varying network structures and dependence. This captures both variation in the structure of the production network and differences in cross-industry demand elasticities. Spillover effects among industries appear to be important in periods of elevated economic and financial uncertainty, often coinciding with tight credit market conditions and financial stress. Cross-sectional differentials can be explained by how close industries are to end-consumers.

Keywords: High-frequency identification; monetary policy shocks; production networks; spatio-temporal modeling

JEL classification: *C*11; *C*23; *C*32; *C*58; *E*52

I. Introduction

There is a growing body of literature that explores how shocks on the micro and macro level propagate through economic networks, and how such shocks relate to aggregate fluctuations (see, for instance, Gabaix, 2011; Acemoglu *et al*., 2012, 2015; Carvalho and Gabaix, 2013; Elliott *et al*., 2014; Baqaee and Farhi, 2019). We contribute to this literature by analyzing the transmission of monetary policy shocks through the granular US production network. Our interest centers on assessing time variation

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in the strength of network dependence, and the effects of monetary policy shocks on industry-level returns that are allowed to vary over time and the cross-section.

Our approach relates to Ozdagli and Weber (2020), who generalize the set-up proposed in Bernanke and Kuttner (2005) and Gürkaynak *et al*. (2005) for analyzing the effects of changes in monetary policy on equity prices.[1] While Bernanke and Kuttner (2005) and Gürkaynak *et al*. (2005) identify a significant and substantial effect of monetary surprises on aggregate stock market indices, Ozdagli and Weber (2020) decompose these estimates into direct effects and spillovers through the production network. They use a conventional network panel model, and provide evidence for significant higher-order effects of monetary policy on stock market returns between 55 and 85 percent using disaggregate data on the industry-level.

These higher-order dynamics originate from cross-industry demand elasticities to the same shock, amplifying direct effects of monetary policy interventions in the interconnected US production network. We provide extensions from an econometric and empirical perspective by drawing from the vast literature on Bayesian state-space modeling (see Kim and Nelson, 1999), combining these methods with network panel data models (see, for instance, Elhorst, 2014; Aquaro *et al*., 2015; LeSage and Chih, 2016).

Neglecting heterogeneities over time or the cross-section can conceal important transmission channels, for two reasons. First, there is evidence for structural breaks in the transmission of monetary policy shocks to macroeconomic and financial variables (Cogley and Sargent, 2005; Primiceri, 2005; Paul, 2020). Several studies find that returns respond much more strongly to surprise monetary policy shocks during tight credit market conditions, or during bear markets (see Chen, 2007; Basistha and Kurov, 2008; Kurov, 2010; Kontonikas *et al*., 2013). It is unclear, however, if these differences originate from changes in the covariance structure across industries that reflect network dependency and higher-order effects, or whether they stem from direct responses in the conditional mean of conventional regressions (captured, for instance, via time-varying parameters, TVPs). While Ozdagli and Weber (2020) assume constant parameters, they characterize the production network as non-linear and to exhibit cycles (see Section II of their paper). This motivates our approach of introducing time-varying network dependence alongside TVPs.

[1]These articles are among a larger body of diverse literature focusing on measuring monetary non-neutrality using high-frequency market surprises around central bank policy announcements (see Cook and Hahn, 1989; Thorbecke, 1997; Kuttner, 2001; Cochrane and Piazzesi, 2002; Rigobon and Sack, 2004; Gürkaynak *et al*., 2005; Gertler and Karadi, 2015; Lucca and Moench, 2015; Nakamura and Steinsson, 2018; Neuhierl and Weber, 2018; Altavilla *et al*., 2019; Jarociński and Karadi, 2020; Paul, 2020).

Second, pooling information across industries can conceal underlying structural relationships. Also, it potentially distorts the estimated importance of some industries in the disaggregate transmission of monetary policy shocks compared with others (see Ehrmann and Fratzscher, 2004; Gorodnichenko and Weber, 2016). This is a crucial notion, considering that industries differ substantially in size and use vastly different production inputs. In a theoretical framework, Pasten *et al*. (2018, 2020) show that differences in price rigidities originating from such heterogeneities are determinants of how policy interventions are transmitted to the real economy.

To address heterogeneity over time and the cross-section, we develop a flexible Bayesian state-space model. Both the network dependence parameter and the regression coefficients are assumed to vary over time via imposing random-walk state equations. The time-varying regression coefficients can be estimated by relying on a standard conditionally Gaussian state-space model using panel data for industry-level returns in the US. Moreover, as a technical novelty, we propose a sampling algorithm for the time-varying network dependence parameter. Our approach aims to shed light on the question whether network effects play a role in determining the overall time-varying effect of monetary policy shocks on stock returns.

From an empirical perspective, several findings are worth noting. First, we detect substantial differences over time and the cross-section. Our estimates indicate that the overall strength of network effects varies between 40 and 80 percent. Differences over time can be linked to periods of economic and financial uncertainty, often coinciding with tight credit market conditions and financial stress. Second, time variation in network dependence translates to substantial differences in total effects of monetary policy on stock returns. In fact, we find that estimates in some periods are about 2 percent in response to a surprise one percentage point increase in the federal funds rate, while these effects can be as large as 10 percent in others. Third, our results show substantial heterogeneity over the cross-section. We cluster industries by assessing the joint distribution of total and network effects econometrically, and we obtain two main clusters. The clusters can roughly be described as classifying industries regarding their closeness to end-consumers in the production network. The closer an industry is to end-consumers, the smaller is the share attributed to network effects.

The rest of the paper is structured as follows. In Section II, we set forth the model alongside the Bayesian prior set-up and a sampling algorithm for inference. In Section III, we introduce the dataset. Our main results on network dependence in the propagation of US monetary policy shocks are discussed in Secion IV. We conclude in Section V. Appendix A contains further details on the sampling algorithm, Appendix B gives details of the data, and there is also a supplementary Online Appendix with additional empirical results.

II. A Time-Varying Network Dependence Panel Model

We define the measurement equation for industry $i = 1, \ldots, N$ as

$$y_{it} = \rho_t \sum_{j=1}^{N} w_{ijt} y_{jt} + \alpha_{it} + \mathbf{x}'_{it}\boldsymbol{\beta}_{it} + \epsilon_{it}, \quad \epsilon_{it} \sim \mathcal{N}\left(0, \sigma_i^2\right), \tag{1}$$

where y_{it} is the response variable at time $t = 1, \ldots, T$. We include a time-varying intercept term α_{it}, K exogenous covariates in the $K \times 1$ vector $\mathbf{x}_{it}$ with associated observation specific TVP vector $\boldsymbol{\beta}_{it}$ of size $K \times 1$ and a Gaussian error term with zero mean and variance σ_i^2. Equation (1) is a general specification of our model. In the empirical application, the vector $\mathbf{x}_{it}$ reduces to a scalar that is common across all observations i. In particular, $\mathbf{x}_{it} = v_t$ where v_t denotes the identified monetary policy shocks (see Section III for details).

Information on the cross-sectional dependency structure is incorporated using weighted averages of the "foreign" quantities y_{jt} $(j = 1, \ldots, N)$ with time-varying weights w_{ijt}. These weights denote the elements of a pre-determined $N \times N$ weighting matrix $\mathbf{W}_t$ subject to the restrictions $w_{ijt} \geq 0$ and $\sum_{j=1}^{N} w_{ijt} = 1$. Cross-sectional weights are commonly based on observables or simple ad hoc definitions, describing the network structure in a sensible way. We follow Ozdagli and Weber (2020) and use a weights matrix capturing intermediate input shares across industries to model the US production network. The choice of this matrix is derived from a theoretical model of production with intermediate inputs and provides a precise structural interpretation. We explicitly allow for the network structure to change via $\mathbf{W}_t$ in our baseline specification to capture the varying relative importance of industries in the production network (see also Carvalho and Gabaix, 2013).

We propose that the scalar parameter ρ_t should feature time variation.[2] The state equation for the network dependence parameter ρ_t is a random-walk process:

$$\rho_t = \rho_{t-1} + \varsigma \xi_t, \quad \xi_t \sim \mathcal{N}(0, 1). \tag{2}$$

[2]This feature is related to time-varying network structures (see Asgharian *et al*., 2013; Billio *et al*., 2016a), assuming that linkage matrices evolve over time, but keeping the overall strength of network effects constant. By contrast, we introduce additional flexibility by assuming a time-varying network structure and dependence parameter. Our model can be considered as an extended Bayesian version of Blasques *et al*. (2016) and Catania and Billé (2017) that features several technical novelties, resulting in a more flexible specification.

The covariance matrix of the reduced-form errors for the stacked version of the model at time t is given by the expression

$$(\mathbf{I}_N - \rho_t \mathbf{W}_t)^{-1} \mathbf{\Sigma} (\mathbf{I}_N - \rho_t \mathbf{W}_t)^{-1\prime},$$

with $\mathbf{\Sigma} = \text{diag}(\sigma_1^2, \ldots, \sigma_N^2)$. Econometrically, the parameter ρ_t can thus be interpreted as a common factor, capturing a special form of stochastic volatility. $\mathbf{W}_t$ acts as a pre-determined matrix of factor loadings.[3] This relates to measures of dynamic connectedness (Diebold and Yilmaz, 2009; Demirer *et al.*, 2018), and studies capturing financial contagion and systemic risk (see Forbes and Rigobon, 2002; Blasques *et al.*, 2016). The structural interpretation of the proposed $\mathbf{W}_t$ relates our study to investigations regarding network effects of aggregate demand shocks. Intuitively, as $\mathbf{W}_t$ solely captures time-varying relative input shares, ρ_t governs time-varying cross-industry elasticities with respect to the exogenous variables.

