Monetary Policy through Production Networks: Evidence from the Stock Market*

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Abstract

We study the importance of production networks for the transmission of macroeconomic shocks using the stock market reaction to monetary policy shocks as laboratory. We decompose the overall effect into direct and network effects and attribute 55 to 85 percent to network effects. Large network effects are a robust feature of the data, and we document similar patterns in realized fundamentals. A simple model with intermediate inputs predicts the reaction of stock returns to shocks follows a spatial autoregression, which we exploit for our empirical strategy. Our results suggest that production networks are an important mechanism for transmitting aggregate shocks.

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I Introduction

Understanding how shocks transmit through the economy is a central question in macroeconomics. The input-output structure of the economy is a potentially important transmission mechanism generating aggregate fluctuations from idiosyncratic shocks (see Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)). Similarly, the economy's production network structure can be an important transmission mechanism of macroeconomic shocks. For example, expansionary monetary policy shocks may directly increase the demand for cars. Car manufacturers may then increase their tire demand which in turn increases the demand for rubber and ultimately oil. Furthermore, these higher-order demand effects may feed back to car manufacturers because the producers of oil, rubber, and tires demand more vehicles. In this paper, we propose a framework to quantify the higher-order demand effects from the network structure of the economy. We find 55 to 85 percent of the overall effect of macroeconomic shocks can be attributed to network effects.

The quantification of network effects after macroeconomic shocks is important for the conduct of policy because it sheds light on whether production networks should enter models policymakers use. Yet, "[t]he fact that an individual firm's production occurs within a network of firms is typically ignored by macroeconomists" (Christiano, 2015). Indeed, if network effects are small, the cost of reduced tractability may outweigh any benefit of explicitly modeling the input-output structure. On the other hand, large network effects would suggest that production networks should be an integral part of models studying the transmission of macroeconomic shocks to the economy. From this perspective, the quantification of network effects after a policy change achieves for models with production networks what growth accounting does for growth models and what the more recent business cycle accounting does for business cycle models.

We document large network effects following monetary policy shocks. Network effects comprise up to 85% of the overall response of the real economy to monetary policy shocks as measured by the reaction of stock returns. This result might appear surprising because the production network in the U.S. is sparse; that is, most industries are not directly linked to each other. As a result, one may be tempted to infer that network effects should not be important for the transmission of monetary shocks. Consistent with this intuition, we find in simulations that random production networks with the same sparsity as the one observed in the actual U.S. input-output tables generate network effects that are substantially smaller than our baseline estimates. Similarly, large heterogeneity exists in the importance of sectors as suppliers to other sectors (first-order outdegree) or as suppliers to important suppliers of the economy (second-order outdegree). Again, we find networks that match these features of the data but are purely random cannot replicate our findings. Finally, we show that accounting for these salient features in the data and keeping intact their actual industry assignment brings simulated network effects close to our empirical estimates. The large network effects we document stress the importance of the particular structure of the U.S. input-output network as opposed to just the sparsity of the network or the distribution of outdegrees, ignoring the actual industry assignment. An arbitrary input-output structure will not generate large network effects, which emphasizes the importance of quantifying these effects based on the actual structure in the data.

The quantification of network effects poses three challenges: the identification of monetary policy shocks, the identification of the effects of these shocks, and the identification of the network effects. We resolve the first two challenges following Gorodnichenko and Weber (2016) and use the reaction of stock returns to monetary policy shocks, measured by federal funds futures, for identification. Stock prices are the present-discounted value of future cash flows and stock returns fully incorporate the information in monetary policy surprises within minutes (Gürkaynak, Sack, and Swanson, 2005). Investors also pay attention to various sources of heterogeneity in company and industry characteristics when evaluating the impact of monetary policy (Ozdagli and Velikov, 2020; Gürkaynak et al., 2021). This property of stock prices allows us to calculate the total effect of monetary policy on the real economy within a narrow event window, thereby eliminating any confounding effects of other shocks.

We address the third challenge by using spatial autoregressions. We decompose the overall effect of monetary policy shocks on stock returns into direct effects and higher-order network effects. Spatial econometrics typically identifies the spillover effects across geographic regions in a reduced-form approach assuming a given relationship between geographic units. The existence, direction, and intensity of this relationship are captured by the spatial-weighting matrix. An example is the spillover effect of changes in population density in a given region on the commuting time in neighbouring regions using the distance between regions as entries in the weighting matrix. This approach has become popular in several applications, but often the spatial-weighting matrix is ad hoc, which makes the structural interpretation of the spillover effects difficult.[1]

A natural candidate for the weighting matrix in our context are the input-output tables from the Bureau of Economic Analysis (BEA) widely used in the production network literature. We corroborate this intuition by showing that a simple model of production with intermediate inputs a la Acemoglu et al. (2012) delivers the input-output matrix as the weighting matrix. An important contribution of our paper thus lies in providing a precise structural interpretation of this reduced-form approach, while simultaneously using tools previously developed in the spatial econometrics literature to quantify direct and network effects.

We estimate a system of simultaneous equations using spatial autoregressions and decompose the overall effect of monetary policy shocks on stock returns into direct effects and higher-order network effects. Intuitively, this approach generalizes Bernanke and Kuttner (2005) and is akin to regressing returns of industry i on monetary policy shocks and a weighted-average of returns of i's customers with the weights determined by the importance of sectors as customers of sector i. When we bring the model to the data, we find network effects account for 55 to 85 percent of the overall effect, which is a robust feature of the data even when we study different event types, such as policy reversals, large shocks, and positive vs. negative policy

[1]See LeSage and Pace (2009).

surprises.[2]

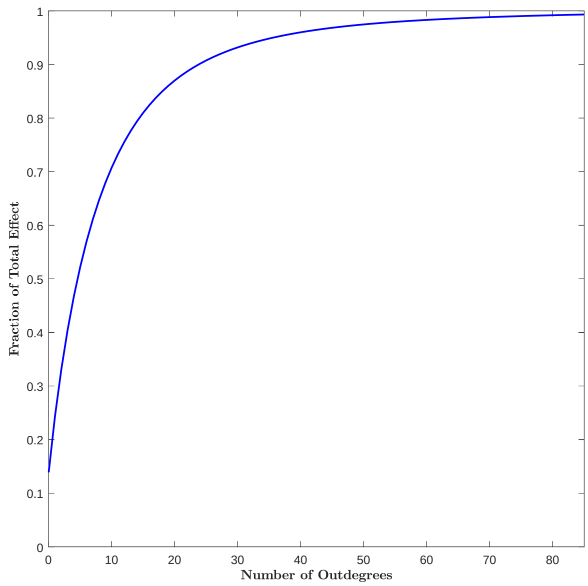
Consumer demand transmits monetary policy through various channels, ranging from the standard New Keynesian intertemporal substitution mechanism to the mortgage refinancing channel in the more recent literature (Eichenbaum, Rebelo, and Wong, 2018). Accordingly, we interpret the monetary policy shock as a demand shock operating through cash flows (see Gürkaynak et al. (2021) for direct evidence on the importance of the cash-flow channel for stock returns). Consistent with a transmission channel through consumer demand, we document substantial heterogeneity in the relative importance of direct and network effects of monetary policy across industries. We show, both theoretically and empirically, that direct effects are larger for firms that sell most of their output directly to end-consumers, as compared to other industries. The greater importance of direct effects for these industries is consistent with the intuition that monetary policy may directly increase consumer demand for goods and services, which then gets transmitted to these firms' suppliers and further upstream in the production network.

Our baseline findings indicate that network effects might account for a substantial fraction of the overall effect that monetary policy shocks have on stock prices. We further support this argument by analyzing similar network effects on ex-post realized fundamentals, such as sales or operating income. Network effects account for 60 percent of the impact effect that monetary policy shocks have on industry fundamentals, a result that is robust to different measures of fundamentals and various weighting schemes. The network effect increases up to seven quarters after the monetary policy shock occurs before it levels off.

A major concern regarding our analysis is that we mechanically assign a large fraction of the overall effect of monetary policy shocks to network effects as we regress industry returns on a weighted average of industry returns. If this concern has any merit, we should observe a similar large network effect with any production network.

[2] Two important advantages of focusing on industry returns rather than individual firms' returns exist. First, industry linkages are stable over time and are determined by technology rather than by choice. Second, because large and financially-unconstrained firms dominate industry returns, we can isolate the demand effects from other effects that might work through financial frictions. Accordingly, we show that external finance dependence of industries does not play a significant role in determining direct and network effects.

Figure 1: **Total Network Effect by Number of Orders in Series Expansion**



This figure plots the share of the total effect of monetary policy shocks on stock returns by the number of orders in the series expansion of the Leontief inverse matrix in equation (21). The zero-order expansion corresponds to the direct effect of monetary policy in the definition of Acemoglu et al. (2016) and the difference between the total effect and zero-order expansion corresponds to network effects.

Because the empirical input-output matrix is sparse and only a few large sectors are important suppliers to the rest of the U.S. economy or to important suppliers to the rest of the U.S. economy (see Acemoglu et al. 2012), we construct input-output matrices with these two characteristics. We find network effects as large as in the data are unlikely in simulations with randomly generated matrices.

First, we show that many orders in the series expansion of the Leontief inverse matrix, which captures higher-order demand effects, are necessary to capture the network effects of monetary policy on stocks returns. The terms of this series expansion correspond to weighted outdegrees. Figure 1 shows the zero-order expansion of the Leontief inverse matrix, which corresponds to the direct effect of monetary policy on stock returns following the definition of Acemoglu et al. (2016), captures only 14% of the total effect. Moreover, we find the first 10 orders capture only 71% of the total effect of monetary policy shocks. An alternative decomposition following Pace and LeSage (2014), which is consistent with the definition the UK government uses, attributes about 80% of total effects to network effects. Our third decomposition compares the estimates from the network economy with an economy under autarky in which each industry only uses its own output as an input into production. This decomposition, which measures the amplification through the network structure, attributes 55% of the total effect to the network effect due to amplification.

Second, our simulations with randomly generated matrices suggest that matching the distribution of sparsity, first- and second-order outdegrees does not generate network effects as large as those we find with the empirical input-output matrix. This result differs from the work of Acemoglu et al. (2012) and Carvalho (2010) who emphasize the distribution of the first two outdegrees for explaining the aggregate fluctuations originating from sectoral shocks. Nevertheless, when we keep the actual industry assignment of these network characteristics intact, rather than fitting the general distribution, network effects are closer to those we observe in the data. Finally, we also show that large diagonal entries in the input-output tables do not drive our results.

In a baseline estimation, we estimate a constant sensitivity for all industries conditional on their respective positions in the network, following Acemoglu et al. (2016).[3] Imposing a constant sensitivity across industries might bias our estimates of network effects. Our model implies that the direct exposure of stock returns to monetary policy shocks varies as a function of the demand by end consumers. When we estimate spatial autoregressions that allow for different exposures to monetary policy shocks following Aquaro, Bailey, and Pesaran (2019), we find results that are almost indistinguishable from our baseline results. Our results are also similar when we account for common risk factors identified in the asset pricing literature.

Finally, we demonstrate that our empirical results on the relative importance of direct versus network effects are consistent with data we simulate from a dynamic model with nominal frictions. Specifically, we simulate data from the model under different assumptions regarding structural parameters, run our baseline specifications on simulated data using the actual input-output matrix as the spatial-weighting

[3]Equation (12) in Acemoglu et al. (2016) assumes that the direct and indirect effects of shocks depend only on the position of industries in the network, as captured by the Leontief inverse.

matrix, and decompose the results into direct and network effects. Across different specifications, we find that network effects constitute 70–80% of the overall effect of monetary policy shocks on stock returns.

Our paper departs from the previous network literature by quantifying the importance of network effects in response to macroeconomic shocks. The recent literature on production networks primarily focuses on how idiosyncratic shocks—that is, shocks to a single firm, industry, or a group thereof—spread through the economy and thereby generate aggregate fluctuations. Instead, we focus on how much of the economy's reaction to a macroeconomic shock, in our case a monetary policy shock, we can attribute to production networks. Our approach and findings can therefore guide future research on the importance of network effects for the impact of other macroeconomic shocks.

In an important extension of our work, di Giovanni and Hale (2022) document the international spillovers of US monetary policy shocks through international value chains and higher-order demand effects. Our paper complements their work in several ways. First, we directly rule out alternative channels such as financial frictions, exposure to shocks other than monetary policy shocks, or exposure to alternative risk factors driving our results. Second, we provide additional evidence supporting the proposed transmission channel through demand by showing that direct effects are stronger for industries closer to end-consumers and that network effects indeed materialize in realized cash-flow fundamentals. Third, our production network is primarily determined by technology and is stable over time, whereas international trade linkages might adjust following shocks as it happened with the recent reallocation of international supply chains following the trade war with China and the recent Russian-Ukrainian crisis. Fourth, we show in extensive simulations of our dynamic model that large network effects materialize across a wide range of calibrations. Finally, we shed light on the central properties of production networks that lead to large measured network effects, through extensive simulations and placebo tests.

A. Related Literature

A growing literature in macroeconomics argues that microeconomic shocks might get transmitted through the production network and contribute to aggregate fluctuations. Prior to this literature, the traditional view was that idiosyncratic shocks cannot contribute to aggregate fluctuations in a highly disaggregated economy (Lucas 1977). However, recent work by Gabaix (2011) and Acemoglu et al. (2012), building on Long and Plosser (1983) and Horvath (1998), shows idiosyncratic shocks can generate aggregate fluctuations when the firm-size distribution or the importance of sectors as suppliers of intermediate inputs to the rest of the economy is fat-tailed. Pasten, Schoenle, and Weber (2020) extend the analysis of these papers to allow for heterogeneity in price stickiness across sectors and identify a frictional origin of aggregate fluctuations. Castro-Cienfuegos (2019) and Rubbo (2019), instead study the relevance of sectoral heterogeneity in models of production networks for the conduct of monetary policy and the implications for the Phillips curve and La'O and Tahbaz-Salehi (2019) study optimal monetary policy in production networks. Acemoglu, Akcigit, and Kerr (2016) show networks are empirically important for aggregate fluctuations as well as for the transmission of federal spending, trade, technology, and knowledge shocks. Barrot and Sauvagnat (2016), Boehm et al. (2019), and Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) study the propagation of idiosyncratic shocks due to natural disasters. Oberfield (2018) endogenizes the input-output structure of the economy in a model in which each firm chooses its supplier. Kelly, Lustig, and Van Nieuwerburgh (2013) study the joint dynamics of the firm-size distribution and stock return volatilities, and Herskovic et al. (2016), Herskovic (2018), Ramirez (2017) and Gofman, Segal, and Wu (2020) study the asset-pricing implications. We build on this work and study the importance of production networks for the transmission of aggregate shocks. We also differ in that we study the transmission of demand shocks, which in our setting – building on Acemoglu et al. (2012) – propagate upstream in the production network. Supply shocks, instead, which have been the focus of the nascent literature, travel downstream. We also focus on industry linkages which are stable over time and are determined by technology rather than by choice. Baqaee (2019) studies how supply chains affect the intensity with which an industry uses labor.[4]

The present paper is also related to the large literature investigating the effect of monetary shocks on asset prices. In a seminal study, Cook and Hahn (1989) use an event-study framework and a daily event window to examine the effects of changes in the federal funds rate on bond rates. They show that changes in the federal funds target rate are associated with interest rate changes in the same direction, with larger effects at the short end of the yield curve. Bernanke and Kuttner (2005) – also using a daily event window – focus on unexpected changes in the federal funds target rate. They find that an unexpected interest rate cut of 25 basis points leads to an approximately 1-percent increase in the CRSP value-weighted market index. Gürkaynak, Sack, and Swanson (2005) focus on intraday event windows and find effects of similar magnitudes for the S&P 500. We build on this literature in that we also exploit variation in stock prices in narrow event windows to gain identification. We differ in that we use industry returns as a laboratory to quantify the importance of network effects using spatial autoregressions.

We make the following three contributions to the literature. First, we provide evidence that production networks are also an important transmission channel for aggregate demand shocks. The existing literature has focused almost exclusively on the propagation of micro (supply) shocks. In many production-based models, supply shocks travel downstream from suppliers to customers, whereas demand shocks travel upstream in the production network. Second, we show that higher-order demand effects are responsible for a large part of the overall effect that monetary policy shocks have on the stock market. Our findings open up novel avenues to develop asset-pricing theories based on the network feature of the economy and highlight the importance of allowing for sectoral interlinkages in the models policy makers use. Third, we make a methodological contribution by combining methods from spatial econometrics with network theory to provide a structural interpretation of

[4] Other recent contributions to this fast-growing literature are Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017); Atalay (2017); Baqaee (2018); Baqaee and Farhi (2019); Baqaee and Farhi (2020); Baqaee and Farhi (2018); Bigio and La'O (2020); Caliendo et al. (2018); Carvalho and Gabaix (2013); Carvalho and Grassi (2019); Foerster, Sarte, and Watson (2011); Gofman (2013); Grassi (2017); Taschereau-Dumouchel (2017); Cox et al. (2020); and Bouakez et al. (2018). Carvalho (2014) as well as Carvalho and Tahbaz-Salehi (2019) synthesize this literature.

our findings.

II A Simple Network Model

This section develops a static model with intermediate inputs in which money has heterogeneous effects on firms' net income. The simplicity of the model allows us to focus on the transmission of monetary policy shocks to the real economy via input-output linkages and motivates our empirical specification. In Section VI, we present a dynamic version of the model and estimate our baseline empirical specification on model-simulated data.

Firms increase their purchases of intermediate goods when they face increased demand for their products in models with intermediate production. Intermediate input producers need to increase production to satisfy the increased demand for their goods, which results in higher demand for the goods produced in other sectors further upstream. Since the production network is not linear, but rather exhibits cycles, this effect can feed back to firms initially hit by the demand shock as well. Hence, expansionary monetary policy shocks not only directly increase the demand for goods of firms selling to consumers, but also lead indirectly to higher-order demand effects through increased demand for intermediate inputs.