Allowing for TVPs is straightforward by drawing from the vast literature on state-space models (see Kim and Nelson, 1999, for a textbook overview). The regression coefficients are stacked in a $(K+1)\times 1$ vector $\boldsymbol{\theta}_{it} = (\alpha_{it}, \boldsymbol{\beta}'_{it})'$. We assume independent random-walk state equations for industries $i = 1, \ldots, N$:

$$\boldsymbol{\theta}_{it} = \boldsymbol{\theta}_{it-1} + \boldsymbol{\eta}_{it}, \quad \boldsymbol{\eta}_{it} \sim \mathcal{N}(\mathbf{0}, \mathbf{\Omega}_i).$$

Here, $\boldsymbol{\eta}_{it}$ is a zero-mean Gaussian error term and diagonal covariance matrix $\mathbf{\Omega}_i = \text{diag}(\omega_{i1}, \ldots, \omega_{iK+1})$ of size $(K+1) \times (K+1)$. The state innovation variances in $\mathbf{\Omega}_i$ govern the degree of time-variation in the regression coefficients.

Interpreting the Model Coefficients

The approach to modeling network dependence pursued in this paper establishes a large system of simultaneous equations with specific parametric restrictions. Consequently, standard interpretations for linear regressions have to be adapted to account for the notion of cross-sectional dependence.

We follow LeSage and Chih (2016) and derive the impact matrix that contains the partial derivatives for all industries in $\mathbf{y}_t = (y_{1t}, \ldots, y_{Nt})'$ with respect to a change in the kth exogenous covariate $\mathbf{x}_{kt} = (x_{1kt}, \ldots, x_{Nkt})$ of industry $i = 1, \ldots, N$, $k = 1, \ldots, K$, $t = 1, \ldots, T$. Assuming time-varying

[3]Although network multipliers (see the next subsection) can also be estimated in unrestricted multivariate systems by decomposing the covariance matrix of the reduced-form errors, the identification of specific network connections and their interpretation are less straightforward (Diebold and Yilmaz, 2009; Bianchi *et al.*, 2015; Billio *et al.*, 2016b).

network dependence and regression coefficients, we obtain an impact matrix $\mathbf{S}_{kt}$:

$$\begin{aligned}
\frac{\partial \mathbf{y}_t}{\partial \mathbf{x}_{kt}} &= \mathbf{S}_{kt} = \begin{bmatrix} \partial y_{1t}/\partial x_{1kt} & \partial y_{1t}/\partial x_{2kt} & \dots & \partial y_{1t}/\partial x_{Nkt} \\ \partial y_{2t}/\partial x_{1kt} & \partial y_{2t}/\partial x_{2kt} & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \partial y_{Nt}/\partial x_{1kt} & \dots & \dots & \partial y_{Nt}/\partial x_{Nkt} \end{bmatrix} \\
&= (\mathbf{I}_N - \rho_t \mathbf{W}_t)^{-1} \mathbf{B}_{kt}.
\end{aligned}$$

Here, $\mathbf{B}_{kt} = \text{diag}(\beta_{1kt}, \dots, \beta_{Nkt})$ with β_{ikt} referring to the kth coefficient of industry i at time t, and the term $(\mathbf{I}_N - \rho_t \mathbf{W}_t)^{-1}$ is a network multiplier matrix governing the propagation of the shocks through the network structure. We define the variants of the effects, as follows.

1. *Direct effects per industry* are given by the main diagonal of $\mathbf{S}_{kt}$. This corresponds to the partial derivative of the response variable of industry i with respect to the kth exogenous variable of the same industry adjusted for higher-order effects stemming from the network multiplier matrix. The *average direct effect* is $1/N \times \text{tr}(\mathbf{S}_{kt})$, that is, the average of the main diagonal of the impact matrix $\mathbf{S}_{kt}$.

2. The *total effects per industry* can be calculated by $\mathbf{S}_{kt}\iota_N$ (with ι_N denoting an $N \times 1$-vector of ones), reflecting the sum of all derivatives of the response variable in industry i with respect to the kth explanatory variable of all other industries and itself. The *average total effect* is defined as $1/N \times \iota_N' \mathbf{S}_{kt} \iota_N$.

3. The *average indirect effect* or network effect is the difference between the total and direct effects, and can also be computed per industry (*indirect effects per industry*). This measure thus captures cross-industry partial derivatives on the off-diagonal positions in $\mathbf{S}_{kt}$. The share of *network effects in percent* is calculated as indirect divided by total effects.

Prior Specification

We estimate the proposed model using Bayesian methods. This involves selecting suitable prior distributions for all parameters and combining them with the likelihood of the data given by equation (1). We choose the prior distributions, as follows.

1. To define the prior distribution on the time-varying regression coefficients, we consider the state-space model in its non-centered parametrization (for details, see Frühwirth-Schnatter and Wagner,

2010). Let $\sqrt{\mathbf{\Omega}_i} = \text{diag}(\sqrt{\omega_{i1}}, \ldots, \sqrt{\omega_{iK+1}})$. Then, we split the coefficients into a constant and time-varying part: $\boldsymbol{\theta}_{it} = \boldsymbol{\theta}_{i0} + \sqrt{\mathbf{\Omega}_i}\tilde{\boldsymbol{\theta}}_{it}$. Using this transformation, $\tilde{\boldsymbol{\theta}}_{it}$ follows a random walk with standard normal shocks. For the prior on the initial state of the time-varying regression coefficients, we assume $\boldsymbol{\theta}_{i0} \sim \mathcal{N}(\mathbf{0}, a\mathbf{V}_i)$ where $\mathbf{V}_i$ collects the ordinary least-squares variances on its main diagonal and $a = 100$ determines the tightness of the prior. This establishes a weakly informative variant of the g-prior (see Zellner, 1986) for the time-invariant part of the coefficients. We use independent Gamma priors on the state innovation variances, which translates to a Gaussian prior on their square root (see Frühwirth-Schnatter and Wagner, 2010): $\sqrt{\mathbf{\Omega}_i} \sim \mathcal{N}(\mathbf{0}, b\mathbf{V}_i)$. The tightness parameter b is set to 0.1, resulting in a comparatively tight prior that is required for regularizing the high-dimensional TVPs.

2. For the initial state of the network dependence parameter ρ_0, we choose the prior $\rho_0 \sim \mathcal{N}(\mu_0, \varsigma_0^2)$ with $\mu_0 = 0$ and $\varsigma_0^2 = 0.1$.
3. On the state innovation variances of the network dependence parameter, we assume a mildly informative inverse Gamma prior, $\varsigma^2 \sim \mathcal{G}^{-1}(c_\varsigma, d_\varsigma)$ with $c_\varsigma = 3$ and $d_\varsigma = 0.03$.
4. The measurement equation error variances are assigned weakly informative independent inverse Gamma priors, $\sigma_i^2 \sim \mathcal{G}^{-1}(c_\sigma, d_\sigma)$, with $c_\sigma = d_\sigma = 0.01$.

Estimating Time-Varying Network Dependence

Combining the likelihood of the model with the proposed prior distributions yields a set of well-known conditional posterior distributions for most parameters. These conditional posteriors can be used for setting up a Markov chain Monte Carlo (MCMC) sampling algorithm involving forward-filtering backward-sampling (FFBS; see Carter and Kohn, 1994; Frühwirth-Schnatter, 1994). Most of the quantities involved are standard, and we discuss details in Appendix A.

However, producing draws for the full history of the time-varying network dependence parameter is novel to the literature. In the following, we propose a sampling algorithm for the time-varying network dependence parameter. Because of the non-Gaussian set-up, Kalman-filter based methods (such as FFBS) are inapplicable. Simulation from the posterior distribution can be carried out using a Metropolis–Hastings algorithm.

We label the current draw of the respective quantity by $s-1$, and s refers to a proposal from the candidate density. The procedure is similar to the algorithm proposed in the context of Bayesian stochastic volatility models in

Jacquier *et al.* (2002). As no initial value ρ_0 is available, we rely on Jacquier *et al.* (2002) who show that this quantity can be obtained by drawing from a Gaussian distribution $\rho_0^{(s)} \sim \mathcal{N}(\bar{\mu}_0, S_0)$. The corresponding moments are $S_0 = (\varsigma_0^2 \varsigma^2)/(\varsigma_0^2 + \varsigma^2)$ and $\bar{\mu}_0 = \varsigma_0^2(\mu_0/\varsigma_0^2 + \rho_1^{(s-1)}/\varsigma^2)$. Moreover, we rely on the following three conditional prior distributions defined by equation (2).

1. The conditional prior at $t = 1$ is given by $\rho_1^{(s)} \sim \mathcal{N}(\bar{\mu}_1, S_1)$, where $\bar{\mu}_1 = (\rho_0^{(s)} + \rho_1^{(s-1)})/2$ and $S_1 = \varsigma^2/2$.

2. For all points in time other than the first and last period, the conditional prior distribution for $\rho_t^{(s)}$ is $\rho_t^{(s)} \sim \mathcal{N}(\bar{\mu}_t, S_t)$, with $\bar{\mu}_t = (\rho_{t-1}^{(s)} + \rho_{t+1}^{(s-1)})/2$ and $S_t = \varsigma^2/2$.

3. For the final value at $t = T$, because ρ_{T+1} is not available, the conditional prior density is $\rho_T^{(s)} \sim \mathcal{N}(\bar{\mu}_T, S_T)$ with $\bar{\mu}_T = \rho_{T-1}^{(s)}$ and $S_T = \varsigma^2$.

For each period, we generate a proposal $\rho_t^{(s)} \sim \mathcal{N}(\rho_t^{(s-1)}, c)$ where c is a tuning parameter. This proposal is used to calculate the acceptance probability of the Metropolis–Hastings algorithm. To simplify notation, we define $\tilde{y}_{it}(\rho_t^{(s)}) = \rho_t^{(s)} \sum_{j=1}^{N} w_{ij,t} y_{jt} \times \sigma_i^{-1}$ and $\tilde{\mathbf{y}}_t(\rho_t^{(s)}) = (\tilde{y}_{1t}(\rho_t^{(s)}), \ldots, \tilde{y}_{Nt}(\rho_t^{(s)}))'$ as the vector of network lags depending on the current value $\rho_t^{(s)}$, with σ_i^2 referring to the error variance of industry i, and we set $\tilde{\epsilon}_{it} = (y_{it} - \alpha_{it} - \mathbf{x}_{it}'\beta_{it}) \times \sigma_i^{-1}$. Again, we stack these quantities in $\tilde{\boldsymbol{\epsilon}}_t = (\tilde{\epsilon}_{1t}, \ldots, \tilde{\epsilon}_{Nt})'$. Let

$$\mathcal{L}(\rho_t^{(s)}) = \det(\mathbf{I}_N - \rho_t^{(s)}\mathbf{W}_t) \times \exp\{-0.5(\tilde{\boldsymbol{\epsilon}}_t - \tilde{\mathbf{y}}_t(\rho_t^{(s)}))'(\tilde{\boldsymbol{\epsilon}}_t - \tilde{\mathbf{y}}_t(\rho_t^{(s)}))\}.$$

Then, the acceptance probability ζ of the proposal $\rho_t^{(s)}$ implied by the likelihood is

$$\zeta = \min\left(\frac{\mathcal{L}\left(\rho_t^{(s)}\right) \times \mathcal{N}\left(\rho_t^{(s)}; \bar{\mu}_t, S_t\right)}{\mathcal{L}\left(\rho_t^{(s-1)}\right) \times \mathcal{N}\left(\rho_t^{(s-1)}; \bar{\mu}_t, S_t\right)}, 1\right).$$

The candidate draw $\rho_t^{(s)}$ is accepted with probability ζ. Otherwise, we retain the previous draw $\rho_t^{(s-1)}$. After obtaining the full history for ρ_t, we simulate the variance ς^2 using standard posterior moments for the error variance in Bayesian linear regression models.

III. Data and Model Specification

In this section, we describe the dataset. We first provide information on the exogenous monetary policy shocks. This discussion is followed by our classification of industries and the construction of the cross-sectional linkages. Michael Weber kindly provided us with the original industry-level dataset and the exogenous monetary policy measure used in Ozdagli and Weber (2020). All our codes and the dataset are available at https://github.com/mpfarrho/tvp-network-panel.

Measuring Monetary Policy Shocks

As an exogenous measure of the monetary policy shocks, we rely on high-frequency changes in federal funds futures. The predetermined nature of monetary policy announcement dates – eight regular Federal Open Market Committee (FOMC) meetings per year, with press releases communicating policy decisions typically around 14:15 Eastern time – allows for extracting the surprise component of the monetary policy action. We use high-frequency data on forward-looking financial instruments in a tight window of $\Delta t = \tau(1) + \tau(2) = 30$ minutes around the press release. In particular, we define monetary policy shocks v_t as

$$v_t = \frac{D}{D-t}\left(\mathrm{FF}_{t+\tau(2)} - \mathrm{FF}_{t-\tau(1)}\right).$$

Here, $\mathrm{FF}_{t+\tau(2)}$ is the rate implied by federal funds futures after the announcement at time t, $\mathrm{FF}_{t-\tau(1)}$ denotes the same rate before the FOMC announcement, and D is the number of days in the month, which is needed for adjusting for the fact that the federal funds futures settle on the average effective overnight federal funds rate. The tight window around the announcement defined by $\tau(1) = 10$ minutes and $\tau(2) = 20$ minutes reduces the risk of other events than monetary policy decisions affecting futures prices, and provides support for the claim of exogeneity (see also Bernanke and Kuttner, 2005; Gürkaynak *et al*., 2005).

We focus on scheduled FOMC meetings and exclude emergency meetings to reduce the risk of biasing our estimates with confounding signaling effects (see, for instance, Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). Our information set includes data between February 1994 and December 2008 (i.e., $T = 120$). The sample starts in 1994 because the Federal Reserve (Fed) changed its communication strategy at this time and tick-by-tick stock market data are not available prior to 1993. It ends in 2008 to exclude the period when the Fed started its various unconventional monetary policy measures when approaching the zero lower bound.

The exogenous vector $\mathbf{x}_{it}$ in equation (1) features the scalar shock v_t that is common to all i, while β_{it} is the associated time-varying observation-specific parameter capturing the sensitivity of industry i to the monetary policy shock at time t. Moreover, we include an industry-specific constant α_{it}.

Industry-Level Event Returns

The industries are selected based on the availability of input–output (IO) tables published by the Bureau of Economic Analysis (BEA) and the United States Department of Commerce. These tables are needed to calculate the cross-sectional linkages in $\mathbf{W}_t$. They are published every five years, and we utilize their 1992, 1997, and 2002 versions.

We aggregate industries at the four-digit IO aggregation level, which can be mapped to the Standard Industrial Classification (SIC) and North American Industry Classification System (NAICS). The event returns for industry i used as dependent variables y_{it} are constructed based on returns for all common stocks trading on the New York Stock Exchange, American Stock Exchange or National Association of Securities Dealers around press releases by the FOMC, weighted by the corresponding market capitalization at the end of the previous trading day for industries $i = 1, \ldots, N$. The dependent variable is defined as the difference between the last trade observation before, and the first observation after, the event window. Note that we exclude industries with fewer than three firms to ensure diversified industry returns and to limit the risk of outliers affecting our results.

The panel framework requires consistent availability of event returns over time. Industry classifications change between 1992 and subsequent IO table publications. For our main results in Section IV, we thus rely on the codes in use from 1997 onwards. Following Ozdagli and Weber (2020), we exclude zero event returns, which results in $N = 58$ industries in our baseline specification. Details on the industries are provided in Appendix B. For the robustness checks provided in the Online Appendix, we also present estimates using time-invariant weighting matrices, resulting in different numbers of available non-zero industry returns due to differences in the aggregation scheme governed by the IO tables.

Cross-Sectional Dependency

To establish the cross-sectional dependency structure via the weighting matrix $\mathbf{W}_t$, we use IO tables capturing dollar trade flows between industries. The BEA provides so-called “make” (denoted by an industry-by-commodity matrix $\mathbf{W}_t^{(\text{make})}$ of size $N \times C$ with elements $w_{ict}^{(\text{make})}$, the production of goods by industries) and “use” tables (denoted by a commodity-by-industry matrix

$\mathbf{W}_t^{(\text{use})}$ of size $C \times N$ with elements $w_{cjt}^{(\text{use})}$, the uses of commodities by intermediate and final users).

Following Ozdagli and Weber (2020), we define the market shares $\mathbf{W}_t^{(\text{share})}$ of the production industries as

$$w_{ict}^{(\text{share})} = \frac{w_{ict}^{(\text{make})}}{\sum_{i=1}^{N} w_{ict}^{(\text{make})}}.$$

The share and use tables are used to calculate the amount of dollars industry j sells to industry i, denoted by the $N \times N$ matrix $\mathbf{W}_t^{(\text{rev})}$:

$$\mathbf{W}_t^{(\text{rev})} = \mathbf{W}_t^{(\text{share})} \mathbf{W}_t^{(\text{use})}.$$

The final step uses this matrix to derive the percentage of industry i inputs purchased from industry j, which defines the elements of the weight matrix $\mathbf{W}_t$ introduced in Section II:

$$w_{ijt} = \frac{w_{ijt}^{(\text{rev})}}{\sum_{c=1}^{C} w_{cjt}^{(\text{use})}}.$$

In our baseline model, we allow for time variation in $\mathbf{W}_t$. We achieve this by using the consistently available coding of industries starting 1997, using the 1997 IO tables from 1994 to the last FOMC announcement in 2001, and we rely on the 2002 IO tables from this point onwards. Because of the changes of industry classifications in 1997, we cannot use the 1992 weights matrix in this context. Thus, the weights matrix changes once at the first FOMC meeting in 2002. This specification allows for changes in the strength of overall network dependence, while addressing changes in the overall structure of industry relations via the weights matrix.

IV. Network Effects of US Monetary Policy

In a first step, we compare the results estimated with our proposed model to a set of related specifications from the established literature. For the models featuring heterogeneous coefficients, we take the arithmetic mean over all industries and over time per iteration of the algorithm and report the resulting posterior percentiles (the posterior median, and the bounds marking the 99 percent posterior credible set). This provides a measure of the average impact of monetary policy shocks on heterogeneous industry returns.

The different specifications are summarized in Table 1. "Data" indicates whether the model was estimated using aggregate (S&P 500) or granular industry-specific data (Industries). The aggregate S&P 500 returns in 30-minute windows around FOMC announcement dates are taken from

Table 1. *Model specifications*

Model	Data	Heterogeneity	Network	References
A1	S&P 500	–	–	Gürkaynak *et al.* (2005)
A2	S&P 500	t	–	Chen (2007)
B1	Industries	–	–	Bernanke and Kuttner (2005)
B2	Industries	i	–	Ehrmann and Fratzscher (2004)
B3	Industries	–	ρ	Ozdagli and Weber (2020)
B4	Industries	i	ρ	Ozdagli and Weber (2020)
C1	Industries	–	ρ_t	
C2	Industries	i	ρ_t	
C3	Industries	i, t	–	Basistha and Kurov (2008)
C4	Industries	i, t	ρ	
C5	Industries	i, t	ρ_t	

Notes: "Data" indicates whether the model was estimated using aggregate (S&P 500) or granular industry-specific (Industries) data. "Heterogeneity" marks whether we pool estimates over time and the cross-section (–), or allow for variation over the cross-section (i), over time (t), or the cross-section and over time (i, t). "Network" refers to the specification of the network dependence parameter, where "–" means no network dependence, ρ marks constant network dependence, and ρ_t refers to time-varying network dependence model proposed in this paper. In the final column, we provide references to similar specifications in the established literature.