A. Firms and Consumers

Our setup closely follows Acemoglu et al. (2016) and Carvalho (2014) but adds money to the economy. We also introduce wage stickiness in the form of pre-set wages to generate real effects of monetary policy. We have a one-period model with variable inputs that each firm can purchase from other firms, including itself. Therefore, the firm's net income determines its stock price. Moreover, a firm has a pre-determined fixed nominal obligation. We are agnostic about the origin of the fixed costs, but these might include rent payments or repayments of nominal debt.[5]

Firm i's objective is to maximize profits, π_i, by choosing homogeneous labor, l, and intermediate inputs, x_{ij}, from firms $i = 1 \ldots N$, taking prices, $\{p_i\}_{i=1}^N$, and the pre-determined wage rate, w, as given:

$$\pi_i = \max p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - w l_i - f_i \qquad \text{with} \tag{1}$$

$$y_i = l_i^{\lambda_i} \left(\prod_{j=1}^{N} x_{ij}^{\omega_{ij}} \right)^{\alpha_i}. \tag{2}$$

In equations (1) and (2), y_i is the output of firm i, λ_i and α_i are the factor shares ($\lambda_i + \alpha_i \leq 1$), and ω_{ij} is the share of input firm i uses in the production from firm j such that $\sum_{j=1}^N \omega_{ij} = 1$.

In the firm's first-order conditions, we see that a larger factor share in the production function leads to larger spending on that factor,

$$\alpha_i \omega_{ij} R_i = p_j x_{ij}, \tag{3}$$

$$\lambda_i R_i = w l_i, \tag{4}$$

where $R_i \equiv p_i y_i$ is the firm's revenue. A substitution of the first-order conditions into the objective function gives

$$\pi_i = (1 - \alpha_i - \lambda_i) R_i - f_i. \tag{5}$$

The representative consumer maximizes utility

$$\max \sum_{i=1}^{N} b_i \log (c_i), \text{ with } \sum_{i=1}^{N} b_i = 1 \tag{6}$$

and supplies labor perfectly elastic in exchange for the pre-determined wages. The

[5] We focus on wage stickiness given its empirical relevance (Christiano et al., 2005; Barattieri et al., 2014) but also given the simplicity of modeling it. Online appendix Section II discusses an extension of our framework with price stickiness. Moreover, a recent literature suggests nominal fixed obligations to be potentially important because unanticipated changes in inflation, such as those generated by expansionary monetary policy, can influence the real burden of debt (Gomes et al., 2016). We have incorporated fixed nominal costs as an additional term to show that our model is general enough to account for nominal liabilities.

consumer is subject to the budget constraint

$$\sum_{i=1}^{N} p_i c_i = w \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} \pi_i + \sum_{i=1}^{N} f_i. \tag{7}$$

We assume fixed costs are a transfer from firms to consumers and that consumers passively supply labor to firms and collect income from wages, profits, and fixed costs.

The first-order condition is

$$c_i = b_i \frac{w \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} (\pi_i + f_i)}{p_i} = \frac{b_i \sum_{i=1}^{N} (1 - \alpha_i) R_i}{p_i}, \tag{8}$$

where the second equality follows from equations (4) and (5).

The goods-market-clearing condition is

$$y_i = c_i + \sum_{j=1}^{N} x_{ji} \Rightarrow y_i = \frac{b_i \sum_{i=1}^{N} (1 - \alpha_i) R_i}{p_i} + \frac{\sum_{j=1}^{N} \alpha_j \omega_{ji} p_j y_j}{p_i}, \tag{9}$$

which simplifies to

$$R_i = b_i \sum_{i=1}^{N} (1 - \alpha_i) R_i + \sum_{j=1}^{N} \alpha_j \omega_{ji} R_j. \tag{10}$$

Equation (10) shows shocks to consumer demand, captured by the first term, can affect the revenues of firm i and then get transmitted through the economy's production network, captured by the second term. The role of the production networks in transmitting monetary policy shocks to the real economy depends on both the size of the industries that buy the intermediate goods as part of their supply chain, R_j, and the importance of these firms as a customer of industry i, $\alpha_j \omega_{ji}$.

Define $W = [\omega_{ij}]$ as the input-output matrix and $R = (R_{1,}..., R_N)'$ as the vector of revenues, which leads to

$$(I - W' D(\alpha)) R = \begin{pmatrix} b_1 \\ \vdots \\ b_N \end{pmatrix} \sum_{i=1}^{N} (1 - \alpha_i) R_i, \tag{11}$$

where $\alpha \equiv (\alpha_1, ..., \alpha_N)'$ and the matrix $D(\alpha)$ is a diagonal matrix with elements of the vector α as entries.

B. Money Supply and Equilibrium Network Effects

We assume intermediate inputs are financed through trade credit between firms, whereas consumption goods are purchased with cash.[6] Therefore, money supply determines prices through the following cash-in-advance constraint

$$\sum_{i=1}^{N} p_i c_i = \sum_{i=1}^{N} (1-\alpha_i) R_i = M, \tag{12}$$

where M is money supply.[7] Combining equation (12) with the goods-market-clearing condition (11), we get

$$(I - W' D(\alpha)) R = bM, \tag{13}$$

where $b \equiv (b_1, ..., b_N)'$. Therefore, the distribution of revenues across sectors depends on the sectors' position in the network.

Define $\pi \equiv (\pi_{1,...,} \pi_N)'$ and $f \equiv (f_{1,...,} f_N)'$. We get

$$\pi = (1 - \alpha - \lambda) R - f \tag{14}$$

which we can log-linearize and use equation (13) to get

$$\hat{\pi} = (I - W' D(\alpha))^{-1} \beta \hat{M}, \tag{15}$$

where $\beta \equiv (\beta_{1,...,} \beta_N)'$ with

$$\beta_i = \frac{(1 - \alpha_i - \lambda_i) \bar{M}}{\bar{\pi}_i} b_i.^{8} \tag{16}$$

Note we can rewrite the reaction of the deviation of net income as

$$\hat{\pi} = \beta \hat{M} + W' D(\alpha) \hat{\pi}. \tag{17}$$

The changes in net incomes react to the monetary shock $\hat{M}$ and the reaction of its customers' net incomes to the shock, $W' D(\alpha) \hat{\pi}$.

Equation (17) has the form of a spatial autoregression (SAR) which we formally

[6] See Cooley and Hansen (1989).

[7] The results remain the same if we allow for different degrees of credit-dependence for different consumption goods. In particular, if we let a_i denote the share of consumption good i that the consumer needs to purchase with cash, equation (12) becomes $\sum_{i=1}^{N} a_i p_i c_i = M$ and the following results hold once we replace M with $M / (\sum_{i=1}^{N} a_i b_i)$.

[8] Throughout, let $\bar{x}$ be the deterministic steady-state value, and $\hat{x}$ be the log deviation from the steady state so that $x = \bar{x} \exp(\hat{x}) \approx \bar{x}(1 + \hat{x})$.

introduce in the next section.[9] Following Gorodnichenko and Weber (2016), we use stock returns to measure the response in net incomes to monetary policy shocks because stock returns allow us to observe the present discounted value of changes in future net incomes within minutes around monetary policy shocks.

III Framework

Section II shows how the SAR specification that we define in this section, arises naturally from a model of production networks. After we introduce SARs, we define how we identify the direct and network effects, and then discuss how we measure monetary policy shocks.

A. Spatial Autoregressions

We use methods from spatial econometrics to decompose the overall stock market reaction to a monetary policy surprise into a direct demand effect and higher-order network effects.

Our econometric model is given by

$$r_t = \beta v_t + W' D(\rho) r_t + \varepsilon_t, \tag{18}$$

which implies the following data-generating process

$$\begin{aligned} r_t &= (\mathbb{I}_n - W'D(\rho))^{-1}\beta v_t + (\mathbb{I}_n - W'D(\rho))^{-1}\varepsilon_t \\ \varepsilon_t &\overset{N}{\sim} (0, D(\sigma^2)). \end{aligned}$$

In equation (18), r is vector of N industry returns, $r_t = (r_{it})_1^N$, in the interval $[t-10\text{min}, t+20\text{min}]$ around FOMC press release times t as in Gorodnichenko and Weber (2016), β is a vector of N industry sensitivities to (scalar) monetary policy shocks v which we will introduce below, $D(\rho)$ is a diagonal matrix that captures heterogeneous contributions of different industries to network effects through heterogenous input shares, and W' is a row-normalized spatial-weighting matrix. W corresponds to the

[9] The SAR structure remains similar when we relax the assumptions on Cobb-Douglas functional forms and fixed costs in a static framework, as argued in di Giovanni and Hale (2022). Section VI and Online Appendix Section III provide a more general and dynamic version of our model, discusses the conditions under which the simple SAR structure provides a reasonable approximation, and shows the robustness of our estimated direct and network effects using simulated data.

BEA input-output matrix, which we describe in Section IV. The standard SAR model is a special case of equation (18) in which $D(\rho)$ is a scalar and β is identical across industries (see LeSage and Pace (2009)). We allow for heteroskedasticity in error terms, $D(\sigma^2)$, in our main SAR specification which is estimated following Aquaro et al. (2019).[10]

We estimate the following empirical specification to assess whether monetary policy might result in higher-order network effects

$$r_t = constant + \beta v_t + W' D(\rho) r_t + \varepsilon_t. \tag{19}$$

β and ρ are the vectors of coefficients we estimate. In equation (19), the overall response of industries to monetary policy shocks depends on the input-output matrix W, which governs the response of industry returns to monetary policy shocks via its effect on intermediate-input production; the vector $D(\rho)$, which determines the strength of spillover effects; and the vector β. We bootstrap standard errors, sampling events at random, and re-estimate the model 500 times for samples with the same number of events as our empirical sample.

B. Return Decomposition

We can interpret parameter estimates in standard linear regression models as partial derivatives of the dependent variable with respect to the independent variable. The interpretation of parameters in a spatial model differs from linear regression models because they incorporate information from related industries (or neighboring regions in a spatial application). We can see this difference more clearly when we re-write equation (18) as

$$r = S(W')v + V(W')\varepsilon,$$

where we omit time subscripts for brevity and

$$S(W') = V(W')\beta \tag{20}$$

$$V(W') = (\mathbb{I}_n - W' D(\rho))^{-1} = \mathbb{I}_n + W' D(\rho) + (W' D(\rho))^2 + \dots \tag{21}$$

To illustrate our method, we focus on a simple example with three industries.

[10]We detail the estimation in Online Appendix Section I.

We can expand the data-generating process to

$$\begin{pmatrix} r_1 \\ r_3 \\ r_3 \end{pmatrix} = \begin{pmatrix} V(W')_{11} & V(W')_{12} & V(W')_{13} \\ V(W')_{21} & V(W')_{22} & V(W')_{23} \\ V(W')_{31} & V(W')_{32} & V(W')_{33} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \end{pmatrix} v + V(W')\varepsilon,$$

where $V(W')_{ij}$ denotes the ij^{th} element of the matrix $V(W')$.

We focus on industry 1,

$$r_1 = V(W')_{1,1}\beta_1 v + V(W')_{1,2}\beta_2 v + V(W')_{1,3}\beta_3 v + V(W')_1\varepsilon, \tag{22}$$

where $V(W')_i$ denotes the i^{th} row of matrix $V(W')$.

We see from equation (22) the response of returns in industry 1 (r_1) to a monetary policy shock v depends on the reaction of other industries to the same shock. Studying equations (20) and (21), $V(W')_{1,1}\beta_1$ captures the reaction of industry 1 to the monetary policy shock, v, that is, the demand response of sector 1 on impact, β_1, but also demand responses from sectors 2 and 3 that initiated in sector 1 and traveled back to it. For example, an increase in aggregate demand might increase the demand for goods in sector 1, β_1. Firms in sector 1 start producing more, requiring more intermediate inputs from sectors 2 and 3. Sectors 2 and 3 might then also increase their production and require more intermediate inputs, including goods sector 1 produces. Of course, firms in sector 1 itself might purchase more intermediate inputs from other firms in sector 1.

$V(W')_{1,2}\beta_2$, instead, gives the reaction of industry 1 to the monetary policy shock that directly increases the demand for goods of industry 2, β_2. This entry of the matrix measures the spillover effect of monetary policy on industry 1 through intermediate input linkages, that is, the demand of industry 2 for the goods that industry 1 produces and all higher-order spillover effects that travel back to industry 1. Similarly, $V(W')_{1,3}\beta_3$ measures the higher-order demand effect originating from industry 3.

This discussion indicates that SAR models allow for rich interdependencies in the reaction of industry returns to monetary policy shocks. We define three different decompositions of the total response of stock returns to monetary policy shocks into direct effects and higher-order network effects. The first decomposition follows Pace and LeSage (2014) and has the flavor of average partial derivatives, that is, the total return response to an increase in end-consumer demand for the goods of industries including intermediate input demands that travel back to the shocked sectors through the network. In the example above, $V(W')_{1,1}\beta_1$ gives the direct effect of the monetary policy shock, v, on industry 1, whereas $V(W')_{1,2}\beta_2$ and $V(W')_{1,3}\beta_3$ give the network effects due to industry 1's exposure to industry 2 and industry 3 through input-output linkages.

Hence, in the first decomposition, the diagonal elements of $V(W')$ contain the direct effects of monetary policy shocks on industry returns, and the off-diagonal elements present network effects. The average direct effect corresponds to $\frac{1}{n}\sum_{i=1}^{N} V(W')_{i,i}\beta_i$.[11] The average total effect is $\frac{1}{n}\iota_n' V(W')\beta$, where ι_n is n-by-1 vector of ones. And the average network effect is the difference between the average total effect and the average direct effect.

Algebraically, the series expansion of equation (21) demonstrates the first decomposition for an arbitrary number of industries. In particular, the direct effect for industry 1 corresponds to the sum of the diagonal elements in this series expansion, multiplied by β_1. Therefore, the direct effect for industry 1 is given by the sum of the demand response on impact, captured by the the first term in the series expansion (β_1); this impact effect traveling back to industry 1 through its linkages to itself, captured by the diagonal element of the second term ($\omega_{11}\rho_1\beta_1$); and the impact effect traveling back to industry 1 through its nth order linkages captured by the diagonal element of the corresponding $(n+1)$th term in the series expansion multiplied by β_1. Similarly, the off-diagonal elements in the first column give the spillovers from industry 1 to other industries through their direct and higher-order links to industry 1.

The second decomposition of total effects into direct and network effects directly follows Acemoglu et al. (2016) who label the estimates of β direct effects, that is, the first term in the series expansion of equation (20), and all the higher-order terms

[11] In the standard SAR model with constant β across industries, the average direct effect corresponds to the average of the trace of $V(W')\beta$.

network effects. This decomposition is motivated by the idea that direct effects correspond to the direct return response to a monetary policy shock on impact and network effects capture all higher-order effects due to changes in intermediate input demands and is consistent with the definition used by the UK government.[12] Hence, the direct effect is independent of the network structure. In particular, the direct effect tells us the share of the total response that would materialize if firms would not purchase intermediate inputs after an expansionary monetary policy shock.

Our third decomposition compares the estimates from the network economy with an economy under autarky in which each industry only uses its own output as an input into production. We use the heterogeneous coefficient estimates from the SAR model under the empirical input-output matrix and replace the input-output matrix with the identity matrix to abstract from cross-industry spillovers. $(I - D(\rho))^{-1}\beta$ gives the reaction of industry returns to monetary policy shocks under autarky. The difference between our original total effect and the effect under autarky gives the network amplification effect. The heterogeneity in coefficients is an essential ingredient for this decomposition because when β and shares of intermediate inputs in production, hence ρ, are constant across industries, the average of the total effect $\frac{1}{n}\iota_n'(I - \rho W')^{-1}\beta$ is equal to $\beta/(1-\rho)$ regardless of the W matrix despite the fact that the W matrix affects the policy sensitivity of individual sectors.

C. Monetary Policy Shocks

The identification of unanticipated and presumably exogenous shocks to monetary policy is central to our analysis. In standard macroeconomic contexts (for example, structural vector autoregressions), one may achieve identification by appealing to minimum delay restrictions whereby monetary policy is assumed to be unable to influence the economy (say, real GDP or the unemployment rate) within a month or a quarter. However, asset prices are likely to respond to changes in monetary policy within minutes.

To address this identification challenge, we employ an event-study approach in

[12]See Howse (2017) "Input-output analytical tables: methods and application to UK National Accounts," in particular Section 5.3, available at https://www.ons.gov.uk/economy/nationalaccounts/supplyandusetables/articles/inputoutputanalyticaltables/methodsandapplicationtouknationalaccounts/pdf.

the tradition of Bernanke and Kuttner (2005). Specifically, we examine the behavior of stock market returns in response to changes in the Fed's policy instrument in narrow time windows around FOMC press releases when the only relevant shock (if any) is likely due to changes in monetary policy. To isolate the unanticipated part of the announced changes in the policy rate, we use federal funds futures, which provide a high-frequency, market-based measure of the anticipated path of the federal funds rate.

We calculate the surprise component of the announced change in the federal funds rate, that is, our common monetary policy shock that hits all industries on a given event, as

$$v_t = \frac{D}{D-t}(ff^0_{t+\Delta t^+} - ff^0_{t-\Delta t^-}), \tag{23}$$

where t is the time when the FOMC issues an announcement, $ff^0_{t+\Delta t^+}$ is the rate implied by the federal funds futures shortly after t, $ff^0_{t-\Delta t^-}$ is the same rate just before t, and D is the number of days in the month. The $D/(D-t)$ term adjusts for the fact that the federal funds futures settle on the average effective overnight federal funds rate.

IV Data

In this section, we detail different data sources we are using.

A. Bureau of Economic Analysis Input and Output Tables

This section discusses the benchmark input-output (IO) tables that the BEA at the U.S. Department of Commerce publishes, as well as how we employ these tables to create an industry-to-industry matrix of dollar trade flows.[13]

The BEA produces benchmark input-output tables, which detail the dollar flows between all producers and purchasers in the United States. Purchasers include industrial sectors, households, and government entities. The BEA constructs the IO tables using Census data that are collected every five years. The BEA has published IO tables every five years beginning in 1982.

[13]Pasten, Schoenle, and Weber (2019) use similar data.

The IO tables consist of two basic national accounting tables: a "make" table and a "use" table. The make table shows the production of commodities by industries. Rows present industries, and columns present the commodities each industry produces. Looking across columns for a given row, we see all the commodities that a given industry produces. The sum of the entries adds up to the industry's total output. Looking across rows for a given column, we see all the industries producing a given commodity. The sum of the entries adds up to the total output of that commodity.

The use table documents the uses of commodities by intermediate and final users. The rows in the use table contain the commodities, and the columns show the industries and final users that utilize them. The sum of the entries in a row is the total output of that commodity. The columns document the products each industry uses as inputs and the three components of "value added": employee compensation, taxes on production and imports less subsidies, and gross operating surplus. The sum of the entries in a column adds up to an industry's total output.

The basic measure the BEA uses to estimate output differs across industries, although it is generally referred to as "receipts." However, the output for industries that buy and resell merchandise but do not provide any additional fabrication is measured as "margin," that is, sales receipts less the cost of goods sold. The use of this margin treatment enables the IO accounts to focus on the commodity-producing sectors of the economy and on the use of these commodities by other industries and by final users. Otherwise, all or most of the commodities in the economy would appear to emanate from the distributive industries (trade and transportation). In sum, the measured output of these distributive industries is the services they provide to other sectors, such as the bundling of goods or the provision of convenience or period maintenance services.[14]

We utilize the IO tables for 1992, 1997, and 2002 to create an industry network of trade flows. The BEA defines industries at two levels of aggregation, detailed and summary accounts. We use the summary accounts in our analysis to create

[14] For the detailed discussion of BEA's approach to distributive sectors, see Chapter 5 of the BEA publication, https://www.bea.gov/sites/default/files/methodologies/IOmanual_092906.pdf.

industry-by-industry trade flows at the four-digit IO industry aggregation to ensure a sufficiently large numbers of firms within each industry and hence well-diversified industry portfolios.

A.1 Industry Aggregations

The IO tables follow a BEA-specific industry classification but the BEA provides concordance tables that allow us to map their classification to Standard Industrial Classification (SIC) and North American Industry Classification System (NAICS) codes. The 1992 IO tables provide mappings to the 1987 SIC codes, the 1997 IO tables provide mappings to the 1997 NAICS codes, and the 2002 IO tables provide mappings to the 2002 NAICS codes. We follow the BEA's IO classifications but make minor modifications to create our industry classifications for the subsequent estimation. We account for duplicates when SIC and NAICS codes are not as detailed as the IO codes. In some cases, different IO industry codes are defined by an identical set of SIC or NAICS codes. For example, for the 2002 IO tables, a given NAICS code maps to both dairy farm products (010100) and cotton (020100). We aggregate industries with overlapping SIC and NAICS codes to remove duplicates.

A.2 Identifying Supplier-to-Customer Relationships

We combine the make and use tables to construct an industry-by-industry matrix that details how much of an industry's inputs other industries produce. We use the make table ($MAKE$) to determine the share of each commodity each industry k produces. We define the market share ($SHARE$) of industry k's production of commodities as

$$SHARE = MAKE \oslash (\mathbb{I} \times MAKE)\,, \tag{24}$$

where $\mathbb{I}$ is a matrix of ones with suitable dimensions and $\oslash$ represents the Hadamard division (element by element).

We multiply the share and use tables (USE) to calculate the dollar amount industry k' sells to industry k. We label this matrix revenue share ($REVSHARE$), which is a supplier industry-by-consumer industry matrix,

$$REVSHARE = SHARE \times USE. \tag{25}$$

We then use the revenue-share matrix to calculate the percentage of industry k inputs purchased from industry k', and label the resulting matrix $SUPPSHARE$

$$SUPPSHARE = [REVSHARE \oslash (\mathbb{I} \times USE)]' . \tag{26}$$

$SUPPSHARE$ corresponds to the theoretical W matrix of Section II and its empirical counterpart in Section III.

B. Federal Funds Futures

Federal funds futures started trading on the Chicago Board of Trade (CBOT) in October 1988. These contracts have a face value of $5,000,000. Prices are quoted as 100 minus the daily average federal funds rate as reported by the Federal Reserve Bank of New York. Federal funds futures have limited counterparty risk due to daily marking to market and the CBOT's collateral requirements.

The FOMC has eight scheduled meetings per year and, starting with the first meeting in 1994, most of its press releases announcing monetary policy decisions are issued around 2:15 p.m. Eastern time. Table A.4 in the Online Appendix reports event dates, time stamps of the press releases, actual target rate changes, and expected and unexpected changes for 30-minute (starting 10 minutes before the event) and 60-minute (starting 15 minutes before the event) event windows. We obtained these statistics from Gorodnichenko and Weber (2016). In our empirical analysis, we follow Paul (2018) and focus on scheduled FOMC meetings to ensure signaling or information effects of monetary policy do not drive our findings (see Nakamura and Steinsson (2018)) and use a 30-minute event window around the press release to ensure no other shocks are hitting industry returns within the event window.

C. Event Returns

We sample returns for all common stocks trading on the NYSE, AMEX, or NASDAQ for all event dates. We link the CRSP identifier to the ticker of the NYSE TAQ database via historical CUSIPs (an alphanumeric code identifying North American securities). NYSE TAQ contains all trades and quotes for all securities traded on the NYSE, AMEX, and the NASDAQ National Market System. We use the last trade observation before the start of the event window and the first trade observation after the end of the event window to calculate the change in stock market prices following the monetary policy announcement. We exclude zero event returns to make sure that stale returns do not drive our results. We aggregate individual stock returns to industry returns following the BEA industry definition but require that each industries consists of at least three firms to ensure well-diversified industry returns and minimize the effect of outliers. We have on average 61–71 industries, depending on whether we use the SIC or NAICS codes for the aggregation. We calculate industry returns by value-weighting firm returns in a given industry. We use the market cap at the end of the previous trading day or calendar month as weights.

Our sample period starts on February 2, 1994, the first scheduled FOMC meeting and goes through December 16, 2008, the last announcement date in 2008 after which the target rate remained at the zero-lower bound until the end of 2015. Our sample starts in 1994 because our tick-by-tick stock price data are not available before 1993, and because in 1994 the FOMC changed the way it communicates its policy decisions. Prior to 1994, the market became aware of changes in the federal funds target rate through the size and the type of open-market operations conducted by the New York Fed's trading desk. Moreover, most of the changes in the federal funds target rate took place on non-meeting days. With its first meeting in 1994, the FOMC started to communicate its decisions by issuing press releases after meetings and policy decisions. Therefore, the starting date of our sample and our use of scheduled meetings eliminates any timing ambiguity. The increased transparency and predictability makes the use of our intraday identification scheme more appealing, as our identification assumptions are more likely to hold.

V Empirical Results

This section provides our empirical results.

A. Aggregate Stock Market

We first document the effects of monetary policy shocks on the returns of the CRSP value-weighted index. Column (1) of Table 1 reports the results from regressing returns of the CRSP value-weighted index in the 30-minute event window surrounding the FOMC press releases on monetary policy surprises for the full sample of regular (scheduled) FOMC meetings from 1994 until 2008. The announcement of a federal funds target rate that is 1 percentage point higher than expected leads to a drop in stock prices of roughly 3 percentage points. The reaction of stock prices to monetary policy shocks is similar in magnitude to the previous results reported in the literature (see Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2005)).

Column (2) repeats the regression at the industry instead of the market level and confirms the results. Federal funds rate decisions that are 25 basis points (bps) higher than expected lead to an average drop in industry returns of three quarters of a percentage point.

B. Estimation with Constant Coefficients

We then estimate the standard SAR model of Pace and LeSage (2014), which assumes identical parameters across industries. We regress event returns at the industry level on monetary policy surprises (column (2) of Table 1) and on a weighted average of industry stock returns (columns (3)–(5)) assuming constant loadings on the monetary policy shocks (β), a scalar coefficient ρ, and homoskedastic error term variances in equation (19). We relax this assumption in the following sections to ensure cross-industry heterogeneity in these parameters does not drive our decomposition into direct and network effects.

We see in column (3) and (4) that the estimates for β as well as for ρ are highly statistically significant, independent of whether we use the previous month's or previous trading day's market capitalization as weights to calculate industry returns.

Economically, a negative estimate of β means that a tighter-than-expected monetary policy announcement leads to a drop in stock returns. The positive estimate of ρ means that this effect is transmitted through the production network: a higher-than-expected federal funds rate results in a decline in industry returns, which leads to an additional decline in industry returns through spillover effects.

So far, we have used a fully pre-determined spatial weighting matrix which is a reasonable assumption given production technologies and intermediate input demands change slowly over time. In column (5) we report results from a specification in which we use a time-varying matrix. We use the 1992 tables until 1997, the 1997 tables until 2002, and the 2002 tables afterwards. The point estimates remain similar and the estimate for the network parameter ρ remains statistically significant.

The positive and statistically significant point estimates of ρ indicate that part of the responsiveness of stock market returns to monetary policy shocks might be due to higher-order network effects.[15] Panel B of Table 1 decomposes the overall effect of monetary policy shocks on stock returns into direct and network effects according to the decompositions outlined in Section III. Network effects, ranging from –2.6 to –3 percent, are an important component of the overall effect of –3.3 to –3.5 percent; they account for roughly 80 to 85 percent of the total effect of monetary policy shocks on stock returns.

In Section V of the Online Appendix (Table A.1), we show our conclusion does not change when we study different subsamples. We study turning points in monetary policy, such as the first increase in the federal funds rate after a series of decreasing or constant rates, economically large shocks, because monetary policy has become more predictable over time resulting in many small shocks, and contractionary versus expansionary monetary policy shocks.

C. Heterogeneity in Coefficients

So far, we have estimated a constant exposure of industry returns to monetary policy shocks in line with the estimation strategy in Acemoglu et al. (2016).

[15] Note a large estimate of ρ does not guarantee a large network effect, especially if industries mainly rely on own output as intermediate input. To see this more clearly, assume $\rho = 1$ and $W = I$, which leads to zero network effects under the first and third decompositions.

Imposing a constant β across industries might bias our estimate of ρ upward. In fact, the model we develop in Section II predicts heterogeneous reactions due to differences in consumption shares across sectors. Therefore, we now estimate models with heterogeneous βs. Moreover, empirically, the share of intermediate inputs in production also varies at the industry level which translates into variation in ρ across sectors (see equation (17)). Therefore, we discipline our estimation by replacing the scalar ρ with the diagonal matrix $D(\rho)$ whose entries are a function of the intermediate input shares. Calibrating these shares improves the efficiency of our estimates.[16]

Table 2 reports the results. We report the average β and ρ estimates across industries for the sake of parsimony and to make the results comparable to Table 1.[17] Because we estimate heterogeneous coefficients, we now can also study the amplification through the network in our third decomposition.

Columns (2) and (3) estimate the model imposing homeskedastic error terms and columns (4) and (5) relax this assumption and allow for heteroskedastic error terms across industries. We report averages of industry-specific estimates of β and ρ. Across columns, we find average estimates of β that are close to the estimates of the model with constant β. Moreover, the estimates of ρ barely change and are around 0.80.

Panel B of Table 2 reports the previous two decompositions and the new decomposition 3. Across columns, we see that the network effect 1 still accounts for around 80% of the total effect. When we apply the Acemoglu et al. (2016) decomposition, we find network effects also account for 80% of the total effect. Finally, the network effect due to amplification in the third decomposition is around 55%.

[16] In particular, we restrict ρ for different industries to be proportional to their empirical input shares from the BEA so that the spillover coefficient multiplied by the sector-specific intermediate input shares vary in line with the empirical intermediate input shares.

[17] Given that we now allow for heterogeneous coefficients across industries, we can no longer estimate a model with time-varying weighting matrix W because the industry definition and industry classification would change over time and we would not have enough observations at the industry level to estimate sector-specific coefficients.

D. Robustness

Returns in the cross section may vary because of exposures to risk factors such as the size and value factors of Fama and French (1992). If the position in the production network is correlated with exposures to these sources of risk, we might partially attribute these risk exposures to higher-order network effects. In column (1) of Table 3, we re-estimate the SAR model with heterogeneous coefficients using excess returns relative to a three-factor model. Specifically, we estimate exposures to the market, size, and value factors using daily industry and factor returns in the 365 days before the respective FOMC event, excluding all FOMC event days and the days prior to them to ensure the pre-FOMC drift of Lucca and Moench (2015) does not drive the exposures to these factors. We then calculate excess returns in the event window as the industry returns minus their loadings on the factors times the market, size, and value factor returns in the event windows.[18] We find estimates of average βs and ρs that are barely distinguishable from our estimates for raw industry returns and network effects explain a similar amount of the overall effects as in Table 2.

Moreover, the empirical input-output matrix has non-zero entries on the diagonal, which means, for example, that General Motors purchases seating systems from Magna International. One concern is that these within-industry demand effects are largely responsible for determining large estimates of ρ (see Figure 2). As we discuss in footnote 15, large diagonal entries in the input-output matrix do not result in large estimates of network effects. Nevertheless, in column (2) of Table 3, we constrain the diagonal entries of the input-output matrix to zero but ensure that the intermediate input shares still add up to 1. Network effects still make up between 56% and 81% depending on the decomposition. The result is reassuring. Even if we bias our specification against finding network effects, we still attribute economically large parts of the overall stock market reaction to higher-order network effects.

Industries differ in their cyclicality of demand or durability of output (see D'Acunto, Hoang, and Weber (2017)). In column (3) of Table 3, we look at

[18]Here and subsequently we use value-weighted returns with end of previous month market cap as weights.

industry-adjusted returns to control for those systematic differences. We first regress industry returns within our 30-minute event window for all FOMC announcements on industry dummies and then use the industry-demeaned returns in the SAR. The adjustment has little impact on point estimates, the industry's overall response to monetary policy shocks, and the relative importance of direct and network effects. The consistency of the results is not surprising because we already allow for heterogeneous exposure to monetary policy shocks in Table 2 by estimating heterogeneous βs.

Table A.2 in the Online Appendix also shows robustness results for a balanced panel of industries where we estimate the same model as in Table 2 using MCMC, following LeSage and Chih (2018). Moreover, given that many entries in the input-output matrix are small but non-zero, Table A.2 also presents robustness tests in which we normalize small entries to zero but still ensure that intermediate input shares add up to one. The remaining robustness test in Table A.2 relaxes the restriction of a minimum of three firms for an industry-event observation, a restriction we imposed in the baseline results to create well-diversified industry returns. Overall, our results are very similar to the baseline estimates in Table 2.

E. The Importance of Network Characteristics

Acemoglu et al. (2012) and Carvalho (2010) study the propagation of sectoral shocks to aggregate fluctuations and find two statistics are sufficient for explaining the aggregate fluctuations originating from sectoral shocks: the first-order outdegree, that is, the importance of sectors as suppliers to the rest of the economy, and the second-order outdegree, that is, the importance of sectors as suppliers of big suppliers to the rest of the economy. Figure 1 in the introduction shows the zero-order outdegree, which corresponds to the direct effect of monetary policy on stock returns following the definition of Acemoglu et al. (2016), captures only 14% of the total effect. Moreover, we find the first 10 weighted outdegrees from the series expansion of equation (20) capture only 71% of the total effect of monetary policy shocks. In the decomposition into direct and network effect of Acemoglu et al. (2016), the difference between 71% and 14% is the contribution of the first ten terms in the series expansion of equation (20) to the network effect. Hence, many outdegrees are necessary to capture the total network effect of monetary policy shocks on stock returns.

To study which properties of the empirical input-output tables are the key determinants for the propagation of monetary policy shocks to the stock market, we perform several simulations. Figure 2 is a heatmap of the 1992 customer-supplier matrix that we use for most of our tests. Customers are on the y-axis and suppliers on the x-axis, with entries ω_{ij} representing the share of intermediate input consumption of industry i from industry j. Darker blue colors indicate higher values. Intermediate input shares are between 0 and 1 and add to 1 for a given customer industry. Table A.3 in the Online Appendix contains the industry classification.

We want to discuss several properties of the empirical input-output matrix that the previous literature has established as important for the propagation of shocks. First, the matrix is sparse, that is, many sectors consume intermediate input shares from only a subset of other supplying sectors (Gabaix, 2011). Second, the diagonal of the matrix contains large entries, that is, GM tends to purchase many car parts directly from suppliers in the same industry such as Magna International.[19] Third, large variation exists in the importance of sectors as suppliers to other sectors, that is, the first-order outdegrees: $\sum_i \omega_{ij}$. Outdegrees range from as little as 0.04 to as high as 6.68. Finally, and not directly visible from Figure 2, Acemoglu et al. (2012) show large heterogeneity also exists in the second-order outdegree, the importance of suppliers to large suppliers of other sectors.

We now want to explore to which extent these properties of the input-output matrix shape the propagation of monetary policy shocks to the stock market. We start with a simple example that only matches sparsity. We add more and more realistic features of the W matrix by matching sparsity and the distribution of first-order outdegrees and then by matching sparsity and the distribution of second-order outdegrees. We perform this analysis by simulating 1,000 W matrices with these properties, estimate SAR specifications with heterogeneous β and ρ,

[19] We already know from Table 3 that large diagonal entries are not central to generate large network effects and ignore this feature of the data in the simulations below.

perform all three decompositions into direct and network effects, and plot the distribution of the difference between our actual network effects in Table 2 and the estimated network effects from simulated W matrices. Since these simulated W matrices are not diagonal, we still expect them to generate non-zero network effects. We are interested in whether these network effects are of comparable size to the actual network effects we estimate in Table 2.

Specifically, we condition on the number of non-zero entries in the empirical input-output matrix and draw random numbers from a generalized Pareto distribution with a tail index parameter of 2.90137632289464 and a scale parameter of 0.00021053821934. We estimate these parameter values by minimizing the squared distance between the empirical distribution function and the Pareto distribution function using the 1992 input-output matrix. But given the empirical input-matrix has many small entries that are close to zero, we constrain entries smaller than 10^{-4} to zero (see Figure 2).[20] In the second experiment, we use the actual first-order outdegrees (column sum of W matrix), randomly assign them to different industries, draw random numbers from the Pareto distribution and assign them to column entries using a random number generator, constrain small entries to zero, and renormalize the entries so that the simulated first-order outdegrees match assigned first-order outdegree. We follow the same steps when matching the second-order outdegree in the third experiment.

Figure 3 reports the results from 1,000 simulations for all three experiments. The left figures report the difference between empirical estimates of network effect 1 from column (3) of Table 2 with the estimates from the simulations, the middle panels report the difference for network effect 2, and the right panels plot the histograms for the difference in amplification effects.

We see in Panel A that purely matching the sparsity of the W matrix results in network effects of monetary policy that are substantially smaller than the estimates from the empirical W matrix. For the first two decompositions, we find simulated network effects that are smaller than our estimates in Table 2 by about 0.9 percentage point for a 1 percent policy rate surprise. In the right panel, we see even larger

[20]Our results remain similar without this constraint.

differences for the amplification through the network effects. In Panels B and C, we see similar differences between the empirical and simulated network effects when we use simulated input-output matrices that match not only sparsity but also the distribution of first-order outdegree (panel B) and the distribution of second-order outdegrees (panel C).