Gorodnichenko and Weber (2016), and the exercise corresponds roughly to Bernanke and Kuttner (2005) and Gürkaynak *et al.* (2005). The industry-level data are constructed as discussed in Section III.

"Heterogeneity" marks which coefficients allow for heterogeneity. Relevant cases are pooled specifications over time and the cross-section (–), implying that we rule out time variation in the coefficients and set $\boldsymbol{\theta}_1 = \ldots = \boldsymbol{\theta}_N$ and $\sigma_1^2, = \ldots = \sigma_N^2$. Specifications marked with an i indicate that we allow for industry-specific coefficients $\boldsymbol{\theta}_i$ and σ_i^2, but suppress time variation in the regression coefficients. Those marked with t refer to time-varying regression coefficients (relevant only for the aggregate data), while i, t refers to all parameters being estimated freely across industries and over time. All of these specifications are nested in our proposed model.

"Network" refers to the specification of the network dependence parameter, where "–" denotes no network dependence, ρ marks constant network dependence, and ρ_t refers to the time-varying network dependence model proposed in this paper. The weights matrix $\mathbf{W}_t$ features time variation and is described in detail in Section III.

"References" provides an overview of papers with similar specifications referred to in Section I. Note that Chen (2007) and Basistha and Kurov (2008), referenced in the context of TVP models, rely on a different specification of the TVPs using regime-switching models. Chen (2007) uses a two-state Markov-switching model for aggregate stock market data, estimating the regime allocation endogenously (disregarding the production network), while Basistha and Kurov (2008) use firm-level data with pre-determined (binary) recession indicators to differentiate between two regimes and do not consider spillover effects. By contrast, we allow for gradual changes in the regression coefficients and consider granular industry-level data in our time-varying network dependence model.

The results across the different model types are displayed in Table 2. For the cases where there is no network dependence or where we rely on aggregate data, the regression coefficient associated with the monetary policy shocks corresponds to the total effect (no spillovers). Negative values for total effects imply stock market responses in line with standard economic theory. Monetary tightening induces a reduction of future expected dividends, and by basic asset pricing theory, higher interest rates increase the discount rate of future dividends, resulting in stock market declines. Robustness checks showing very similar results for different specifications of the weights matrix or industry aggregations, alongside a split-sample analysis, are provided in the Online Appendix.

We start by comparing the disaggregate, industry-based estimates with those obtained from regressing aggregate S&P 500 returns around announcement dates on the monetary policy shocks displayed in the first row of Table 2. For this purpose, we replicate the set-up in Gürkaynak *et al*. (2005), who rely on data from January 1990 to December 2004, using our updated dataset from February 1994 to December 2008. At this point, we note that our estimates of the total effects are rather similar for point estimates across all different specifications (with minor differences in posterior credible sets), indicating that our proposed model produces reasonable results in line with the established literature.

Accounting for posterior uncertainty and the different sample period, our estimates for the aggregate Model A1 corroborate the findings in Gürkaynak *et al*. (2005). A surprise increase of 1 percentage point in the federal funds rate translates to a decline in stock market returns of about 3.1 percent. Considering a hypothetical positive 25 basis point (bp) shock to the federal funds rate – the usual magnitude of Fed policy adjustments for the considered period – yields a decline of the S&P 500 index between 1.2 and 0.3 percent. These effects are in line with Gürkaynak *et al*. (2005) and Bernanke and Kuttner (2005), and also mirror those of Ozdagli and Weber (2020) in the context of an identical replication exercise for our sample period. Allowing for time variation in the coefficient measuring the sensitivity of S&P 500 returns to monetary policy shocks (Model A2) and aggregating the response over time ex post yields marginally larger point estimates with a slightly inflated posterior credible interval. We discuss time-varying dynamics below, but note that effect sizes differ strongly over time, a finding in line with Chen (2007).

Table 2. *Estimated effects of monetary policy on stock returns across industries*

	Parameters				Effects			
	α	β	σ^2	ρ	Indirect	Direct	Total	Network (%)
A1	−0.13	−3.11	0.23			−3.11	−3.11	
	(−0.24, −0.02)	(−4.90, −1.17)	(0.17, 0.33)			(−4.90, −1.17)	(−4.90, −1.17)	
A2	−0.15	−3.49	0.19			−3.49	−3.49	
	(−0.25, −0.04)	(−5.45, −1.58)	(0.14, 0.27)			(−5.45, −1.58)	(−5.45, −1.58)	
B1	−0.12	−3.19	0.15			−3.19	−3.19	
	(−0.14, −0.11)	(−3.49, −2.89)	(0.14, 0.15)			(−3.49, −2.89)	(−3.49, −2.89)	
B2	−0.12	−3.01	0.34			−3.01	−3.01	
	(−0.14, −0.11)	(−3.30, −2.75)	(0.32, 0.36)			(−3.30, −2.75)	(−3.30, −2.75)	
B3	−0.04	−1.05	0.15	0.67	−1.78	−1.40	−3.19	56.0
	(−0.06, −0.03)	(−1.27, −0.86)	(0.14, 0.15)	(0.65, 0.70)	(−2.16, −1.49)	(−1.67, −1.15)	(−3.85, −2.64)	(53.6, 58.6)
B4	−0.02	−0.49	0.13	0.84	−2.19	−0.79	−2.98	73.5
	(−0.03, −0.01)	(−0.66, −0.29)	(0.12, 0.14)	(0.82, 0.86)	(−2.97, −1.42)	(−1.04, −0.53)	(−3.97, −1.99)	(70.6, 76.2)
C1	−0.05	−1.08	0.15	0.52	−1.43	−1.34	−2.78	51.8
	(−0.07, −0.04)	(−1.32, −0.84)	(0.14, 0.16)	(0.49, 0.55)	(−1.87, −1.13)	(−1.63, −1.06)	(−3.43, −2.22)	(48.5, 56.1)
C2	−0.03	−0.61	0.13	0.72	−2.04	−0.88	−2.93	69.7
	(−0.04, −0.02)	(−0.82, −0.43)	(0.12, 0.14)	(0.70, 0.75)	(−2.92, −1.44)	(−1.16, −0.66)	(−4.01, −2.05)	(66.3, 74.8)
C3	−0.12	−3.05	0.34			−3.05	−3.05	
	(−0.14, −0.11)	(−3.36, −2.78)	(0.32, 0.36)			(−3.36, −2.78)	(−3.36, −2.78)	
C4	−0.02	−0.49	0.12	0.85	−2.54	−0.84	−3.37	75.2
	(−0.03, −0.01)	(−0.67, −0.29)	(0.12, 0.14)	(0.83, 0.86)	(−3.41, −1.80)	(−1.09, −0.59)	(−4.52, −2.40)	(72.9, 77.5)
C5	−0.03	−0.63	0.13	0.74	−2.41	−0.96	−3.36	71.3
	(−0.04, −0.02)	(−0.82, −0.42)	(0.12, 0.14)	(0.72, 0.77)	(−3.64, −1.60)	(−1.22, −0.69)	(−4.73, −2.28)	(67.5, 78.1)

Notes: For model specifications, see Table 1. For those featuring heterogeneous coefficients over the cross-section i or over time t, we take the arithmetic mean over all industries and over time per iteration of the algorithm and report the resulting posterior percentiles (the posterior median, and the bounds in parentheses marking the 99 percent posterior credible set). The effects are defined as in Section II.

The results for models estimated with industry-level data, disregarding time variation in the regression coefficients or the network dependence parameter for the moment, are summarized in rows three to six (labeled Model B1–B4) in Table 2. Starting with Models B1 and B2, abstracting from higher-order effects captured by network dependence models, we find point estimates to be similar to those obtained from estimating the model using aggregate data. It is worth mentioning that the posterior credible sets are much narrower. We provide a detailed discussion of cross-sectional heterogeneity below, but note that our estimates corroborate the notion of asymmetric effects of monetary policy shocks on industry returns, as suggested by Ehrmann and Fratzscher (2004).

Crucial benchmarks are Model B3 and B4, which are the main specifications in Ozdagli and Weber (2020). Recall that our proposed specifications feature the time-varying weights matrix $\mathbf{W}_t$ and are estimated using the balanced panel of $N = 58$ industries. Compared with the original paper, the estimates are remarkably robust to this different sample in terms of total effect sizes. However, our estimates for the parameter ρ_t are appreciably lower. While Ozdagli and Weber (2020) estimate the network dependence parameter for the homogeneous coefficient specification (Model B3) to be around 0.87, our estimate lies in the credible set between 0.65 and 0.7. Turning to Model B4 featuring idiosyncratic regression coefficients and variances, our results are almost identical to those presented in Table 2, column 5 in Ozdagli and Weber (2020), which is the corresponding specification. Calculating relative network effects, this implies that roughly 74 percent of the overall market response can be explained by higher-order effects.

Specifications featuring TVPs or a time-varying network dependence parameter are shown in the bottom panel of Table 2 (labeled Model C1–C5). Starting with Model C1, ruling out TVPs and pooling over the cross-section but allowing for a time-varying ρ_t, we find that the total effects are slightly lower than in all others. The estimates for network effects in percent are comparable with Model B3. Relaxing the assumption of homogeneity over the cross-section increases the share attributed to network effects substantially. Estimated effects and network effects are similar to those in Model B4, the main specification of Ozdagli and Weber (2020). For Model C3, where we neglect higher-order effects, we find average total effects of −3.05 percent in response to a surprise increase of 1 percentage point in the federal funds rate.[4]

[4]These estimates are smaller in size compared with Basistha and Kurov (2008) who neglect spillover effects. Note, however, that we rely on a different sampling period, and rather than using a deterministic regime-switching model, we allow for gradually evolving coefficients and observe substantial variation in the effects over time.

Model C4 and C5 reflect variants of our main specification. We obtain significantly larger estimates for the network dependence parameter if we rule out time-varying network dependence. This translates to a slightly higher share of the total effects attributed to higher-order network effects of about 75 percent. Relaxing the assumption of constant regression coefficients slightly increases (decreases) our estimates for direct effects (indirect effects). This dynamic yields an estimate for the network effects between 67.5 and 71.3 percent, leaving the total effects roughly unchanged. Interestingly, our estimates for total effects are comparable with Model A2 using aggregate data, albeit with narrower credible sets.

Summing up, we observe small differences across the model specifications. However, all of them are in line with the established literature and our proposed modeling approach appears to deliver plausible results. In the following, we illuminate driving factors of these differences based on cross-sectional heterogeneities, time variation in regression coefficients and the network dependence parameter.

Time-Varying Effects of Monetary Policy Shocks on Stock Returns

In this section, we investigate average effects over time. Direct, indirect, total, and network effects in percent are displayed in Figure 1. We focus on Models B4 (constant parameter benchmark model), C2, and C4, and we compare them with our main specification C5. As an aggregate benchmark, we also include Model A2. The models are selected based on illuminating differences over time, arising from the introduction of different types of heterogeneities.

Before turning to explanations of why effects change over time, we provide a description of the estimated effects. Several findings are worth noting. Direct effects mostly exhibit a smooth path, albeit with several high-frequency spikes. Differences across model specifications featuring TVPs appear especially in 1999, and between 2002 and 2003. In particular, Model C2 estimates much smaller effects in absolute value alongside movements in the opposite direction when compared with C4 and C5. It is worth mentioning that indirect effects for C2 are extremely smooth over time (and look similar to direct effects, given the constant specification of ρ_t), while the models featuring a time-varying network parameter exhibit numerous high-frequency spikes. Comparing Models C4 and C5 in detail and assessing the effect of allowing for time-varying regression coefficients, we find that differences are muted. We estimate slightly larger direct effects in absolute value for C4, but the dynamic evolution of the impact measures is rather similar.

One of the main questions this paper aims to address is how total effects of monetary policy on stock market returns evolve over time.

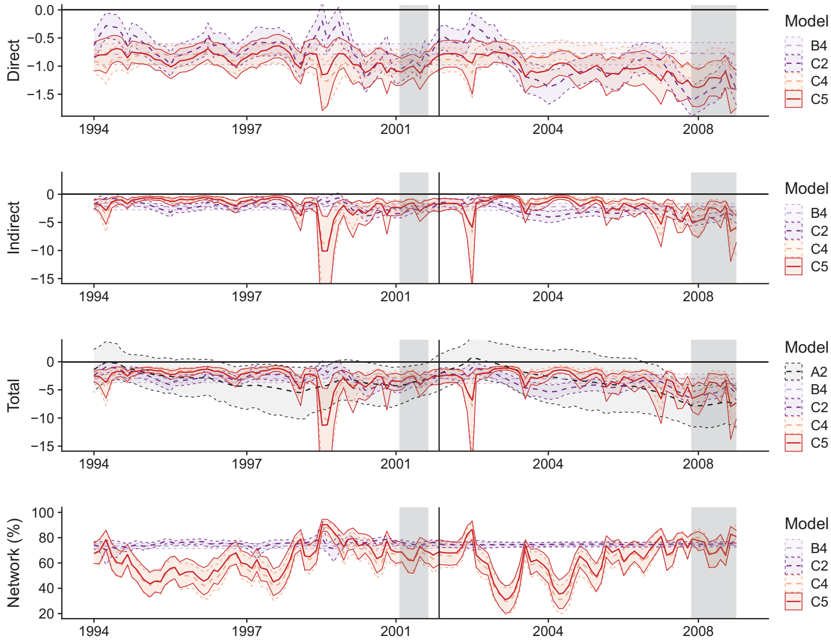

Fig. 1. Effects over time across different model specifications
Notes: Details on the impact measures are described in Section II. For model specifications, see Table 1. Solid lines and shaded areas depict the 99 percent posterior credible set and the posterior median. The gray shaded area marks recessions dated by the NBER Business Cycle Dating Committee. The vertical black solid line indicates the policy meeting on 30 January 2002, where the weights matrix changes (because of changes in the industry classification scheme, we cannot use the 1992 weights matrix for this exercise).

The third panel in Figure 1 shows these effects for several models estimated using industry-level data, and also plots Model A2, which is based on the aggregate S&P 500 index. With aggregate data, the credible sets are inflated and include zero for a substantial part of the sample. Time variation in the estimates is occurring at a rather low frequency, similar to C2. The overall dynamic evolution is comparable to models C4 and C5, although we observe differences in 1999 and 2002/2003. These differences can be explained by the fact that the time-varying network dependence model allows for shifts in the covariance structure across industries (and thus time-varying variances), a feature that is not present in the case of our aggregate data specification. We refer to the discussion of interpreting ρ_t as a common factor capturing a form of stochastic volatility. Trends towards larger effects at the end of the sample are clearly visible.

Part of the total effect can be explained by higher-order network effects, which are shown in the bottom panel in percent. We observe that network effects for Models C4 and C5 are approximately the same. Similarly, C2 and B4 are rather similar, and correspond to the average of C4 and C5 over time (about 80 percent). Interestingly, we observe substantial variation in the strength of network effects over time. Between 1994 and 1998, about 50 percent of the total effect can be explained by network effects. After a period of elevated network effects and several higher-frequency movements exceeding 80 percent, we observe the posterior median to drop to about 40 percent. Towards the end of the sample, we estimate a persistently high importance of network effects of around 80 percent.

As a next step, we investigate the time-varying dependence parameter ρ_t in the upper panel of Figure 2. Comparing this time-series to indirect, total, and network effects in Figure 1, high-frequency movements are clearly driven by the network dependence parameter. Recall that the parameter ρ_t can be interpreted as a common factor scaling the covariance matrix of the reduced-form errors, and thus captures a special form of stochastic volatility. As such, the parameter captures time-varying cross-industry

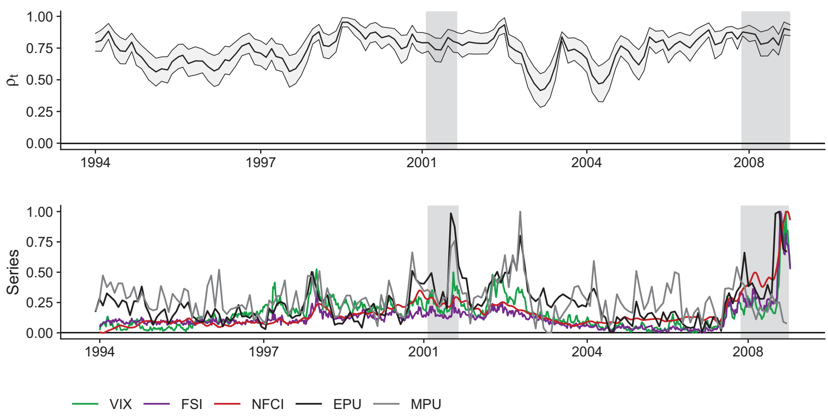

Fig. 2. Explaining time variation in the network dependence parameter
Notes: Posterior median of the network dependence parameter ρ_t alongside the 99 percent posterior credible set. "VIX" is the Chicago Board Options Exchange Volatility Index, "FSI" is the St Louis Fed Financial Stress Index, "NFCI" is the Chicago Fed National Financial Conditions Credit Subindex, "EPU" is the three-component economic policy uncertainty index developed by Baker *et al*. (2016), and "MPU" is the monetary policy uncertainty index of Husted *et al*. (2020). These series are normalized such that they lie in the unit interval to be comparable in scale. For values x, with min and max referring to the minimum and maximum values, the normalization is $[x - \min(x)]/[\max(x) - \min(x)]$. The gray shaded areas marks recessions dated by the NBER Business Cycle Dating Committee.

elasticities. The lower panel of Figure 2 collects several series that we link to the observed dynamics in higher-order network effects of monetary policy to explain the time variation.

The related literature provides several potential explanations for time variation in the transmission of monetary policy interventions. They include differences across investor sentiments over stock market regimes (bull and bear markets), credit conditions and financial stress, but also financial and economic uncertainty (see Chen, 2007; Kurov, 2010; Kontonikas *et al.*, 2013; Baker *et al.*, 2019; Husted *et al.*, 2020). The parameter ρ_t drives the magnitude of cross-industry elasticities, and monetary policy shocks act as demand shocks in the production network. In light of the characteristics that uncertainty shocks share with demand shocks (see Leduc and Liu, 2016), we argue that monetary policy interventions are amplified during such periods, a notion that is reflected in our results and discussed in more detail below.

We focus on five series of interest that reflect such conditions. They are obtained from the FRED database maintained by the Federal Reserve Bank of St Louis, and normalized to lie in the unit interval to make them commensurable in scale. We include the Chicago Board Options Exchange Volatility Index (VIX), which captures the stock market's expectation of volatility based on S&P 500 index options. The VIX captures overall financial market uncertainty. Moreover, we investigate the St Louis Fed Financial Stress Index (FSI) and the Chicago Fed National Financial Conditions Credit Subindex (NFCI). These indices serve as measurements for financial stress and the tightness of credit market conditions. As a broader measure of uncertainty, we refer to the economic policy uncertainty (EPU) index developed by Baker *et al.* (2016), accompanied by a measure of monetary policy uncertainty (MPU; Husted *et al.*, 2020).[5]

It is worth mentioning that all series exhibit a substantial degree of comovement, with EPU and MPU showing several differences, particularly between 2002 and 2005. Table 3 shows pairwise correlations. If publication frequencies are higher than monthly, we aggregate them at a monthly frequency using the arithmetic mean and match them with the FOMC meeting dates. The network dependence parameter exhibits the highest correlation with NFCI, followed by FSI and the VIX. This points towards the importance of financial uncertainty increasing higher-order demand effects of monetary policy, alongside tight credit market conditions.