So far, we see that purely matching the sparsity of the network and the empirical distribution of first- and second-order outdegrees is not enough to generate network effects as large as those in the data. To better understand which features of the empirical production network are central to capture the importance of network effects, we now perform two additional simulations. In each of these simulations, we match salient features of the empirical input-output structure but also match these characteristics to the actual industries to which they belong in the data. In a first simulation, we match the sparsity of the network and first-order outdegree industry-by-industry, draw random numbers from the fitted Pareto distribution, and constrain small numbers to 0. In the second experiment, we match industry-by-industry the sparsity of the network, the first-order outdegree, and the second-order outdegree and fill the entries with random numbers of the fitted distribution. These exercises differ from those in Figure 3 because the network statistics are not randomly assigned anymore. The only difference between simulated and actual W matrices are the entries of the W matrix which we draw from a fitted distribution.

Figure 4 reports the histograms for the differences between our empirical estimates and the simulated network effects. We see that matching sparsity and first-order outdegrees industry-by-industry reduces the differences between our empirical network effects and the simulated effects by around 50% (compare Panel A of Figure 4 to Panel B of Figure 3). When we instead also match second-order outdegrees industry-by-industry, we see that the differences between estimates and simulations for the network effects are reduced by almost two thirds on average (compare Panel B of Figure 4 to Panel C of Figure 3). Hence, we capture almost 85% of the network effects when we match sparsity and first two outdegree industry-by-industry.[21]

These results suggest that purely matching salient features of input-output matrices such as sparsity and the distribution of lower-order outdegrees is not sufficient to match the empirical network effects of monetary policy shocks on the stock market. It is also central to match the sectors to which these network properties belong. After ensuring the actual industry assignment, we find network effects close to the empirical estimates. The remaining gap between simulations and estimates arises because higher-order effects might also play a role and because the entries of the W matrix in simulations differ from the empirical entries.

F. Closeness to End-Consumers

Our model interprets monetary policy shocks as demand shocks. Therefore, one would intuitively expect that the relative importance of direct and network effects for an industry depends on how close the industry is to end-consumers. Industries that sell most of their output directly to consumers should have most of their overall response to monetary policy shocks originating from direct effects. On the contrary, the sensitivity of input producers, such as the oil sector, should mainly come from network effects. In this section, we show that this prediction holds theoretically when intermediate input shares across industries are sufficiently close to each other and test this prediction empirically.

We divide the industries into two groups for our analysis. Industries in the first group are close to end-consumers, in the sense that they sell most of their output to consumers or other industries in the same group. Empirically, we define "most" as 90% but, for the sake of expositional clarity in the theoretical analysis below, we assume that industries in the first group sell all their production to consumers or other industries in the same group. The remaining industries, those in the second group, are far from end-consumers.

For simplicity, we study here the case of one representative industry in each group and discuss the case with multiple industries in each group in the Online

[21] Figure A.2 in the Online Appendix reports the distribution of the difference between the log-likelihood from Table 2 and the ones that come from our simulations. These histograms suggest a substantially better fit of the model with the empirical input-output matrix compared to the models with simulated W matrices.

Appendix. Let α_i be the share of intermediate inputs for industry i and ω_{ij} be the share of input of industry j in industry i's production function. Also note that $\omega_{11} + \omega_{12} = 1$. We can write Equation (17) as

$$\begin{pmatrix} \hat{\pi}_1 \\ \hat{\pi}_2 \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \hat{M} + \begin{bmatrix} \alpha_1\omega_{11} & 0 \\ \alpha_1\omega_{12} & \alpha_2 \end{bmatrix} \begin{pmatrix} \hat{\pi}_1 \\ \hat{\pi}_2 \end{pmatrix}. \tag{27}$$

Solving these equations gives

$$\begin{aligned} \hat{\pi}_1 &= \frac{\beta_1}{1-\alpha_1\omega_{11}}\hat{M}, \\ \hat{\pi}_2 &= \frac{\beta_2\hat{M} + \alpha_1\omega_{12}\hat{\pi}_1}{1-\alpha_2}. \end{aligned}$$

Since the two decompositions of direct and network effects based on Pace and LeSage (2014) and Acemoglu et al. (2016) provide similar results empirically, we focus on the latter. The two groups' fractions of direct effect from our decomposition based on Acemoglu et al. (2016) are

$$\begin{aligned} Direct_1 &= \frac{\beta_1\hat{M}}{\hat{\pi}_1} = 1-\alpha_1\omega_{11}, \\ Direct_2 &= \frac{\beta_2\hat{M}}{\hat{\pi}_2} = (1-\alpha_2)\frac{\beta_2\hat{M}}{\beta_2\hat{M} + \alpha_1\omega_{12}\hat{\pi}_1} \\ &= (1-\alpha_2)\frac{(1-\alpha_1\omega_{11})\,\beta_2}{(1-\alpha_1\omega_{11})\,\beta_2 + \alpha_1(1-\omega_{11})\,\beta_1} < 1-\alpha_2. \end{aligned}$$

So, unless $\alpha_1\omega_{11} >> \alpha_2$, that is unless group 1 firms spend a much larger share of their revenue on the output of group 1 than group 2 firms do on the output of group 2, we should expect larger direct effects for firms close to end-consumers. In our data, $\alpha_1\omega_{11} < \alpha_2$ trivially holds because, on average, $\alpha_1 = 0.425$, $\alpha_2 = 0.545$, and $\omega_{11} \leq 1$ by the nature of being intermediate input shares.

In the case of autarky, $W = I$, firms purchase intermediate inputs only from other firms in their own industry. The reaction of net income in this case, denoted as $\hat{\pi}^0$, for a unit monetary shock ($\hat{M} = 1$) becomes

$$\begin{aligned} \hat{\pi}_1^0 &= \frac{\beta_1}{1-\alpha_1} > \hat{\pi}_1 = \frac{\beta_1}{1-\alpha_1\omega_{11}}, \\ \hat{\pi}_2^0 &= \frac{\beta_2}{1-\alpha_2} < \hat{\pi}_2 = \frac{\beta_2 + \alpha_1\omega_{12}\hat{\pi}_1}{1-\alpha_2}. \end{aligned}$$

So, the network amplification effect of our third decomposition is negative for industries close to end-consumers (group 1) and it is positive for industries far away from end-consumers (group 2).

We now discuss how we operationalize the measure of closeness to end-consumers. We follow Carvalho, Nirei, Saito, and Tahbaz-Salehi (2021) to create an empirical proxy for the closeness to end-consumers, using data from the BEA. Specifically, we sort industries into layers by the fraction of output sold directly and indirectly to end-consumers.[22]

We assign an industry to layer 1 if it sells more than 90 percent of its output to consumers. Layer 2 consists of industries not in layer 1 that sell more than 90 percent of their output either directly to consumers or indirectly to consumers via inputs to layer-1 industries. Similarly, layer $n+1$ consists of industries not in layer n but that sell more than 90 percent of their output either directly to consumers or indirectly as inputs to layer $1, ..., n$ industries. After eight rounds, we have assigned each industry to a layer. We label industries in layers 1–4 "close to end-consumers." Industries in layers 5–8 are "far from end-consumers."

Table 4 reports our decomposition into direct and network effects for both sets of industries. In column (1), we report results for industries close to end-consumers and in column (2), we report results for industries far from end-consumers. We take the estimates from Table 2 and perform the decompositions into direct and network effects using the relevant parts of the Leontief inverse. Across decompositions, we find substantially larger direct effects for industries close to end-consumers than for industries far away from end-consumers. Moreover, consistent with our derivations above, we find negative amplification through the network effects in the third decomposition for industries close to end-consumers, whereas the network amplification effect is large and positive for industries far away from end-consumers.

G. External Finance Dependence

Our results suggest that monetary policy may directly increase consumer demand for goods and services, which then gets transmitted to these firms' suppliers and further upstream in the production network. Nevertheless, monetary policy can

[22]Section IV in the Online Appendix details the procedure. The measures is also similar to the downstreamness measures of Antràs and Chor (2018).

affect the economy through firms' cost of external financing as well. In order to see if this additional channel might contribute to our large estimates of the network effect, we separate the industries into two groups based on their external finance dependence and based on their Kaplan-Zingales (KZ) index. We follow Demirgüç-Kunt and Maksimovic (2002) and D'Acunto et al. (2018) to calculate the external finance needs of firms in our sample and aggregate it to the industry level.

Table 5 reports our decomposition into direct and network effects for both sets of industries. We report results for the external finance gap in Panel A and for the KZ index in Panel B. The direct and network effects for both groups of firms are similar to each other and to the decompositions we report in previous sections, suggesting the effect of monetary policy through cost of external financing is not a central driver of our main results. This result is consistent with the fact that large and financially-unconstrained firms dominate value-weighted industry returns, which allows us to isolate the demand effects from other effects that might work through financial frictions and funding conditions (Bigio and La'O (2020)).

H. Fundamentals

Our baseline findings presented in Table 1 indicate that higher-order network effects might be responsible for up to 80 percent of the reaction of stock returns to monetary policy shocks. We argue that demand effects account for the transmission of monetary policy shocks through the production network. Such demand effects suggest that we should see similar network effects in ex-post realized fundamentals, such as sales or operating income. For a sample period similar to ours, Bernanke and Kuttner (2005) and Weber (2015) find that cash flow news is as important as news about future excess returns in explaining the reaction of the overall stock market to monetary policy shocks.

Data on cash flow fundamentals are only available at the quarterly frequency, and detecting network effects in these fundamentals might be difficult. We add policy shocks v_t in a given quarter and treat this sum as the unanticipated shock to match the lower frequency, following Gorodnichenko and Weber (2016) and Wong (2019). We denote the quarterly shock as $\tilde{v}_t$. We also construct the following measure of change in a firm's sales between the previous four quarters and quarters running from $t + H$ to $t + H + 3$:

$$\Delta sale_{it,H} = \frac{\frac{1}{4}\sum_{s=t+H}^{t+H+3} sale_{is} - \frac{1}{4}\sum_{s=t-4}^{t-1} sale_{is}}{TA_{it-1}} \times 100, \tag{28}$$

where *sale* is net sales at the quarterly frequency, TA is total assets, and H is the time horizon associated with the sales' response to the policy change. We create similar measures for operating income OI. We use four quarters before and after the monetary policy shock to address seasonality in sales and operating income and scale by total assets to normalize the change. We construct measures at the sector level, equally-weighting and value-weighting cash flow fundamentals and total assets. Using these measures of fundamentals, we estimate the following modification of our baseline specification:

$$\Delta sale_{t,H} = \beta_0 + \beta_1 \tilde{v}_t + W' D(\rho) \Delta sale_{t,H} + \varepsilon_t. \tag{29}$$

Table 6 shows higher-order network effects correspond to about 60 percent of the immediate effect ($H = 0$) that monetary policy shocks have on different measures of fundamentals and weightings.[23] The network effect increases in size up to eight quarters ($H = 4$) after the monetary policy shock before it levels off.

The network effects that we document in industry fundamentals indicate that monetary policy shocks affect the real economy at least partially through demand effects, a result that is consistent with earlier findings.

VI Dynamic Model: Simulation

Our static benchmark model predicts a SAR structure for stock returns around monetary policy announcements. Our empirical results attribute a large fraction of the overall stock market response to network effects. Even if our robustness checks might have missed a confounding factor driving our findings, we can abstract from such factors in a model and assess whether we can rationalize the size of the network effect in calibrations in which the network structure is the only source of comovement

[23]The impact response includes the quarters when the monetary policy shocks occur and the following three quarters relative to the four quarters before the FOMC meeting when the policy change was announced.

across sectors. We sketch the central differences between the static model of Section II and the dynamic model that we bring to the data and provide additional details in Section III of the Online Appendix.

A. Economic Environment

Firms produce goods using labor and intermediate inputs with a constant elasticity of substitution (CES) production function that flexibly accommodates perfect substitution across factors, a Cobb-Douglas, or a Leontief production function. The firms' profit function is identical to the benchmark model.

Combining the goods-market clearing condition with the cash-in-advance constraint for consumption goods gives the following equation for revenues:

$$R_i = b_i M + \sum_{j=1}^{N} \left[a\theta_j \omega_{ji} R_j \right],$$

where a is the degree of homogeneity of the production function and θ_i is the share of intermediate inputs in the production of industry i, determined endogenously in equilibrium.

This model changes the relationship between $\sum_{i=1}^{N} R_i$ and M, and the network structure affects the reaction of the aggregate stock market to monetary policy through θ_i.

Wages are set dynamically,

$$w_t = \psi w_{t-1} + (1-\psi)\, w_t^*, \tag{30}$$

where w_t^* is the equilibrium wage under flexible wages. We can interpret ψ as the degree of wage stickiness, and money supply growth is mean-reverting, as in Cooley and Hansen (1989).

The deviations of revenues are

$$\hat{R}_i = b_i \frac{\bar{M}}{\bar{R}_i} \hat{M} + \sum_{j=1}^{N} \frac{\bar{p}_i \bar{x}_{ji}}{\bar{p}_i \bar{y}_i} \left(\hat{\theta}_j + \hat{R}_j \right), \tag{31}$$

where $\bar{p}_i \bar{x}_{ji} / \bar{p}_i \bar{y}_i$ is the share of industry i's revenues from industry j. A larger value for this term implies that industry j is a more important customer of industry i. Monetary policy affects industry i through industry j via two channels: first, via the effect of higher revenues of customer industry j, $\hat{R}_j$; second, via an additional effect from $\hat{\theta}_j$, which captures the change in the relative importance of intermediate inputs for industry j. The latter channel is absent with a Cobb-Douglas production function. The more industry j shifts from labor toward intermediate inputs, the more it will affect the revenue stream of its suppliers. The Online Appendix shows how we can rewrite this equation as a function of this system's state variables, $\hat{m}_t$ and $\hat{w}_t$, after solving for $\hat{\theta}_t$ as a function of $\hat{R}_t$.

Preferences are

$$U\left(\{c_{i,t+s}\}\right) = E_t\left(\sum_{s=0}^{\infty}\delta^s\sum_{i=1}^{N}b_i\log\left(c_{i,t+s}\right)\right), \tag{32}$$

where δ is the rate at which consumers discount utility of consuming different goods, $c_{i,t}$. These preferences result in the "nominal stochastic discount factor" (see Campbell (2000)),

$$SDF_{t+s} = \delta\frac{c_{i,t}}{c_{i,t+s}}\frac{p_{i,t}}{p_{i,t+s}} = \delta\frac{M_t}{M_{t+1}}, \tag{33}$$

where the second equality comes from the cash-in-advance constraint. Therefore, the market value of industry i, $V_{i,t}$, with profit stream $\{\pi_{i,t}\}$, is

$$V_{i,t} = E_t\left(\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}\pi_{i,t+s}\right). \tag{34}$$

In the Online Appendix, we show stock prices have a spatial structure that is closely tied to the spatial structure of revenues.

B. Calibration

We calibrate the model to the data and perform a battery of robustness checks. The consumption shares, b_i, equal consumer spending on different industries' products. The discount factor, $\delta = 0.99$, is calibrated so that we have a 1 percent interest rate per quarter. We calibrate the parameter for the curvature of the production function, a, to a value of 0.85, using the operating profit margin, $1 - a$, of 0.15 in Compustat data (EBITDA / Sales ratio). We set the autocorrelation and standard deviation of money growth to $\rho_M = 0.5$ and $\sigma_M = 0.01$, respectively, following Cooley and Hansen (1989). We calibrate the parameter for wage stickiness,

ψ, to a value of 0.2 to capture the autocorrelation of nominal wage growth during the 1964–2016 time period (see discussion in the Online Appendix). We set substitution and share parameters, $\phi = -0.5$ and $\eta = 0.1$, so that we have an average labor share of 0.4 and the elasticity of substitution between intermediate inputs and labor is smaller than the elasticity of substitution between different intermediate inputs. We normalize factor productivity, z_i, to 1, and we set m/w to a value of 1 in steady state.

C. Simulation Results

Table 7 presents point estimates for β and ρ as well as the fraction of the network effect from running our SAR regression on simulated data from the dynamic model. In our benchmark calibration, a contractionary monetary policy shock results in a drop in stock prices ($\beta < 0$). This drop is transmitted through the production network ($\rho > 0$). Interestingly, the point estimates for ρ and the fractions of network effects are very similar to our empirical estimates across specifications. The findings remain robust across various calibrations. In particular, neither the properties of the processes for money-supply growth and wages, nor variations in fundamental parameters, result in large changes in the fraction of the network effect. The estimates for ρ vary between 0.74 and 0.78. The network effects range between 63% and 68% for decomposition 1, between 74% and 78% for decomposition 2, and between 44% and 54% for decomposition 3. The robustness of the measured network effect to various parameterizations suggests that our SAR framework is robust to relaxing the assumptions embedded in the benchmark static model and that network effects originating from intermediate input linkages are an important determinant of the sensitivity of industry returns to monetary policy shocks.

As a final analysis, we study how the measured effects would change if a dense network, $\omega_{ij} = 1/N$ for all i and j as in Basu (1995), characterized the input-output linkages. The last line of Table 7 presents the results. For the first two decompositions, we still find a significant fraction of the total effect being due to network effects. Note, however, that the estimates of both β and ρ are now substantially smaller compared to our baseline estimates and the other calibrations, implying smaller total effects. Moreover, the network amplification (last column) is effectively zero. This result is akin to those in Acemoglu et al. (2012) and Carvalho and Tahbaz-Salehi (2019). In particular, they argue extensive heterogeneity in network centrality is necessary to generate aggregate fluctuations from sectoral shocks. In our case, monetary policy shocks hit sectors differently and a necessary condition to generate large aggregate effects is high dispersion in sectors' multipliers mapping sectoral exposure to shocks onto aggregate fluctuations, as in Pasten et al. (2020). A dense network reduces this heterogeneity and hence the network amplification effect.

VII Concluding Remarks

Financial markets reflect the real effects of monetary policy decisions within minutes because stock returns around monetary policy changes reflect the changes in the present discounted value of all future cash flows. We use this property of equity markets in order to identify the importance of network effects for the transmission of monetary policy shocks. We document that intermediate input linkages across sectors introduce higher-order network effects that are responsible for a large fraction of the overall real effect of monetary policy. We motivate our empirical analysis using a simple network model in which firms use intermediate inputs as a production factor.