The first substantial peak occurs during the Asian financial crisis in 1997, followed by the Russian crisis and the related collapse of the hedge-fund Long-Term Capital Management in late 1998. During these periods, all

[5]The economic policy and monetary policy uncertainty indices (see Baker *et al.*, 2016; Husted *et al.*, 2020) are obtained from https://www.policyuncertainty.com.

Table 3. *Correlation matrix of the network dependence parameter with various indices*

	ρ_t	NFCI	FSI	VIX	EPU
NFCI	0.533***				
FSI	0.447***	0.720***			
VIX	0.429***	0.623***	0.845***		
EPU	0.205*	0.491***	0.611***	0.525***	
MPU	0.255**	0.208	0.314	0.290**	0.501***

Notes: "VIX" is the Chicago Board Options Exchange Volatility Index, "FSI" is the St Louis Fed Financial Stress Index, "NFCI" is the Chicago Fed National Financial Conditions Credit Subindex, "EPU" is the three-component economic policy uncertainty index developed by Baker *et al*. (2016), and "MPU" the monetary policy uncertainty index of Husted *et al*. (2020). If publication frequencies are higher than monthly, we aggregate them at a monthly frequency using the arithmetic mean and match them with FOMC meeting dates. $^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

measures indicate elevated levels, pointing towards these events increasing US stock market volatility, uncertainty, and financial stress. The second major peak occurs in the context of the burst of the dot-com bubble in 2000. From this point on, network dependence is persistently high, with minor high-frequency movements during the 9/11 terrorist attacks and the outbreak of Gulf War II. The latter is mainly observable in the EPU and MPU indices, pointing towards increased demand effects of monetary policy measures during periods of high economic uncertainty. Significant drops are observable in early 2003 and mid-2004, periods where EPU and MPU show large decreases. We detect persistently increasing high network dependence up to the collapse of Lehman Brothers in late 2008.

Our findings corroborate those of the earlier literature that time variation in stock market responses to monetary policy shocks are related to economic and financial uncertainty, investor sentiment in bull and bear markets, and financial stress and credit market conditions.

Assessing Heterogeneity and Clustering of Industries

In this section, we shed light on industry-specific effects over time. As a first step, we abstract from the time dimension and assess clusterings of industries based on average values over the full sample period. The methods proposed in our paper do not allow for clustering the effects in a unified econometric approach. This is due to non-linearities in the conditional mean of the model, and because the effects of interest are non-linear functions depending on the reduced-form parameters.

As a solution, we rely on k-means clustering of industries using the joint distribution of total and network effects based on each individual draw from the posterior. We choose total and network effects for assessing clusters based on arguments of structural differences arising from how close the respective industries are to end-consumers, provided in Ozdagli and Weber (2020).

Table 4. *Identifying the number of clusters*

	Number of clusters			
	2	3	4	5
Probability (percent)	86.9	8.5	2.4	2.2

Notes: Industries are clustered based on total and network effects per industry. We use silhouette analysis for all posterior draws using a maximum value of 15 clusters. The number of clusters is selected based on the so-called silhouette coefficient, which yields an empirical distribution for the most adequate number of clusters.

Our analysis requires the number of clusters k to be chosen a priori. A common way to choose k is to rely on silhouette analysis to study the separation distance between the resulting clusters. We set the maximum number of clusters to 15 and compute so-called silhouette coefficients for all of them. For all draws, we choose the optimal number of clusters based on this coefficient, which yields an empirical distribution of the number of clusters. Our findings are displayed in Table 4. The procedure selects $k = 2$ in 86.9 percent of the draws, and more clusters than $k = 5$ are never supported. Consequently, we choose $k = 2$ for all subsequent analyses.

The procedure outlined above produces empirical inclusion probabilities in clusters for all industries, across posterior draws.[6] The findings for this exercise are summarized in Figure 3. To provide a more detailed interpretation of the obtained clusters, Figure 4 shows a scatter plot between the posterior median of network and total effects. Industry categories are

Fig. 3. Cluster allocation of industries
Notes: The number of clusters is chosen to be $k = 2$, based on silhouette analysis. Indicated values are empirical inclusion probabilities for industries in clusters across posterior draws. The white line marks the 50 percent threshold. See Appendix B for details on industries.

[6]Note that clusters are subject to identification issues (see Frühwirth-Schnatter, 2006). We solve these by imposing an ordering constraint such that for each draw, the mean of network effects in Cluster 1 is always larger than in Cluster 2.

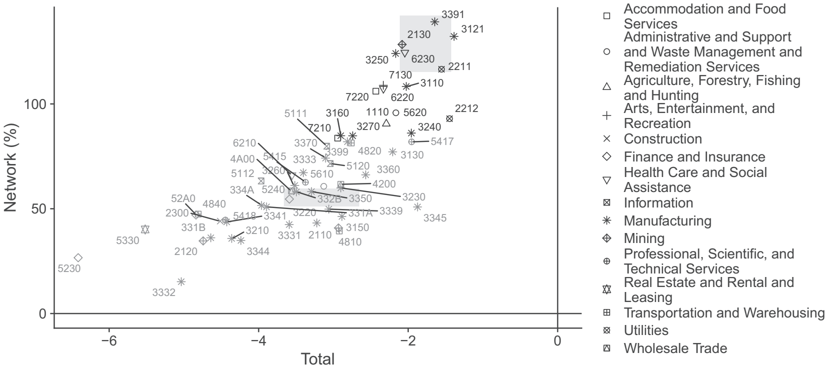

Fig. 4. Effect sizes and clustering of industries
Notes: Points indicate the posterior median of the indicated effect across industries. Industry categories are based on the two-digit level NAICS codes. The number of clusters is chosen to be $k = 2$, based on silhouette analysis. The gray shaded areas mark the empirical distribution of the cluster centers across all posterior draws. See Appendix B for details on industries.

based on the two-digit level NAICS codes. The gray shaded areas mark the empirical distribution of the cluster centers across all posterior draws.

The clusters are of different sizes, and Cluster 1 features fewer observations than Cluster 2. For industries assigned to Cluster 1, probabilities are often close to 50 percent, indicating that membership assignment is fuzzy. Assessing the means of the estimated clusters in Figure 4, we find that Cluster 1 is characterized by high network (exceeding 100 percent) and comparatively small total effects (just below −2), while Cluster 2 exhibits larger total effects (albeit with larger variance across industries) and network effects of about 55 percent. Interestingly, we find a negative correlation between total effect sizes in absolute value and the strength of network effects per industry.

Zooming in on industry characteristics in the context of our clustering analysis, several findings are worth noting. First, there is no clear-cut assignment of industries by their aggregate category. We can explain this finding by the respective closeness to end-consumers of industries. Monetary policy shocks in our framework are interpreted as demand shocks, which implies that industries that are closer to end-consumers are affected directly, while these effects are transmitted upstream via network effects to the suppliers of these industries in the production network. An illustrative example is "Securities, Commodity Contracts, and Other Financial Investments and Related Activities (5230)", with a small magnitude of network effects, but large total effects. Second, with some exceptions, most manufacturing industries are located in Cluster 1,

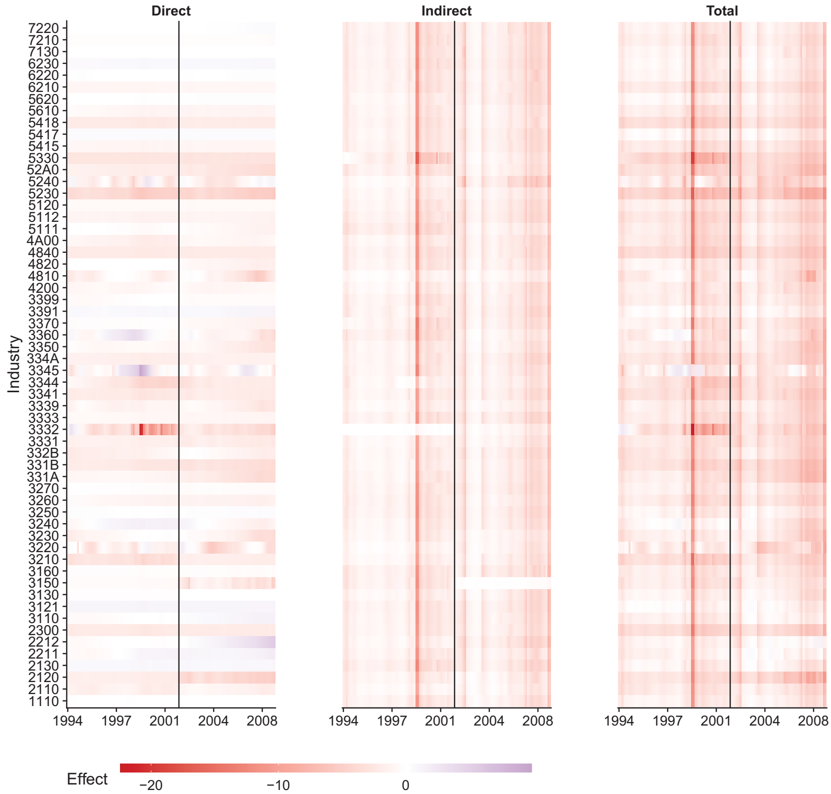

Fig. 5. Industry effects over time

Notes: Details on the impact measures are described in Section II. The heatmap shows the estimated posterior median effects across industries and over time. The vertical black solid line indicates the policy meeting on 30 January 2002, where the weights matrix changes (because of changes in the industry classification scheme, we cannot use the 1992 weights matrix for this exercise).

indicating comparatively low network effects. Assessing the manufacturing industries associated with Cluster 2 in detail, we find that these are mainly industries located further up the supply chain (based on calculations using IO tables), such as "Food/Beverage manufacturing (3110/3121)", or "Medical Equipment and Supplies Manufacturing (3391)".