Recent macroeconomic studies show that idiosyncratic shocks are important for aggregate fluctuations. So far, however, limited evidence exists on whether network effects are also important for the transmission of macro shocks, such as monetary policy shocks. We use the industry-level stock market response to monetary policy shocks as a laboratory to test whether production networks matter for the transmission of monetary shocks. Around 70 percent of the stock market's response to monetary shocks comes from higher-order network effects. These effects are robust to different sample periods, event types, and alternative robustness tests. We document similar network effects in ex-post realized fundamentals, such as sales and operating income. The direct effects are larger for industries selling most of their output directly to end-consumers compared to other industries, a result that is consistent with the intuition that indirect demand effects through the production network should be less important for industries that are "close to end-consumers."

Our findings indicate that production networks might not only be important for the propagation of idiosyncratic shocks, but might also be a mechanism that transmits monetary policy to the real economy. The importance of network effects for the transmission of aggregate shocks suggests that macroeconomic models used to evaluate the effectiveness of various polices should incorporate input-output structures. Our results also suggest interesting questions for future research, such as the importance of different sectors for the transmission of monetary policy shocks and how optimal policy looks when the economy is characterized by a network.

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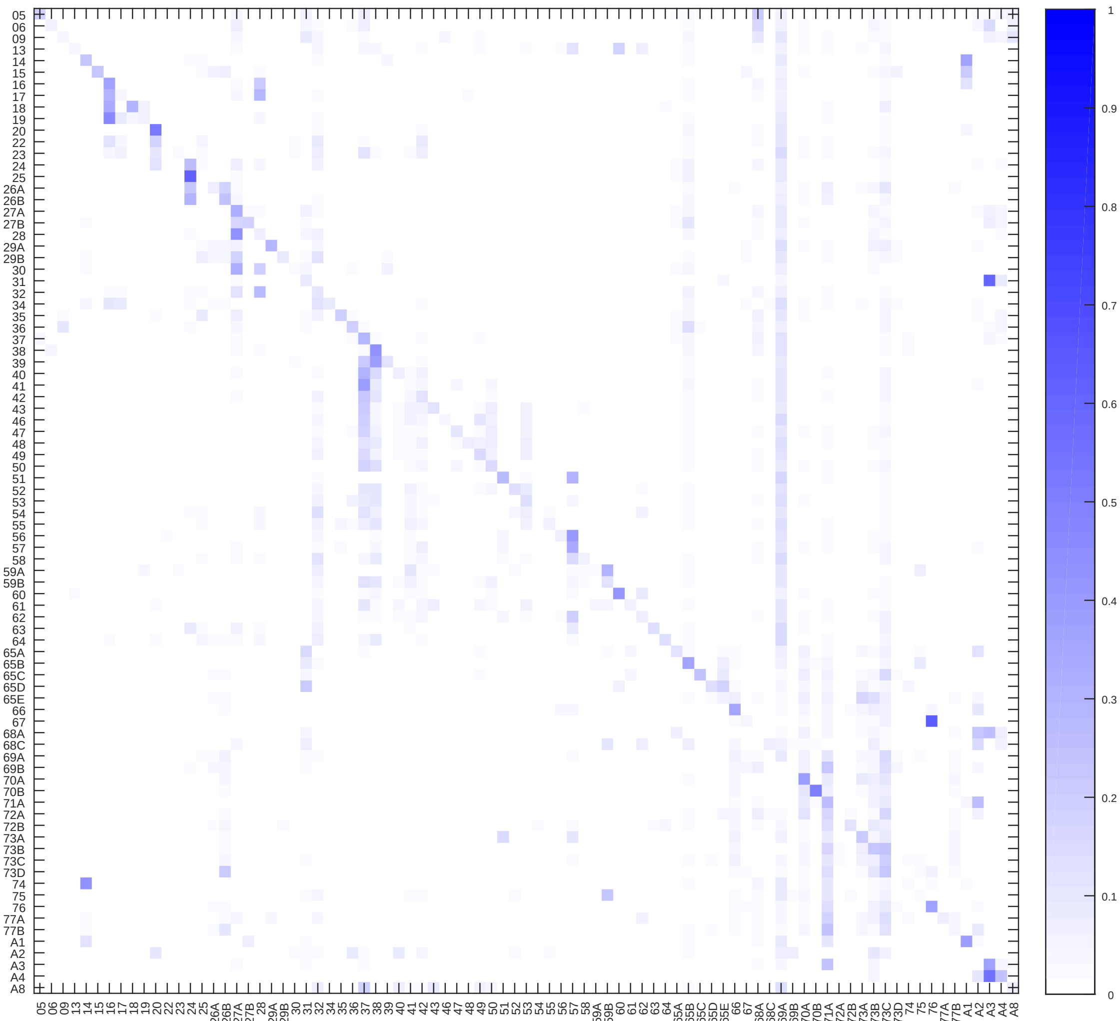
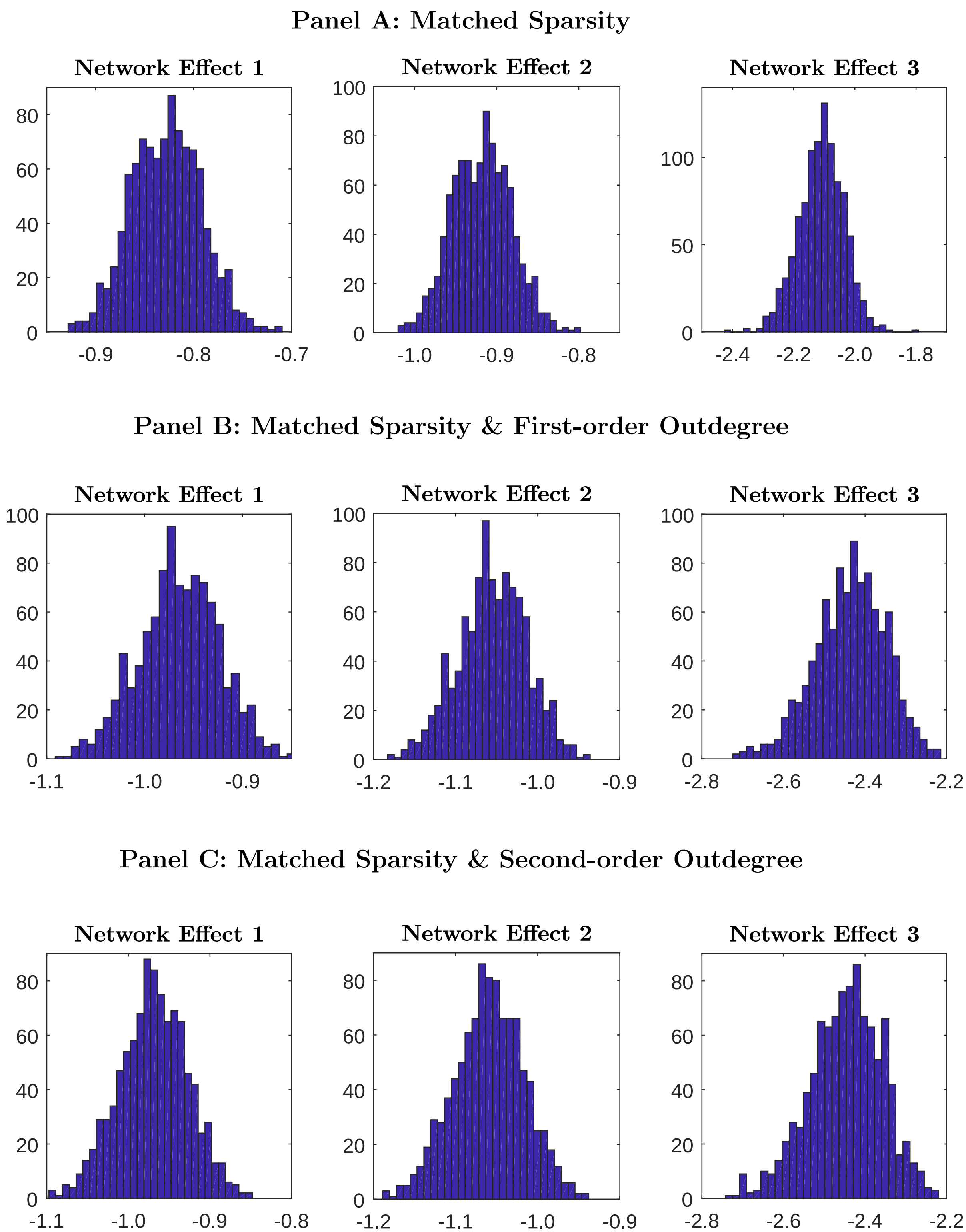
Figure 2: **Production Network Corresponding to U.S. Input-Output Data**



This figure plots the empirical input-output relationship in the United States using data from the benchmark input-output tables of the Bureau of Economic Analysis for the year 1992. See Table A.3 in the Online Appendix for industry descriptions. Customers are on the y-axis and suppliers on the x-axis with entries $\omega_{i,j}$ that represent the share of intermediate input consumption of industry i from industry j. Darker blue colors indicate higher values.

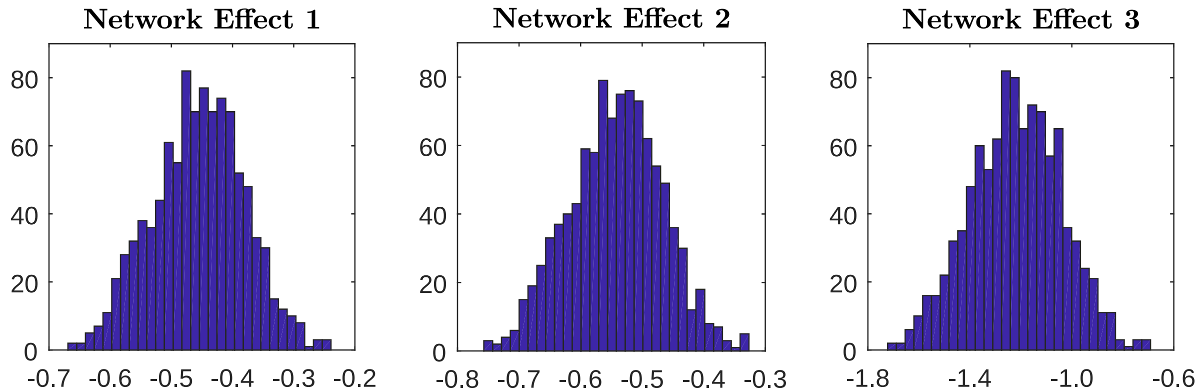
Figure 3: **Placebo Network Effects: Monte Carlo Simulation**



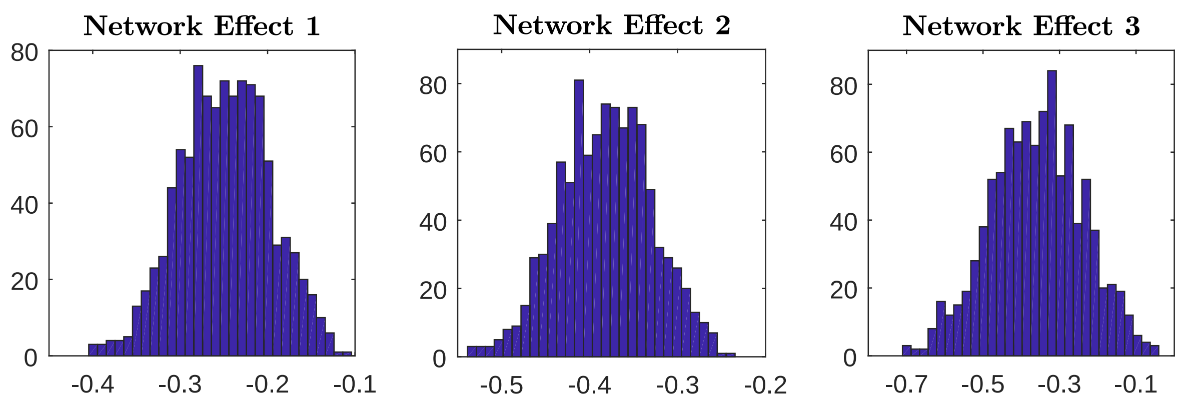
This figure plots the histogram of the actual network effects estimated in Table 2 column (3) minus estimates of the network effects for different assumptions on simulated input-output matrices. Each simulation consists of 1,000 draws. Panel A matches the sparsity and draws entries for the pseudo input-output table from a fitted Pareto distribution. Panel B matches the sparsity, draws entries for the pseudo input-output table from a fitted Pareto distribution and matches distribution of first-order outdegree of the actual input-output tables. Panel C matches the sparsity, draws entries for the pseudo input-output table from a fitted Pareto distribution and matches the distribution of second-order outdegrees of the actual input-output tables.

Figure 4: **Placebo Network Effects: Monte Carlo Simulation Industry-by Industry**

Panel A: Matched Sparsity & First-order Outdegree Industry-by Industry



Panel B: Matched Sparsity & First- and Second-order Outdegree Industry-by Industry



This figure plots the histogram of the actual network effects estimated in Table 2 column (3) minus estimates of the network effects for different assumptions on simulated input-output matrices. Each simulation consists of 1,000 draws. Panel A matches the sparsity and first-order outdegree and draws entries for the pseudo input-output table from a fitted Pareto distribution but ensures for each simulation industries have sparsity and first-order outdegree as in the actual data. Panel B matches the sparsity, draws entries for the pseudo input-output table from a fitted Pareto distribution and matches the first-order and second-order outdegree of the actual input-output tables but ensures for each simulation industries have sparsity, first-order outdegree and second-order outdegrees as in the actual data.

Table 1: **Response of Industry Returns to Monetary Policy Shocks: Constant Coefficients**

This table reports the results of regressing (industry) returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t (column (1)–(2)), and an input-output network-weighted average of industry returns (columns (3)–(5)) (see equation (19)). The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Bootstrapped standard errors are reported in parentheses for columns (3) to (5) and OLS standard errors in columns (1) and (2). Direct and Network Effects 1 follow Pace and LeSage (2014); Direct and Network Effects 2 follow Acemoglu et al. (2016).

	OLS Index	OLS Industry	SAR: 1992 Tables Previous Month Mcap	SAR: 1992 Tables Previous Day Mcap	SAR: Time-Varying Previous Month Mcap
	(1)	(2)	(3)	(4)	(5)
Panel A. Point Estimates					
β	-3.25^{***}	-3.11^{***}	-0.45^{***}	-0.45^{***}	-0.47^{***}
	(0.71)	(0.13)	(0.12)	(0.12)	(0.13)
ρ			0.87^{***}	0.87^{***}	0.87^{***}
			(0.01)	(0.01)	(0.01)
Constant	-0.13^{***}	-0.11^{***}	-0.01^{**}	-0.01^{**}	-0.02^{***}
	(0.04)	(0.01)	(0.01)	(0.01)	(0.01)
Adj R^2	14.74	10.86	10.76	10.74	9.89
Observations	120	9,040	9,040	9,040	9,823
Log-L			-2,450	-2,447	-3,501
Panel B. Decomposition					
Direct Effect 1			-0.72^{***}	-0.72^{***}	-0.68^{***}
			(0.18)	(0.18)	(0.19)
Network Effect 1			-2.65^{***}	-2.64^{***}	-2.83^{***}
			(0.65)	(0.65)	(0.75)
Direct Effect 2			-0.45^{***}	-0.45^{***}	-0.47^{***}
			(0.12)	(0.12)	(0.13)
Network Effect 2			-2.91^{***}	-2.91^{***}	-3.04^{***}
			(0.72)	(0.72)	(0.81)

Standard errors in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 2: **Response of Industry Returns to Monetary Policy Shocks: Heterogenous Coefficients and Heteroskedastic Error Variance**

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t (column (1)), and an input-output network-weighted average of industry returns (columns (2)–(5)) (see equation (19)). The value of β is the average of β_i for individual industries and ρ is the average of the diagonal elements of $D(\rho)$. The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Bootstrapped standard errors are reported in parentheses. Direct and Network Effects 1 follow Pace and LeSage (2014), Direct and Network Effects 2 follow Acemoglu et al. (2016), Direct Effect 3 refers to the total effect under autarky, and Network Effect 3 refers to amplification due to network effects, i.e. the difference between total effect under the empirical input-output matrix and the total effect under autarky.

	OLS	SAR: 1992 Tables			
		Previous Month Mcap	Previous Day Mcap	Previous Month Mcap	Previous Day Mcap
		Homoscedastic Errors		Heteroskedastic Errors	
	(1)	(2)	(3)	(4)	(5)
Panel A. Point Estimates					
β	-3.11^{***}	-0.60^{***}	-0.53^{***}	-0.49^{***}	-0.49^{***}
	(0.13)	(0.18)	(0.16)	(0.15)	(0.15)
ρ		0.79^{***}	0.82^{***}	0.84^{***}	0.84^{***}
		(0.02)	(0.02)	(0.01)	(0.01)
Constant	-0.11^{***}	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adj R^2	10.86	11.02	11.18	11.00	11.17
Observations	9,040	9,040	9,040	9,040	9,040
Log-L		-4,056	-4,056	-3,335	-3,313
Panel B. Decomposition					
Direct Effect 1		-0.63^{***}	-0.64^{***}	-0.60^{***}	-0.60^{***}
		(0.19)	(0.19)	(0.18)	(0.18)
Network Effect 1		-2.34^{***}	-2.33^{***}	-2.36^{***}	-2.36^{***}
		(0.67)	(0.66)	(0.67)	(0.67)
Direct Effect 2		-0.60^{***}	-0.53^{***}	-0.49^{***}	-0.49^{***}
		(0.18)	(0.16)	(0.15)	(0.15)
Network Effect 2		-2.38^{***}	-2.44^{***}	-2.47^{***}	-2.47^{***}
		(0.68)	(0.69)	(0.70)	(0.70)
Direct Effect 3		-1.40^{***}	-1.43^{***}	-1.33^{***}	-1.32^{***}
		(0.42)	(0.42)	(0.39)	(0.39)
Network Effect 3		-1.57^{***}	-1.54^{***}	-1.63^{***}	-1.63^{***}
		(0.48)	(0.46)	(0.48)	(0.48)

Standard errors in parentheses.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 3: **Response of Industry Returns to Monetary Policy Shocks (Robustness)**

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t, and an input-output network-weighted average of industry returns (see equation (19)). The value of β is the average of β_i for individual industries and ρ is the average of the diagonal elements of $D(\rho)$. The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Bootstrapped standard errors are reported in parentheses. Direct and Network Effects 1 follow Pace and LeSage (2014), Direct and Network Effects 2 follow Acemoglu et al. (2016), Direct Effect 3 refers to the total effect under autarky, and Network Effect 3 refers to amplification due to network effects, i.e. the difference between total effect under the empirical input-output matrix and the total effect under autarky.