Turning to industry effects over time and the cross-section, Figure 5 shows posterior estimates of direct, indirect, and total effects. Here, we again observe several noteworthy patterns. First, average patterns of differences of the effects over time addressed previously are clearly visible in the industry-specific plots. The peak between the years 2002 and 2003 is clearly featured in all industries, while the gradual increase of monetary policy effects towards the end of the sample is visible.

Second, a substantial share of industries shows small or even positive direct effects. Even though some direct effects are positive, total effects are for the most part, as expected, negative. This is mainly driven by the higher-order network effects. These findings relate directly to our previous discussion of industry clusters and closeness to end-consumers as determinants of the share of network effects, in line with Ozdagli and Weber (2020).

Third, while there is clearly a substantial degree of comovement across industries for all three impact measures, we detect several differences in industry-specific effects over time. Starting with direct effects, there are some industries such as "Securities, Commodity Contracts, and Other Financial Investments and Related Activities (5230)" or several of the manufacturing industries where we observe persistently strong or weak direct effects. By contrast, high-frequency movements are, for instance, observable in "Industrial Machinery Manufacturing (3332)", while, in general, higher-frequency movements in total effects are almost exclusively driven by indirect effects. Finally, there appears to be a break in the relative importance of industries in the production network governed by the network structure in $\mathbf{W}_t$. In January 2002, when the weights matrix is updated, we find that indirect effect patterns change for some industries. Examples are "Industrial Machinery Manufacturing (3332)", where indirect effects played only a minor role up to this date, or "Apparel Manufacturing (3150)", where after 2002 indirect effects are muted. It is worth mentioning that this break is not visible in the network dependence parameter or the effects averaged across industries. Additional empirical results on comovements across industries are provided in the Online Appendix.

V. Closing Remarks

This paper studies the effects of monetary policy on stock returns. We propose a novel Bayesian network panel state-space model to capture the propagation of shocks through the US production network. Alongside TVPs, our model addresses time-varying higher-order effects of monetary policy. Our results suggest substantial differences in industry responses that also vary significantly over time. We identify periods featuring increased economic and financial uncertainty, and periods when credit market conditions are tight, as those where the effect of monetary policy actions is amplified. Moreover, our results suggest that policy responses in the US production network can be characterized by two main clusters. The clusters can be related to the closeness to end-consumers of the respective industries.

Appendix A: MCMC Algorithm

We use the following steps to generate draws for all parameters of the model by a standard MCMC sampling algorithm. Specifically, the sampler iterates through the following steps.

1. Conditional on all other parameters of the model, the time-varying regression coefficients are simulated independently on an industry-by-industry basis using an FFBS algorithm (Carter and Kohn, 1994; Frühwirth-Schnatter, 1994).

2. Given the full history of the TVPs $\{\tilde{\boldsymbol{\theta}}_{it}\}_{t=1}^{T}$, the initial state $\boldsymbol{\theta}_{i0}$ and the square root of the state innovation variances $\omega_{i1}, \ldots, \sqrt{\omega_{iK+1}}$ are drawn in one block from their Gaussian posterior distribution (see Frühwirth-Schnatter and Wagner, 2010).

3. The measurement equation error variances σ_i^2 are drawn from their inverse Gamma conditional posterior distributions, again on an industry-by-industry basis. The posterior moments can be found, for instance, in Koop (2003).

4. The full history of the network dependence parameter $\{\rho_t\}_{t=1}^{T}$ conditional on all other model parameters is simulated using the Metropolis–Hastings algorithm discussed in Section II. The algorithm involves proposing new values for ρ_t at each point in time. These values are subsequently evaluated and used for constructing acceptance probabilities.

5. Conditional on $\{\rho_t\}_{t=1}^{T}$, the state innovation variances for the network dependence parameter are simulated from their inverse Gamma posterior distribution, with the moments corresponding to a standard linear regression model (see Koop, 2003).

This completes the MCMC algorithm to simulate from the posterior distribution. After choosing starting values and a sufficient burn-in period, we store draws from the conditional posterior distributions. In particular, we discard the initial 5,000 draws, while Bayesian inference is performed based on every second of the subsequent 10,000 draws, resulting in a set of 5,000 draws from the posterior. For the sake of brevity, we only report posterior estimates of parameters and higher-order functions of them that are of direct interest. Additional results are available upon request.

The sampler takes about 37 minutes to produce the 15,000 draws in the case of the most flexible specification on a 2016 Macbook Pro with a 2.9-GHz Dual-Core Intel Core i5 with 8GB RAM running `R 4.0.0`. This runtime excludes the construction of the impact matrix $\mathbf{S}_{kt}$, which can be quite time-consuming due to the dimensionality of the underlying panel data. However, this step can be performed outside the main sampling loop.

Appendix B: Data

All data and replication files are available from the authors upon request. Table B.1 shows the four-digit NAICS codes alongside a description of the industry and categories derived from two-digit level codes for the aggregation scheme in the context of the 1997 and 2002 IO tables.

Table B.1. *List of industries*

NAICS	Description	Category	Cluster
1110	Crop Production	Agriculture, Forestry, Fishing and Hunting	1
2110	Oil and Gas Extraction	Mining	2
2120	Mining (except Oil and Gas)	Mining	2
2130	Support Activities for Mining	Mining	1
2211	Electric Power Generation, Transmission and Distribution	Utilities	1
2212	Natural Gas Distribution	Utilities	1
2300	Construction (Miscellaneous)	Construction	2
3110	Food Manufacturing	Manufacturing	1
3121	Beverage Manufacturing	Manufacturing	1
3130	Textile Mills	Manufacturing	2
3150	Apparel Manufacturing	Manufacturing	2
3160	Leather and Allied Product Manufacturing	Manufacturing	1
3210	Wood Product Manufacturing	Manufacturing	2
3220	Paper Manufacturing	Manufacturing	2
3230	Printing and Related Support Activities	Manufacturing	2
3240	Petroleum and Coal Products Manufacturing	Manufacturing	1
3250	Chemical Manufacturing	Manufacturing	1
3260	Plastics and Rubber Products Manufacturing	Manufacturing	2
3270	Nonmetallic Mineral Product Manufacturing	Manufacturing	1
3331	Agriculture, Construction, and Mining Machinery Manufacturing	Manufacturing	2
3332	Industrial Machinery Manufacturing	Manufacturing	2
3333	Commercial and Service Industry Machinery Manufacturing	Manufacturing	2

Table B.1. *Continued*

NAICS	Description	Category	Cluster
3339	Other General Purpose Machinery Manufacturing	Manufacturing	2
3341	Computer and Peripheral Equipment Manufacturing	Manufacturing	2
3344	Semiconductor and Other Electronic Component Manufacturing	Manufacturing	2
3345	Navigational, Measuring, Electromedical, and Control Instruments Manufacturing	Manufacturing	2
3350	Electrical Equipment, Appliance, and Component Manufacturing	Manufacturing	2
3360	Transportation Equipment Manufacturing	Manufacturing	2
3370	Furniture and Related Product Manufacturing	Manufacturing	2
3391	Medical Equipment and Supplies Manufacturing	Manufacturing	1
3399	Other Miscellaneous Manufacturing	Manufacturing	2
331A	Primary Metal Manufacturing (A)	Manufacturing	2
331B	Primary Metal Manufacturing (B)	Manufacturing	2
332B	Fabricated Metal Product Manufacturing (B)	Manufacturing	2
334A	Computer and Electronic Product Manufacturing (A)	Manufacturing	2
4200	Wholesale Trade (Miscellaneous)	Wholesale Trade	2
4A00	Commercial (Miscellaneous)	Wholesale Trade	2
4810	Air Transportation	Transportation and Warehousing	2
4820	Rail Transportation	Transportation and Warehousing	2
4840	Truck Transportation	Transportation and Warehousing	2
5111	Newspaper, Periodical, Book, and Directory Publishers	Information	2
5112	Software Publishers	Information	2
5120	Motion Picture and Sound Recording Industries	Information	2
5230	Securities, Commodity Contracts, and Other Financial Investments and Related Activities	Finance and Insurance	2
5240	Insurance Carriers and Related Activities	Finance and Insurance	2

Table B.1. *Continued*

NAICS	Description	Category	Cluster
52A0	Finance and Insurance (Miscellaneous)	Finance and Insurance	2
5330	Lessors of Nonfinancial Intangible Assets (except Copyrighted Works)	Real Estate and Rental and Leasing	2
5415	Computer Systems Design and Related Services	Professional, Scientific, and Technical Services	2
5417	Scientific Research and Development Services	Professional, Scientific, and Technical Services	2
5418	Advertising and Related Services	Professional, Scientific, and Technical Services	2
5610	Administrative and Support Services	Administrative and Support and Waste Management and Remediation Services	2
5620	Waste Management and Remediation Services	Administrative and Support and Waste Management and Remediation Services	1
6210	Ambulatory Health Care Services	Health Care and Social Assistance	2
6220	Hospitals	Health Care and Social Assistance	1
6230	Nursing and Residential Care Facilities	Health Care and Social Assistance	1
7130	Amusement, Gambling, and Recreation Industries	Arts, Entertainment, and Recreation	1
7210	Accommodation	Accommodation and Food Services	1
7220	Food Services and Drinking Places	Accommodation and Food Services	1

Notes: "NAICS" gives the industry classification code, "Description" is the name of the respective industry, and "Category" provides summary aggregates of industries using the two-digit level codes.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Online Appendix
Replication Files

References

Acemoglu, D., Carvalho, V. M., Ozdaglar, A., and Tahbaz-Salehi, A. (2012), The Network Origins of Aggregate Fluctuations, *Econometrica 80*, 1977–2016.

Acemoglu, D., Ozdaglar, A., and Tahbaz-Salehi, A. (2015), Systemic Risk and Stability in Financial Networks, *American Economic Review 105* (2), 564–608.

Altavilla, C., Brugnolini, L., Gurkaynak, R. S., Motto, R., and Ragusa, G. (2019), Measuring Euro Area Monetary Policy, *Journal of Monetary Economics 108*, 162–179.

Aquaro, M., Bailey, N., and Pesaran, M. H. (2015), Quasi Maximum Likelihood Estimation of Spatial Models with Heterogeneous Coefficients, CESifo Working Paper No. 5428.

Asgharian, H., Hess, W., and Liu, L. (2013), A Spatial Analysis of International Stock Market Linkages, *Journal of Banking & Finance 37*, 4738–4754.

Baker, S. R., Bloom, N., and Davis, S. J. (2016), Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics 131*, 1593–1636.

Baker, S. R., Bloom, N., Davis, S. J., and Kost, K. J. (2019), Policy News and Stock Market Volatility, NBER Working Paper No. 25720.

Baqaee, D. R. and Farhi, E. (2019), The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem, *Econometrica 87*, 1155–1203.

Basistha, A. and Kurov, A. (2008), Macroeconomic Cycles and the Stock Market's Reaction to Monetary Policy, *Journal of Banking & Finance 32*, 2606–2616.

Bernanke, B. S. and Kuttner, K. N. (2005), What Explains the Stock Market's Reaction to Federal Reserve Policy?, *Journal of Finance 60*, 1221–1257.

Bianchi, D., Billio, M., Casarin, R., and Guidolin, M. (2015), Modeling Contagion and Systemic Risk, SYRTO Working Paper Series No. 10.

Billio, M., Caporin, M., Panzica, R., and Pelizzon,L. (2016a), The Impact of Network Connectivity on Factor Exposures, Asset Pricing and Portfolio Diversification, SAFE Working Paper Series No. 166.

Billio, M., Casarin, R., Ravazzolo, F., and Van Dijk, H. K. (2016b), Interconnections between Eurozone and US Booms and Busts Using a Bayesian Panel Markov-Switching VAR Model, *Journal of Applied Econometrics 31*(7), 1352–1370.

Blasques, F., Koopman, S. J., Lucas, A., and Schaumburg, J. (2016), Spillover Dynamics for Systemic Risk Measurement Using Spatial Financial Time Series Models, *Journal of Econometrics 195*, 211–223.

Carter, C. K. and Kohn, R. (1994), On Gibbs Sampling for State Space Models, *Biometrika 81*, 541–553.

Carvalho, V. and Gabaix, X. (2013), The Great Diversification and Its Undoing, *American Economic Review 103* (5), 1697–1727.

Catania, L. and Billé, A. G. (2017), Dynamic Spatial Autoregressive Models with Autoregressive and Heteroskedastic Disturbances, *Journal of Applied Econometrics 32*, 1178–1196.

Chen, S-S. (2007), Does Monetary Policy Have Asymmetric Effects on Stock Returns?, *Journal of Money, Credit and Banking 39*, 667–688.

Cochrane, J. H. and Piazzesi, M. (2002), The Fed and Interest Rates–A High-Frequency Identification, *American Economic Review 92* (2), 90–95.

Cogley, T. and Sargent, T. J. (2005), Drifts and Volatilities: Monetary Policies and Outcomes in the Post WWII US, *Review of Economic Dynamics 8*, 262–302.

Cook, T. and Hahn, T. (1989), The Effect of Changes in the Federal Funds Rate Target on Market Interest Rates in the 1970s, *Journal of Monetary Economics 24*, 331–351.

Demirer, M., Diebold, F. X., Liu, L., and Yilmaz, K. (2018), Estimating Global Bank Network Connectedness, *Journal of Applied Econometrics 33*, 1–15.

Diebold, F. X. and Yilmaz, K. (2009), Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets, *Economic Journal 119*(534), 158–171.

Ehrmann, M. and Fratzscher, M. (2004), Taking Stock: Monetary Policy Transmission to Equity Markets, *Journal of Money, Credit and Banking 36*, 719–737.

Elhorst, J. P. (2014), *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, Springer, Berlin.

Elliott, M., Golub, B., and Jackson, M. O. (2014), Financial Networks and Contagion, *American Economic Review 104* (10), 3115–3153.

Forbes, K. J. and R. Rigobon (2002), No Contagion, Only Interdependence: Measuring Stock Market Comovements, *Journal of Finance 57*, 2223–2261.

Frühwirth-Schnatter, S. (1994), Data Augmentation and Dynamic Linear Model, *Journal of Time Series Analysis 15*, 183–202.

Frühwirth-Schnatter, S. (2006), *Finite Mixture and Markov Switching Models*, Springer, Berlin.

Frühwirth-Schnatter, S. and Wagner, H. (2010), Stochastic Model Specification Search for Gaussian and Partial Non-Gaussian State Space Models, *Journal of Econometrics 154*, 85–100.

Gabaix, X. (2011), The Granular Origins of Aggregate Fluctuations, *Econometrica 79*, 733–772.

Gertler, M. and Karadi, P. (2015), Monetary Policy Surprises, Credit Costs, and Economic Activity, *American Economic Journal: Macroeconomics 7*(1), 44–76.

Gorodnichenko, Y. and Weber, M. (2016), Are Sticky Prices Costly? Evidence from the Stock Market, *American Economic Review 106*(1), 165–199.

Gürkaynak, R. S., Sack, B. P., and Swanson, E. T. (2005), Do Actions Speak Louder Than Words? The Response of Asset Prices to Monetary Policy Actions and Statements, *International Journal of Central Banking 1* (1), 55–94.

Husted, L., Rogers, J., and Sun, B. (2020), Monetary Policy Uncertainty, *Journal of Monetary Economics 115*, 20–36.

Jacquier, E., Polson, N. G., and Rossi, P. E. (2002), Bayesian Analysis of Stochastic Volatility Models, *Journal of Business & Economic Statistics 20*, 69–87.

Jarociński, M. and Karadi, P. (2020), Deconstructing Monetary Policy Surprises: The Role of Information Shocks, *American Economic Journal: Macroeconomics 12*(2), 1–43.

Kim, C-J. and Nelson, C. R. (1999), *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications*, MIT Press, Cambridge, MA.

Kontonikas, A., MacDonald, R., and Saggu, A. (2013), Stock Market Reaction to Fed Funds Rate Surprises: State Dependence and the Financial Crisis, *Journal of Banking & Finance 37*, 4025–4037.

Koop, G. (2003), *Bayesian Econometrics*, Wiley, New York.

Kurov, A. (2010), Investor Sentiment and the Stock Market's Reaction to Monetary Policy, *Journal of Banking & Finance 34*, 139–149.

Kuttner, K. N. (2001), Monetary Policy Surprises and Interest Rates: Evidence from the Fed Funds Futures Market, *Journal of Monetary Economics 47*, 523–544.

Leduc, S. and Liu, Z. (2016), Uncertainty Shocks Are Aggregate Demand Shocks, *Journal of Monetary Economics 82*, 20–35.

LeSage, J. P. and Chih, Y-Y. (2016), Interpreting Heterogeneous Coefficient Spatial Autoregressive Panel Models, *Economics Letters 142*, 1–5.

Lucca, D. O. and Moench, E. (2015), The Pre-FOMC Announcement Drift, *Journal of Finance 70*, 329–371.

Nakamura, E. and Steinsson, J. (2018), High-Frequency Identification of Monetary Non-Neutrality: The Information Effect, *Quarterly Journal of Economics 133*, 1283–1330.

Neuhierl, A. and Weber, M. (2018), Monetary Momentum, NBER Working Paper No. 24748.

Ozdagli, A. and Weber, M. (2020), Monetary Policy Through Production Networks: Evidence from the Stock Market, NBER Working Paper No. 23424.

Pasten, E., Schoenle, R., and Weber, M. (2018), Price Rigidity and the Origins of Aggregate Fluctuations, NBER Working Paper No. 23750.

Pasten, E., Schoenle, R., and Weber, M. (2020), The Propagation of Monetary Policy Shocks in a Heterogeneous Production Economy, *Journal of Monetary Economics 116*, 1–22

Paul, P. (2020), The Time-Varying Effect of Monetary Policy on Asset Prices, *Review of Economics and Statistics 102*, 690–704.

Primiceri, G. E. (2005), Time Varying Structural Vector Autoregressions and Monetary Policy, *Review of Economic Studies 72*, 821–852.

Rigobon, R. and Sack, B. (2004), The Impact of Monetary Policy on Asset Prices, *Journal of Monetary Economics 51*, 1553–1575.

Thorbecke, W. (1997), On Stock Market Returns and Monetary Policy, *Journal of Finance 52*, 635–654.

Zellner, A. (1986), On Assessing Prior Distributions and Bayesian Regression Analysis with g-Prior Distributions, in P. Goel and A. Zellner (eds), *Bayesian Inference and Decision Techniques: Essays in Honor of Bruno de Finetti, Studies in Bayesian Econometrics and Statistics*, Vol. 6, North-Holland, Amsterdam, 233–243.

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