	3 Factors-Adjusted Returns (1)	Zero Diagonal W (2)	Industry-Demeaned (3)
	Panel A. Point Estimates		
β	-0.54***	-0.55***	-0.50***
	(0.14)	(0.17)	(0.15))
ρ	0.82***	0.81***	0.83***
	(0.01)	(0.01)	(0.01)
Constant	-0.01	-0.01	
	(0.01)	(0.01)	
Adj R^2	8.65	11.00	10.61
Observations	9,040	9,040	9,040
Log-L	-1,360	-3,312	-3,392
	Panel B. Decomposition		
Direct Effect 1	-0.75***	-0.58***	-0.61***
	(0.20)	(0.18)	(0.16)
Network Effect 1	-2.55***	-2.38***	-2.35***
	(0.76)	(0.68)	(0.65)
Direct Effect 2	-0.54***	-0.55***	-0.50***
	(0.14)	(0.17)	(0.15)
Network Effect 2	-2.76***	-2.41***	-2.46***
	(0.86)	(0.69)	(0.68)
Direct Effect 3	-1.01***	-1.29***	-1.34***
	(0.34)	(0.38)	(0.39)
Network Effect 3	-2.29***	-1.67***	-1.62***
	(0.63)	(0.49)	(0.46)

Standard errors in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 4: **Response of Industry Returns to Monetary Policy Shocks by Closeness to Consumers**

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t, and an input-output network-weighted average of industry returns (see equation (19)) for industries sorted on closeness to consumers. The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Direct and Network Effects 1 follow Pace and LeSage (2014), Direct and Network Effects 2 follow Acemoglu et al. (2016), Direct Effect 3 refers to the total effect under autarky, and Network Effect 3 refers to amplification due to network effects, i.e. the difference between total effect under the empirical input-output matrix and the total effect under autarky.

	Close to End-Consumer (1)	Far from End-Consumer (2)
Direct Effect 1	88.57%**	25.76%***
Network Effect 1	11.43%**	74.24%***
Direct Effect 2	87.14%**	24.45%***
Network Effect 2	12.86%**	75.55%***
Direct Effect 3	157.14%**	59.39%***
Network Effect 3	−57.14%**	40.61%***

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 5: **Response of Industry Returns to Monetary Policy Shocks by External Finance Dependence**

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t, and an input-output network-weighted average of industry returns (see equation (19)) for industries sorted on the external finance gap (Panel A) and Kaplan-Zingales index of financial constraints (Panel B). The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Direct and Network Effects 1 follow Pace and LeSage (2014), Direct and Network Effects 2 follow Acemoglu et al. (2016), Direct Effect 3 refers to the total effect under autarky, and Network Effect 3 refers to amplification due to network effects, i.e. the difference between total effect under the empirical input-output matrix and the total effect under autarky.

	Panel A. External Finance Dependence	
	High (1)	Low (2)
Direct Effect1	17.17%***	23.39%***
Network Effect 1	82.83%***	76.61%***
Direct Effect 2	15.49%***	22.37%***
Network Effect 2	84.51%***	77.63%***
Direct Effect 3	41.41%***	48.14%***
Network Effect 3	58.59%***	51.86%***
	Panel A. Kaplan Zingales Index	
	High	Low
Direct Effect 1	25.16%***	14.74%***
Network Effect 1	74.84%***	85.26%***
Direct Effect 2	23.86%***	13.99%***
Network Effect 2	76.14%***	86.01%***
Direct Effect 3	53.59%***	35.31%***
Network Effect 3	46.41%***	64.69%***

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 6: **Response of Industry Cash flow Fundamentals to Monetary Policy Shocks**

This table reports the results of regressing future cash flow fundamentals at the quarterly frequency on a quarterly federal-funds-futures-based measure of monetary policy shocks, $\tilde{v}_t$, and an input-output network-weighted average of the industry cash flow fundamentals (see equation (29)). The sample ranges from Q1 1994 through Q4 2008 for a total of 60 observations. Bootstrapped standard errors are reported in parentheses.

Horizon	0	1	2	3	4	5	6	7	8
				Panel A. Value-Weighted Sales					
Direct Effect 1	1.26*	1.71*	2.22**	2.64**	2.77**	2.61*	2.50	2.51	2.71*
	(0.74)	(0.89)	(0.98)	(1.11)	(1.27)	(1.42)	(1.55)	(1.61)	(1.61)
Network Effect 1	1.92*	2.48**	3.13**	3.52**	3.61**	3.50**	3.29*	3.16*	3.21*
	(1.09)	(1.26)	(1.35)	(1.44)	(1.53)	(1.62)	(1.73)	(1.78)	(1.81)
				Panel B. Equally Weighted Sales					
Direct Effect 1	1.10*	1.44**	1.74**	1.97**	1.94**	1.74*	1.56	1.43	1.39
	(0.61)	(0.69)	(0.77)	(0.88)	(0.97)	(1.04)	(1.06)	(1.04)	(0.99)
Network Effect 1	2.27	3.05*	3.69*	4.03*	4.08*	3.87	3.70	3.40	3.21
	(1.48)	(1.72)	(1.91)	(2.13)	(2.30)	(2.41)	(2.46)	(2.47)	(2.45)
				Panel C. Value-Weighted Operating Income					
Direct Effect 1	0.34**	0.42**	0.51***	0.54**	0.52**	0.46*	0.39	0.40	0.43*
	(0.15)	(0.18)	(0.19)	(0.22)	(0.24)	(0.26)	(0.26)	(0.25)	(0.26)
Network Effect 1	0.61**	0.75***	0.88***	0.92***	0.90**	0.83**	0.78**	0.75**	0.77**
	(0.25)	(0.28)	(0.31)	(0.34)	(0.35)	(0.37)	(0.36)	(0.35)	(0.36)
				Panel D. Equally Weighted Operating Income					
Direct Effect 1	0.30**	0.36***	0.41***	0.43***	0.40**	0.34**	0.25*	0.21*	0.19*
	(0.12)	(0.13)	(0.14)	(0.16)	(0.16)	(0.16)	(0.14)	(0.12)	(0.10)
Network Effect 1	0.71***	0.86***	0.95***	0.97***	0.93**	0.83**	0.76**	0.68**	0.62**
	(0.27)	(0.29)	(0.33)	(0.37)	(0.39)	(0.40)	(0.36)	(0.33)	(0.30)

Standard errors in parentheses.

$*p < 0.10, **p < 0.05, ***p < 0.01$

Table 7: **Direct and Network Effects from Simulated Data**

This table reports estimates from our specification with heterogeneous coefficients on simulated data from the dynamic model of Section VI (see equation (19)). The first row reports the results from our benchmark calibration and each subsequent row reports the results from changing one parameter. Monetary policy shocks are multiplied by -1 so that a positive value corresponds to a contractionary shock. We simulate each model calibration 50 times for 1,020 periods and use the last 120 periods to be consistent with our empirical results. We report the means and standard deviations across simulations. Direct and Network Effects 1 follow Pace and LeSage (2014), Direct and Network Effects 2 follow Acemoglu et al. (2016), Direct Effect 3 refers to the total effect under autarky, and Network Effect 3 refers to amplification due to network effects, i.e. the difference between total effect under the empirical input-output matrix and the total effect under autarky.

Model Parameters						
Benchmark	Variation	β	ρ	% Network 1	% Network 2	% Network 3
	Benchmark	-0.73	0.78	67.00%	77.16%	51.81%
		(0.03)	(0.01)			
$\eta = 0.1$	$\eta = 0.2$	-0.70	0.79	68.18%	78.09%	54.04%
		(0.01)	(0.01)			
$a = 0.85$	$a = 0.7$	-0.83	0.74	63.21%	74.03%	44.27%
		(0.04)	(0.01)			
$\phi = -0.5$	$\phi = -0.4$	-0.83	0.74	63.04%	73.88%	43.92%
		(0.04)	(0.01)			
$m/w = 1$	$m/w = 2$	-0.71	0.78	67.48%	77.54%	52.74%
		(0.02)	(0.01)			
$\rho_M = 0.5$	$\rho_M = 0.75$	-1.19	0.78	67.25%	77.36%	52.29%
		(0.04)	(0.01)			
$\sigma_M = 0.01$	$\sigma_M = 0.02$	-0.72	0.78	67.09%	77.23%	51.98%
		(0.03)	(0.01)			
$\psi = 0.2$	$\psi = 0.4$	-0.72	0.78	67.23%	77.35%	52.26%
		(0.02)	(0.01)			
BEA W	$W = [1/N]$	-0.28	0.63	74.46%	75.72%	1.37%
		(0.03)	(0.02)			

Online Appendix:

Monetary Policy through Production Networks: Evidence from the Stock Market

Ali Ozdagli and Michael Weber

Not for Print Publication

I Likelihood function

We estimate the SAR model in equation (18) using quasi maximum likelihood, following Aquaro et al. (2019). The model in Aquaro et al. (2019) assume zero entries on the diagonal of the spatial weighting matrix. A simple renormalization allows us to map equation (18) into the framework of Aquaro et al. (2019).[1]

The SAR model with heterogeneous coefficients is given by

$$r_t = \beta v_t + W' D(\rho) r_t + \varepsilon_t \tag{A.1}$$

$$r_t = \beta v_t + (\text{diag}(W') + \text{offdiag}(W'))D(\rho) r_t + \varepsilon_t \tag{A.2}$$

$$(I - \text{diag}(W')D(\rho))r_t = \beta v_t + \text{offdiag}(W')D(\rho) r_t + \varepsilon_t \tag{A.3}$$

$$r_t = \widetilde{\beta} v_t + \widetilde{W}' \widetilde{D}(\rho) r_t + \widetilde{\varepsilon}_t \tag{A.4}$$

where

$\widetilde{W}'$ is obtained by row-normalizing the matrix offdiag(W')

R=diag(rowsum(offdiag(W')))

$\widetilde{W}' = R^{-1}\text{offdiag}(W')$

$\widetilde{\beta} = (I - \text{diag}(W')D(\rho))^{-1}\beta$

$\widetilde{W}'\widetilde{D}(\rho) = (I - \text{diag}(W')D(\rho))^{-1}\text{offdiag}(W')D(\rho)$

$\widetilde{\varepsilon}_t = (I - \text{diag}(W')D(\rho))^{-1}\varepsilon_t$

The parameters of equation (A.4) can now be estimated by QML following Aquaro et al. (2019) under the following assumptions:

[1] We thank Hashem Pesaran for very helpful correspondence.

Assumption 1 The errors terms are independently distributed over i and t. It implies that $E(\widetilde{\varepsilon}_{it}) = 0, E(\widetilde{\varepsilon}_{it}) = \widetilde{\sigma}^2_{i0}$, for $i = 1, 2, ..., N$ which are standard assumptions.

Assumption 2 (a) v_t is a stationary process with mean zero, and satisfy the moment condition $sup_t E(|v_t|^{2+c}) < K$, for some $c > 0$, and $t = 1, 2, ..., T$. (b) $E(v_t v_t') = \Sigma_{vv} = (\Sigma_{ij})$, where $\Sigma_{ij=E(v_{it}v'_{jt})}$ exist for all i and j, such that $sup_{i,j}||\Sigma_{ij}|| < K$, and Σ_{ii} is a non singular matrix with $inf_i[\lambda_{min}(\Sigma_{ii})] > c > 0$, and $sup_i[\lambda_{max}(\Sigma_{ii})] < K$; (c) $T^{-1}\sum_{i=1}^{N} v_t v_t' \xrightarrow{a.s} \Sigma_{vv}$, as $T \rightarrow \infty$.

This assumption is standard and allows for the regressors to be cross-sectionally correlated. QML estimation also allows the regressors to be weakly exogenous, thus allowing the model to include lagged values of the dependent variable. In our model, there is only one regressor, monetary policy shocks, and an intercept and hence the model satisfies the assumption.

Assumption 3 The parameter vector $\widetilde{\boldsymbol{\theta}}$ belongs to a closed and bounded set $\boldsymbol{\Theta} = \boldsymbol{\Theta_\psi}$ x $\boldsymbol{\Theta_\beta}$ x $\boldsymbol{\Theta_\sigma}$ and this set includes the true value of $\widetilde{\boldsymbol{\theta}}$, denoted by $\widetilde{\boldsymbol{\theta_o}}$, as an interior point of $\boldsymbol{\Theta}$, and $sup_i||\widetilde{\beta}_i||$ is bounded.

Assumption 4 The weight matrix is uniformly bounded in row and column sums in absolute value, and its diagonal elements are zero.

The weight matrix $\widetilde{W}'$ satisfies this assumption because of the normalization and the fact that first-order outdegrees (column sum of W) are finite and W is row-normalized. Also, since ρ is less than 1, it satisfies the condition on spatial autoregressive parameters.

Assumption 5 (*Modification of Assumption 3*) The parameter vector $\widetilde{\boldsymbol{\theta}}$ belongs to the set $\boldsymbol{\Theta_c} = \boldsymbol{\Theta_\psi}$ x $\boldsymbol{\Theta_\beta}$ x $\boldsymbol{N_c}(\sigma^2_o)$ where $\boldsymbol{\Theta_\psi}$ and $\boldsymbol{\Theta_\beta}$ are closed and bounded sets and $\boldsymbol{N_c}(\sigma^2_o)$ is given by $\{\sigma^2_o \in \boldsymbol{\Theta_\sigma}, |\sigma^2_{io}/\sigma^2_i - 1| < c_i, \text{for } i = 1, 2, ..., N\}$ and this set includes the true value of $\widetilde{\boldsymbol{\theta}}$, denoted by $\widetilde{\boldsymbol{\theta_o}}$, as an interior point of $\boldsymbol{\Theta_c}$.

Assumption 3 is a general assumption about the compactness of the set to which the parameters belong, which does not guarantee global identification of the parameters. Therefore, Aquaro et al. (2019) offers a modification of Assumption 3 as Assumption 5 to ensure the local identification of parameters.

Under these assumptions, we can consistently estimate the model of Aquaro et al. (2019). The Log-likelihood function is given by

$$LL(\widetilde{\boldsymbol{\theta}}) = -\frac{1}{2}ln(2\pi)\sum_{i=1}^{N} t_i - \sum_{i=1}^{N}\frac{t_i}{2}ln(\widetilde{\sigma}_i^2) + ln(|\boldsymbol{I_{NT}} - \widetilde{\boldsymbol{W}}'_{\boldsymbol{NT}}\widetilde{\boldsymbol{D}}_{\boldsymbol{NT}}(\boldsymbol{\rho})|)$$
$$-\sum_{i=1}^{N}\frac{(\boldsymbol{r_i} - \widetilde{\boldsymbol{\rho}}\boldsymbol{r_i^\star} - \boldsymbol{v_i}\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}})'(\boldsymbol{r_i} - \widetilde{\boldsymbol{\rho}}\boldsymbol{r_i^\star} - \boldsymbol{v_i}\widetilde{\boldsymbol{\beta}}_{\boldsymbol{i}})}{2\widetilde{\sigma}_i^2}$$

with $\widetilde{\boldsymbol{\theta}} = (\widetilde{\boldsymbol{\rho}}, \widetilde{\boldsymbol{\beta}}_{\boldsymbol{1}}, \widetilde{\boldsymbol{\beta}}_{\boldsymbol{2}}, ..., \widetilde{\boldsymbol{\beta}}_{\boldsymbol{n}}, \widetilde{\boldsymbol{\sigma}}_{\boldsymbol{1}}, \widetilde{\boldsymbol{\sigma}}_{\boldsymbol{2}}, ..., \widetilde{\boldsymbol{\sigma}}_{\boldsymbol{n}})$, where N is the total number of industries, t_i is time periods for industry i, $\boldsymbol{I_{NT}}$, $\widetilde{\boldsymbol{W}}'_{\boldsymbol{NT}}$, $\widetilde{\boldsymbol{D}}_{\boldsymbol{NT}}(\boldsymbol{\rho})$ are block diagonal matrices for all time periods and each diagonal matrix corresponds to all industries that are present in a given time period, $\boldsymbol{r_i} = (r_{i1}, r_{i2}, ..., r_{it_i})'$, $\boldsymbol{r_i^\star} = (r_{i1}^\star, r_{i2}^\star, ..., r_{it_i}^\star)'$ and $\boldsymbol{v_i} = (v_{i1}, v_{i2}, ..., v_{it_i})'$. Here $\widetilde{D}(\rho) = \widetilde{\rho}D(\alpha)$ and $\boldsymbol{r_t^\star} = \widetilde{W}'D(\alpha)r_t$. And $\boldsymbol{\theta}$ can be estimated from $\widetilde{\boldsymbol{\theta}}$.

Aquaro et al. (2019) prove that the true parameter vector $\widetilde{\boldsymbol{\theta_o}}$ is almost surely locally identified and the (quasi) maximum likelihood estimator of $\widetilde{\boldsymbol{\theta_o}}$ is surely locally consistent on $\boldsymbol{\Theta_c}$ under the assumptions 1, 2, 4 and 5, for a given N and as $T \to \infty$. When $T \to \infty$, estimation of the HSAR model can be conducted for any N, and $N \to \infty$ is not required. As we are also interested in the mean group estimators for all the industries, large N is required for the consistent estimation of common means. Our sample comprises of sufficiently large N and T and hence the estimated parameters are almost surely consistent. For more detailed discussion on identification and consistency of the QML estimators please refer to Aquaro et al. (2019))

II Model with Sticky Prices

Our model focuses on wage rather than price stickiness as a nominal friction. The most important reason for our choice is the empirical relevance of wage stickiness, followed by simplicity of modeling it.[2] Nevertheless, we show below that an extension our static framework with price stickiness does not violate the SAR framework for cash flows, in which the spatial weighting matrix is given by the input-output matrix. We start by writing down the first-order and equilibrium conditions from our original model with pre-determined wages

$$
\begin{aligned}
y_i &= l_i^{\lambda_i}\left(\prod_{j=1}^{N} x_{ij}^{\omega_{ij}}\right)^{\alpha_i} \text{ (production function)}\\
\lambda_i p_i y_i &= w l_i \text{ (labor demand)}\\
\alpha_i \omega_{ij} p_i y_i &= p_j x_{ij} \text{ (intermediate input demand)}\\
p_i c_i &= b_i\left[w\sum_{i=1}^{N} l_i + \sum_{i=1}^{N}(\pi_i + f_i)\right] \text{ (consumption demand)}\\
y_i &= c_i + \sum_{j=1}^{N} x_{ji} \text{ (goods market clearing)}\\
\sum_{i=1}^{N} p_i c_i &= M \text{ (cash-in-advance)}
\end{aligned}
$$

[2]Christiano, Eichenbaum, and Evans (2005) argue that wage, rather than price, stickiness is the key feature in a model that accounts for observed fluctuations in output. Micro-level empirical evidence for wage stickiness can be found in Barattieri, Basu, and Gottschalk (2014).

We can rewrite these conditions as

$$\begin{aligned}
\lambda_i R_i &= w l_i \text{ (labor demand)} \\
\alpha_i \omega_{ij} R_i &= p_j x_{ij} \text{ (intermediate input demand)} \\
p_i c_i &= b_i \left[w \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} (\pi_i + f_i) \right] \text{ (consumption demand)} \\
R_i &= p_i c_i + p_i \sum_{j=1}^{N} x_{ji} \text{ (goods market clearing)} \\
\sum_{i=1}^{N} p_i c_i &= M \text{ (cash-in-advance)}
\end{aligned}$$

where we have used $R_i = p_i y_i$. Denoting the spending on consumption of good i as $C_i \equiv p_i c_i$ and using the intermediate input demand equation, we can rewrite the goods market clearing condition as

$$R_i = C_i + \sum_{j=1}^{N} \alpha_j \omega_{ji} R_j,$$

or in matrix format

$$R = C + W' D(\alpha) R,$$

which has the SAR format with a simple intuition: the first term on the right captures the direct effect due to consumption, which responds to money supply through the cash-in-advance constraint, whereas the second term captures the indirect effect that goes through production networks.

Note that we have not used the labor demand equation while driving the equation for revenues, which is important when introducing sticky prices. In particular, it is a common assumption in textbook models with sticky prices that the producer will hire as much labor as required to satisfy the demand for its goods.[3] Accordingly, the labor demand function is eliminated. However, this elimination has no bearing on the cash flow equation as we show above. So, overall we see that the SAR structure for cash flows is preserved in a simple extension of our static

[3]See, for example, Bils, Klenow, and Malin (2012).

framework, suggesting that our framework is reasonable at least to a first-order approximation when studying the response of stock prices, which is the discounted value of cash flows.

Note that price stickiness, its cross-sectional heterogeneity, and how this heterogeneity interacts with the production network are still important for macroeconomic quantities. Suppose that prices are partially sticky and the degree of stickiness is heterogeneous across producers. That is, $p_i = (p_i^*)^{1-\chi_i} \bar{p}_i^{\chi_i}$, where p_i^* is the price without nominal rigidities, $\bar{p}_i$ is the pre-determined price if prices were completely sticky, and χ_i is the degree of price stickiness which can be different across industries. Suppose that we want to study employment. Log-linearizing the intermediate input demand equation and the revenues, we have

$$\begin{aligned} \hat{x}_{ij} &= \hat{R}_i - \hat{p}_j \\ \hat{R}_i &= \hat{p}_i + \lambda_i \hat{l}_i + \alpha_i \sum_{j=1}^{N} \omega_{ij} \hat{x}_{ij}, \end{aligned}$$

where $\hat{X}$ denotes the log-linearized version of variable X. Substituting for $\hat{x}_{ij}$ in the previous equation, we get

$$\hat{l}_i = \frac{1-\alpha_i}{\lambda_i} \hat{R}_i - \frac{1}{\lambda_i} \left[\hat{p}_i - \alpha_i \sum_{j=1}^{N} \omega_{ij} \hat{p}_j \right].$$

Furthermore, note that $\hat{p}_i = (1-\chi_i)\, \hat{p}_i^*$ (because $\bar{p}_i$ is fixed) and $\hat{p}_i^* = \hat{M}$ since prices are proportional to money supply under flexible prices. In this case, we have

$$\hat{l}_i = \frac{1-\alpha_i}{\lambda_i} \hat{R}_i - \frac{1}{\lambda_i} \left[(1-\chi_i) - \alpha_i \sum_{j=1}^{N} \omega_{ij} (1-\chi_j) \right] \hat{M}.$$

The first term in square brackets tells us that higher price stickiness (χ_i) increases the reaction of employment by producer i directly, whereas the second term tells us that the price stickiness of other producers matters for producer i as well, commensurate to the share of these other producers' input in producer i's production.

We do not aim to imply that the simple SAR framework for cash flows will be preserved under any condition. For example, in the dynamic model we allow a more general production function where the relative importance of intermediate inputs for a given producer can respond to monetary policy as well, rather than being a constant (α_i). This production function encompasses the one in the simple static model as a special case; the simulated data from the dynamic model suggests that the measured network effects are reasonably robust to variation in parameters.

III Dynamic Model

Our empirical model is motivated by our static, stylized benchmark model. A natural question is whether our SAR estimation provides reliable estimates of direct and network effects in a dynamic model with less stringent assumptions. Therefore, we replace the production function with a CES function of the form

$$y_i = z_i[\eta X_i^\phi + (1-\eta) l_i^\phi]^{a/\phi}, \tag{A.5}$$

$$X_i = \prod_{j=1}^{N} x_{ij}^{\omega_{ij}}, \tag{A.6}$$

with $a < 1$ and $\phi \leq 1$, with $\phi = 1$ leading to perfect substitution, $\phi = 0$ to Cobb-Douglas, and $\phi = -\infty$ to a Leontief production function. Since variable inputs are likely more substitutable with each other than with labor, $\phi < 0$.

Note that the marginal product of input, x_{ij}, is

$$\begin{aligned}
\frac{\partial y_i}{\partial x_{ij}} &= z_i a \eta \left[\eta X_i^\phi + (1-\eta) l_i^\phi\right]^{a/\phi - 1} X_i^\phi \omega_{ij} x_{ij}^{-1} \\
&= \omega_{ij} z_i a \eta \left[\eta X_i^\phi + (1-\eta) l_i^\phi\right]^{a/\phi} \frac{X_i^\phi}{\eta X_i^\phi + (1-\eta) l_i^\phi} x_{ij}^{-1} \\
&= \omega_{ij} y_i a \frac{\eta X_i^\phi}{\eta X_i^\phi + (1-\eta) l_i^\phi} x_{ij}^{-1},
\end{aligned}$$

and the first-order condition (FOC) with respect to this input is

$$p_i \frac{\partial y_i}{\partial x_{ij}} = p_j \Rightarrow \omega_{ij} a \frac{\eta X_i^\phi}{\eta X_i^\phi + (1-\eta) l_i^\phi} p_i y_i = p_j x_{ij} \tag{A.7}$$

$$\Rightarrow \omega_{ij} a \theta_i p_i y_i = p_j x_{ij}, \tag{A.8}$$

where

$$\theta_i \equiv \frac{\eta X_i^{\phi}}{\eta X_i^{\phi} + (1-\eta) l_i^{\phi}} \tag{A.9}$$

is the share of intermediate inputs in production. Note that the latter is a constant number with Cobb-Douglas production function ($\phi = 0$).

Also note that the marginal product of labor is

$$\begin{aligned} \frac{\partial y_i}{\partial l_i} &= z_i a (1-\eta) \left[\eta X_i^{\phi} + (1-\eta) l_i^{\phi}\right]^{a/\phi - 1} l_i^{\phi-1} \\ &= y_i a \frac{(1-\eta) l_i^{\phi}}{\eta X_i^{\phi} + (1-\eta) l_i^{\phi}} l_i^{-1} = a (1-\theta_i) y_i l_i^{-1}, \end{aligned}$$

which leads to the FOC with respect to labor

$$\begin{aligned} p_i \frac{\partial y_i}{\partial l_i} &= w, \\ a (1-\theta_i) p_i y_i &= w l_i. \end{aligned}$$

Using these FOCs, the profit function then becomes

$$\pi_i = p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - w l_i - f_i = (1-a) p_i y_i - f_i, \tag{A.10}$$

which is the same as in the benchmark model. Accordingly, the consumption-good demand, from the FOC of the household, becomes

$$c_i = b_i \frac{\sum_{i=1}^{N} (\pi_i + w l_i + f_i)}{p_i} = b_i \frac{\sum_{i=1}^{N} (1 - a\theta_i) R_i}{p_i}. \tag{A.11}$$

In this scenario, the goods-market-clearing condition becomes

$$\begin{aligned} y_i &= c_i + \sum_{j=1}^{N} x_{ji} \\ &= b_i \frac{\sum_{i=1}^{N} (1 - a\theta_i) R_i}{p_i} + \frac{\sum_{j=1}^{N} \omega_{ji} a \theta_j R_j}{p_i}, \end{aligned}$$

which, taken together with the cash-in-advance constraint for consumption goods, gives the following equation

$$R_i = b_i M + \sum_{j=1}^{N} \left[a \theta_j \omega_{ji} R_j\right].$$

To summarize, the model's solution is given by the following equations in $y_i, x_{ij}, l_i, X_i, \theta_i, p_i$, or equivalently $y_i, x_{ij}, l_i, X_i, \theta_i, R_i$ (w is pre-determined due to wage stickiness), for $i \in \{1, ..., N\}$:

$$
\begin{aligned}
R_i &= b_i M + \sum_{j=1}^{N} \left[a\theta_j \omega_{ji} R_j \right], \\
\theta_i &\equiv \frac{\eta X_i^{\phi}}{\eta X_i^{\phi} + (1-\eta) l_i^{\phi}}, \\
X_i &= \prod_{j=1}^{N} x_{ij}^{\omega_{ij}}, \\
x_{ij} &= \frac{\omega_{ij} a \theta_i R_i}{p_j} = \frac{\omega_{ij} a \theta_i R_i}{R_j} y_j \text{ (FOC)}, \\
l_i &= \frac{a\left(1-\theta_i\right) R_i}{w} \text{ (FOC)}, \\
y_i &= z_i [\eta X_i^{\phi} + (1-\eta) l_i^{\phi}]^{a/\phi} = z_i \theta_i^{-a/\phi} \eta^{a/\phi} X_i^{a}.
\end{aligned}
$$

We can rewrite the first equation in matrix form as before

$$
(I - aW'D(\theta))R = \begin{pmatrix} b_1 \\ \vdots \\ b_N \end{pmatrix} M = bM, \tag{A.12}
$$

where $D(\theta)$ is a diagonal matrix with entries $\theta_1, ..., \theta_N$.

A. Dynamic Wages, Monetary Policy, and Simulation Equations

In all the equations below, let $\bar{x}$ be the deterministic steady state and $\hat{x}$ be the log-deviation so that $x_t = \bar{x} \exp\left(\hat{x}_t\right) \approx \bar{x}\left(1 + \hat{x}_t\right)$.

We expand the equilibrium conditions above with a dynamic wage equation that captures wage stickiness,

$$
w_t = \psi w_{t-1} + \left(1-\psi\right) w_t^{*}, \tag{A.13}
$$

where w_t^{*} is the equilibrium wage under flexible wages and hence is proportional to the money supply. If we log-linearize this equation, we get

$$\begin{aligned}\bar{w}\hat{w}_t &= \psi\bar{w}\hat{w}_{t-1} + (1-\psi)\,\bar{w}^*\hat{w}_t^*, \text{ or}\\ \hat{w}_t &= \psi\hat{w}_{t-1} + (1-\psi)\,\hat{M}_t,\end{aligned}$$

where the second line uses the steady-state condition $\bar{w} = \bar{w}^*$ and the fact that w_t^* is proportional to the money supply. Furthermore, we impose mean-reverting money supply growth, as in Cooley and Hansen (1989),

$$\Delta\hat{M}_t = \rho_M \Delta\hat{M}_{t-1} + u_t. \tag{A.14}$$

After log-linearizing the equilibrium conditions and imposing the mean-reverting money supply, we get

$$\begin{aligned}
D\left(\frac{\bar{R}}{\bar{M}}\right)\hat{R}_t - aW'D\left(\frac{\bar{\theta}\bar{R}}{\bar{M}}\right)\hat{R}_t &= b\hat{M}_t + aW'D\left(\frac{\bar{\theta}\bar{R}}{\bar{M}}\right)\hat{\theta}_t\\
\hat{\theta}_t + D\left(1-\bar{\theta}\right)\phi\left(\hat{l}_t - \hat{X}_t\right) &= 0\\
\hat{X}_t - \hat{\theta}_t - W\hat{y}_t - (I-W)\,\hat{R}_t &= 0\\
\hat{y}_t + \frac{a}{\phi}\hat{\theta}_t - a\hat{X}_t &= 0\\
\left(\hat{w}_t + \hat{l}_t\right) - \hat{R}_t + D\left(\frac{\bar{\theta}}{(1-\bar{\theta})}\right)\hat{\theta}_t &= 0\\
\hat{w}_t - (1-\psi)\,\hat{M}_t &= \psi\hat{w}_{t-1}\\
\Delta\hat{M}_t &= \rho_M\Delta\hat{M}_{t-1} + u_t.
\end{aligned}$$

$D(\bar{x})$ denotes a diagonal matrix with elements of vector $\bar{x} = (\bar{x}_i)_{i=1}^N$ as entries. This set of linear equations is easy to simulate because it has a recursive form. In particular, we can first simulate the last two equations and then solve for the endogenous variables using the remaining system of linear equations.

Another way to write the first equation is by noting that the log-linearized equation is

$$
\begin{aligned}
\bar{R}_i\hat{R}_i &= b_i\bar{M}\hat{M} + \sum_{j=1}^{N} a w_{ji}\bar{\theta}_j\bar{R}_j\left(\hat{\theta}_j + \hat{R}_j\right) \\
\hat{R}_i &= b_i\frac{\bar{M}}{\bar{R}_i}\hat{M} + \sum_{j=1}^{N} \frac{a w_{ji}\bar{\theta}_j\bar{R}_j}{\bar{R}_i}\left(\hat{\theta}_j + \hat{R}_j\right) \\
\hat{R}_i &= b_i\frac{\bar{M}}{\bar{R}_i}\hat{M} + \sum_{j=1}^{N} \frac{\bar{p}_i\bar{x}_{ji}}{\bar{p}_i\bar{y}_i}\left(\hat{\theta}_j + \hat{R}_j\right),
\end{aligned}
$$

which has an intuitive interpretation. Note $\bar{p}_i\bar{x}_{ji}/\bar{p}_i\bar{y}_i$ is the share of industry i's revenues from industry j. The greater this value is, the more important industry j is for industry i. There are two channels that determine how monetary policy can affect industry i through industry j. The first one is the effect of higher revenues for industry j, $\hat{R}_j$. The second one is the additional effect from $\hat{\theta}_j$, which captures the change in the relative importance of intermediate inputs for industry j: the more industry j shifts towards intermediate inputs, the more it will affect the revenues of its suppliers. In other words, the network effects from industry j to industry i will be modified by how monetary policy affects the relative importance of intermediate inputs in industry j's production.

The last equation can be written in matrix form as

$$
\hat{R} = \tilde{W}\hat{R} + \beta\hat{M} + \tilde{W}\hat{\theta}, \tag{A.15}
$$

where $\beta_i = b_i\bar{M}/\bar{R}_i$ and $\tilde{W}_{ij} = \bar{p}_i\bar{x}_{ji}/\bar{p}_i\bar{y}_i$. We can rewrite this equation as a function of the state variables of this system, $\hat{M}_t$ and $\hat{w}_t$, after solving $\hat{\theta}$ as a function of $\hat{R}_t$. Therefore, we get

$$
\begin{aligned}
\hat{\theta}_t &= -(1-a)\frac{\phi}{(1-\phi)}D\left(1-\bar{\theta}\right)\left(I - aWD\left(\bar{\theta}\right)\right)^{-1}W\hat{R}_t \\
&\quad + (1-a)\frac{\phi}{(1-\phi)}D\left(1-\bar{\theta}\right)\left(I - aWD\left(\bar{\theta}\right)\right)^{-1}\hat{w}_t,
\end{aligned}
$$

which leads to

$$\hat{R} = \tilde{W}\left[I - \frac{(1-a)\,\phi}{(1-\phi)} D\left(1-\bar{\theta}\right)\left(I - aWD\left(\bar{\theta}\right)\right)^{-1} W\right]\hat{R} \qquad \text{(A.16)}$$
$$+\beta\hat{M} + \frac{(1-a)\,\phi}{(1-\phi)}\tilde{W}D\left(1-\bar{\theta}\right)\left(I - aWD\left(\bar{\theta}\right)\right)^{-1}\hat{w}_t.$$

Note that the second term in square brackets multiplying $\hat{R}$ suggests that the additional effect from the change in the use of intermediate inputs will amplify the network effect because $\phi < 0$, meaning the elasticity of substitution between the intermediate inputs and labor is smaller than the elasticity of substitution between different intermediate inputs. Of course, our SAR framework is much simpler than this, although for sufficiently large values of a or for values of ϕ sufficiently close to zero, it should provide a reasonable approximation. In order to see how far our estimates of network effects diverge from the true network effects due to these additional effects, we estimate the SAR model on data simulated from the model.

B. Reaction of Stock Prices to Policy Surprises

Preferences are given by

$$U\left(\{c_{i,t+s}\}\right) = E_t\left(\sum_{s=0}^{\infty}\delta^s\sum_{i=1}^{N} b_i \log\left(c_{i,t+s}\right)\right), \qquad \text{(A.17)}$$

which leads to the "nominal stochastic discount factor" (see Campbell (2000)), that is, the discount factor used to discount nominal cash flows, at time $t+s$

$$SDF_{t+s} = \delta\frac{c_{i,t}}{c_{i,t+s}}\frac{p_{i,t}}{p_{i,t+s}} = \delta\frac{M_t}{M_{t+1}}, \qquad \text{(A.18)}$$

where the second equality comes from the cash-in-advance constraint. Therefore, the market value of industry i, with profit stream $\{\pi_{i,t}\}$, is given by

$$V_{i,t} = E_t\left(\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}\pi_{i,t+s}\right)$$
$$= E_t\left[\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}\left((1-a)\,R_{i,t+s} - f\right)\right].$$

Using $R_t = \left[I - aW'D\left(\theta_t\right)\right]^{-1} bM_t = S\left(W;\theta_t\right)M_t$, we can write this in matrix form, where $V_t' = (V_{i,t})_{i=1}^N$

$$\begin{aligned} V_t &= E_t\left[\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}\left(\left(1-a\right)S\left(W;\theta_{t+s}\right)M_{t+s}-f\right)\right] \\ &= E_t\left[\sum_{s=0}^{\infty}\delta^s\left(\left(1-a\right)S\left(W;\theta_{t+s}\right)M_t-f\frac{M_t}{M_{t+s}}\right)\right] \\ &= \left(1-a\right)E_t\left[\sum_{s=0}^{\infty}\delta^s S\left(W;\theta_{t+s}\right)\right]M_t-E_t\left[\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}f\right], \end{aligned}$$

where the first component gives the expected present value of profits and the second term gives the expected present value of nominal obligations. Stock prices have a spatial-weighting matrix structure that is closely tied to the one for revenues. In particular, for the Cobb-Douglas benchmark model where $S\left(W;\theta_t\right) = S\left(W\right)$, this expression simplifies to

$$V_t = \frac{1-a}{1-\delta}S\left(W\right)M_t - E_t\left[\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}f\right]. \tag{A.19}$$

The method of undetermined coefficients offers the simplest way to solve for the log-linearized version of market values. The pre-dividend stock value is

$$\begin{aligned} V_{i,t} &= E_t\left(\sum_{s=0}^{\infty}\delta^s\frac{M_t}{M_{t+s}}\pi_{i,t+s}\right) \\ &= \pi_{i,t}+E_t\left(\delta\frac{M_t}{M_{t+1}}E_{t+1}\left(\sum_{s=0}^{\infty}\delta^s\frac{M_{t+1}}{M_{t+s+1}}\pi_{i,t+s+1}\right)\right) \\ &= \pi_{i,t}+E_t\left(\delta\frac{M_t}{M_{t+1}}V_{i,t+1}\right). \end{aligned}$$

Log-linearize and use $\pi_{i,t} = \left(1-a\right)R_{i,t} - f$, which gives $\bar{\pi}\hat{\pi}_{i,t} = \left(1-a\right)\bar{R}_i\hat{R}_{i,t}$,

$$\bar{V}_i\hat{V}_{i,t} = \left(1-a\right)\bar{R}_i\hat{R}_{i,t} + E_t\left(\delta\bar{V}_i\left(\hat{V}_{i,t+1} - \Delta\hat{M}_{t+1}\right)\right). \tag{A.20}$$

By the method of undetermined coefficients, we have

$$\hat{V}_{i,t} = s_{Mi}\hat{M}_t + s_{\Delta Mi}\Delta\hat{M}_t + s_{wi}\hat{w}_t, \tag{A.21}$$

and we can plug this expression into last equation, along with the solution for $\hat{R}_{i,t}$, which has the form

$$\begin{aligned}\hat{R}_{i,t} &= r_{Mi}\hat{M}_t + r_{wi}\hat{w}_t \\ \hat{w}_t &= (1-\psi)\,\hat{M}_t + \psi\hat{w}_{t-1} \\ \Delta\hat{M}_t &= \rho_M\Delta\hat{M}_{t-1} + u_t,\end{aligned}$$

where r_{Mi} and r_{wi} can be calculated using equilibrium conditions. The resulting expression can be solved for s_{mi}, $s_{\Delta mi}$, and s_{wi} to obtain $\hat{V}_{i,t}$. The immediate reaction of stock prices to monetary policy surprises is then given by

$$\hat{V}_{i,t} - E_{t-1}\left(\hat{V}_{i,t}\right) = (s_{Mi} + s_{\Delta Mi} + (1-\psi)\,s_{wi})\,u_t. \tag{A.22}$$

C. Calibrating Wage Stickiness, ψ

We want to find $corr(y_t, y_{t-1})$ for the following process

$$\begin{aligned}y_t &= \psi y_{t-1} + (1-\psi)\,x_t \\ x_t &= \rho x_{t-1} + u_t.\end{aligned}$$

This process satisfies the following equations

$$\begin{aligned}cov\,(y_t, y_{t-1}) &= \psi var\,(y_{t-1}) + (1-\psi)\,cov\,(y_{t-1}, x_t) \\ cov\,(y_t, x_t) &= \psi cov\,(y_{t-1}, x_t) + (1-\psi)\,var\,(x_t) \\ var\,(y_t) &= \psi cov\,(y_t, y_{t-1}) + (1-\psi)\,cov\,(y_t, x_t)\,,\end{aligned}$$

which we can simplify using the fact that y_t follows a covariance-stationary process,

$$\begin{aligned}cov\,(y_t, y_{t-1}) &= \psi var\,(y_t) + (1-\psi)\,cov\,(y_{t-1}, x_t) \\ cov\,(y_t, x_t) &= \psi cov\,(y_{t-1}, x_t) + (1-\psi)\,var\,(x_t) \\ var\,(y_t) &= \psi cov\,(y_t, y_{t-1}) + (1-\psi)\,cov\,(y_t, x_t)\,,\end{aligned}$$

which we can solve for $cov\,(y_t, y_{t-1})$, given $var\,(x_t)$ and $var\,(y_t)$.

After some algebraic manipulation, the equations become

$$cov\,(y_t, y_{t-1}) = \psi var\,(y_t) + \frac{1}{\psi}var\,(y_t) - cov\,(y_t, y_{t-1}) - \frac{(1-\psi)^2}{\psi}var\,(x_t)\,. \tag{A.23}$$

We can simplify further to obtain

$$corr\left(y_t, y_{t-1}\right) = \frac{cov\left(y_t, y_{t-1}\right)}{var\left(y_t 4\right)} = \frac{1}{2}\left(\psi + \frac{1}{\psi} - \frac{\left(1-\psi\right)^2}{\psi}\frac{var\left(x_t\right)}{var\left(y_t\right)}\right). \tag{A.24}$$

Using $corr\left(\Delta\hat{w}_t, \Delta\hat{w}_{t-1}\right) = 0.47$ from the autocorrelation of the quarterly growth rate of nominal earnings, $var\left(\Delta\hat{m}_t\right) = 0.01/\left(1-0.5^2\right) = 0.013$, and $var\left(\Delta\hat{w}_t\right) = 0.01$ in the data, we get

$$0.47 = \frac{1}{2}\left(\psi + \frac{1}{\psi} - \frac{\left(1-\psi\right)^2}{\psi}\frac{4}{3}\right), \tag{A.25}$$

which gives $\psi = 0.2$.

IV Closeness to End-Consumer

Closeness to end-consumers and network effects

The following provides the prediction regarding closeness to end-consumers for the case where we have multiple industries in the two groups. In this case, the input-output matrix has the form

$$W = \begin{bmatrix} W_{1,1} & W_{1,2} \\ W_{2,1} & W_{2,2} \end{bmatrix} = \begin{bmatrix} W_{1,1} & W_{1,2} \\ 0 & W_{2,2} \end{bmatrix}. \tag{A.26}$$

We can then express the reaction of profits to monetary innovations as

$$\begin{pmatrix} \hat{\pi}_1 \\ \hat{\pi}_2 \end{pmatrix} = \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \hat{M} + \begin{bmatrix} A'_{1,1} & 0 \\ A'_{1,2} & A'_{2,2} \end{bmatrix} \begin{pmatrix} \hat{\pi}_1 \\ \hat{\pi}_2 \end{pmatrix}, \tag{A.27}$$

where $A \equiv D(\alpha) W$ and $D(\alpha)$ is a diagonal matrix whose diagonal elements correspond to the corresponding element of the input-share vector α, and subscripts refer to corresponding groups. This equation leads to

$$\begin{aligned} \hat{\pi}_1 &= \left(I - A'_{1,1}\right)^{-1} \beta_1 \hat{M} \\ \hat{\pi}_2 &= \left(I - A'_{2,2}\right)^{-1} \left(\beta_2 \hat{M} + A'_{1,2} \hat{\pi}_1\right) \end{aligned}$$

Define $e_{1/N} \equiv 1/N * (1, 1, ..., 1)'$ as an N-by-1 vector where N is the number of industries in a given group. The fraction of average direct effects for two groups are given by

$$\begin{aligned} Direct_1 &= \frac{e'_{1/N} \beta_1}{e'_{1/N} \left(I - A'_{1,1}\right)^{-1} \beta_1} \\ Direct_2 &= \frac{e'_{1/N} \beta_2 \hat{M}}{e'_{1/N} \left(I - A'_{2,2}\right)^{-1} \left(\beta_2 \hat{M} + A'_{1,2} \hat{\pi}_1\right)} \end{aligned}$$

When the input spending shares are sufficiently close to each other, i.e. $\alpha_i \approx \alpha$ for all i, we have

$$\begin{aligned} Direct_1 &= \frac{e'_{1/N}\beta_1}{e'_{1/N}\left(I-\alpha W'_{1,1}\right)^{-1}\beta_1} > 1-\alpha \\ Direct_2 &= \frac{e'_{1/N}\beta_2\hat{M}}{e'_{1/N}\left(I-\alpha W'_{2,2}\right)^{-1}\left(\beta_2\hat{M}+\alpha W'_{1,2}\hat{\pi}_1\right)} < 1-\alpha, \end{aligned}$$

where the first inequality follows from the fact that column sum (sum of rows in a given column) of $W'_{1,1}$ is less than one and the second inequality follows from the fact that the column sum of $W'_{2,2}$ equals one.

For the benchmark model with $W = I$, we have

$$\begin{aligned} \hat{\pi}_1^0 &= \left(I-D\left(\alpha_1\right)\right)^{-1}\beta_1\hat{M} \\ \hat{\pi}_2^0 &= \left(I-D\left(\alpha_2\right)\right)^{-1}\beta_2\hat{M} \end{aligned}$$

The network amplification, i.e. the difference of the total effect and the benchmark effect, is given by

$$\begin{aligned} e'_{1/N}\hat{\pi}_1 - e'_{1/N}\hat{\pi}_1^0 &= e'_{1/N}\left(I-A'_{1,1}\right)^{-1}\beta_1\hat{M} - e'_{1/N}\left(I-D\left(\alpha_1\right)\right)^{-1}\beta_1\hat{M} \\ e'_{1/N}\hat{\pi}_2 - e'_{1/N}\hat{\pi}_2^0 &= e'_{1/N}\left(I-A'_{2,2}\right)^{-1}\left(\beta_2\hat{M}+A'_{1,2}\hat{\pi}_1\right) - e'_{1/N}\left(I-D\left(\alpha_2\right)\right)^{-1}\beta_2\hat{M} \end{aligned}$$

When the input spending shares are sufficiently close to each other, i.e. $\alpha_i \approx \alpha$ for all i, we have

$$\begin{aligned} \frac{e'_{1/N}\hat{\pi}_1 - e'_{1/N}\hat{\pi}_1^0}{\hat{M}} &= e'_{1/N}\left(I-\alpha W'_{1,1}\right)^{-1}\beta_1 - e'_{1/N}\frac{\beta_1}{1-\alpha} < 0 \\ \frac{e'_{1/N}\hat{\pi}_2 - e'_{1/N}\hat{\pi}_2^0}{\hat{M}} &= e'_{1/N}\left(I-\alpha W'_{2,2}\right)^{-1}\left(\beta_2+\alpha W'_{1,2}\frac{\hat{\pi}_1}{\hat{M}}\right) - e'_{1/N}\frac{\beta_2}{1-\alpha} \\ &= e'_{1/N}\left(I-\alpha W'_{2,2}\right)^{-1}\alpha W'_{1,2}\left(I-\alpha W'_{1,1}\right)^{-1}\beta_1 > 0, \end{aligned}$$

where the first inequality comes from the fact that the column sum of $W'_{1,1}$ is less than one. So, the amplification effect is negative for the group 1 and it is positive for group 2.

Industries close and far from end-consumers in the data

This section details the construction of our empirical proxy for an industry's closeness to end-consumers. We first define a matrix, C_{ij}, which is the dollar amount that sector i pays j to purchase goods from j, $\forall$ $(i, j) \in$ (households, industry 1 to industry n). The matrix D is a $(n+1) \times (n+1)$ matrix and takes the form

$$D = \begin{bmatrix} 0 & \mu^\top \\ 0 & \Gamma \end{bmatrix}, \tag{A.28}$$

where μ is the dollar amount of household consumption spending, Γ is defined as dollar amount of intermediate input purchases from industry i to industry j, and 0 are vectors of zeros of suitable dimensions. In order to construct μ, we use the BEA USE table to extract the amount of personal consumption expenditure. Personal consumption expenditure P is a $C \times 1$ vector where C are commodities. We multiply the MAKE table by P and then standardize it by the total commodity output to transform P into the dollar amount that households buy from industry i,

$$\mu = (MAKE * P) * \frac{1}{\sum_{i=1}^{C} C_i}. \tag{A.29}$$

We define Γ as an $n \times n$ matrix of intermediate input purchases that industry j makes from industry i. Γ corresponds to the REVSHARE matrix in Section IV (see equation (25)).

Next, we column normalize D in order to obtain industries' sales shares:

$$D^{c.n} = D * diag(D * 1)^{-1} = \begin{bmatrix} 0 & \hat{\mu}^\top \\ 0 & \hat{\Gamma} \end{bmatrix}. \tag{A.30}$$

We then define steps to end-consumer, S, as follows:

$$\begin{aligned} S &= (1 - \hat{\Gamma}^\top)^{-1}\hat{\mu} \\ &= .... + (\hat{\Gamma}^\top)^2\hat{\mu} + \hat{\Gamma}^\top\hat{\mu} + \hat{\mu} \\ &= 1. \end{aligned} \tag{A.31}$$

The first step, $\hat{\mu}$, is the percentage of sales from industry i to the household sector as a percentage of industry i's total sales. The second step, $\hat{\Gamma}^\top\hat{\mu} + \hat{\mu}$, is the percentage of sales from industry i to households, both directly and via other industries. In the limit, the expansion approaches 1.

V Subsample Analysis

In this section, we report several robustness checks.

The sensitivity of stock market returns to monetary policy shocks varies across types of events and shocks and might influence the importance of higher-order demand effects. Table A.1 in the Online Appendix presents the results for different event types.[4] Column (1) focuses on reversals in monetary policy, such as the first increase in the federal funds rate after a series of decreasing or constant rates. We see that reversals lead to monetary policy shocks having a larger impact on stock returns. The point estimate for β doubles compared to the overall sample (see column (4) of Table 1) but statistical significance is sparse, which might be due to reduced power, with a similar point estimate for ρ of 0.85. A federal funds rate that is 1 percentage point higher than expected leads to an average decline in industry returns of 5.5 percent. The network effects account for more than 75 percent of this overall sensitivity.

Empirically, monetary policy has become more predictable over time because of increased transparency and communication by the Fed and a higher degree of monetary policy smoothing (see Figure A.1 in the Online Appendix and discussion in Neuhierl and Weber (2019)). As a result, many policy shocks are small in size. To ensure that these observations do not drive the large higher-order demand effects, column (2) presents the findings when we restrict our sample to events with shocks larger than 5 basis points in absolute value. The significance and point estimates remain stable when we exclude small policy surprises. For large shocks, the network effect still constitutes about 80 percent of the total effect.

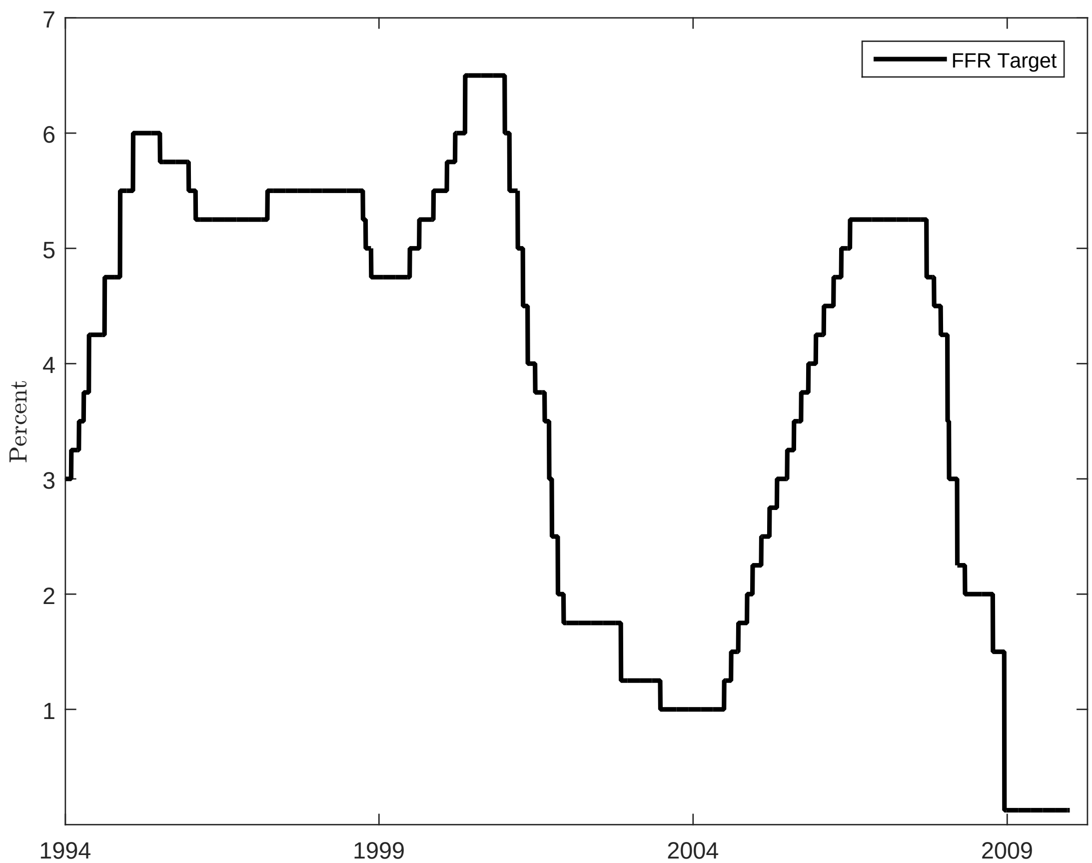
We see in columns (3) and (4) that the response of stock returns to monetary policy shocks is asymmetric. Tighter-than-expected monetary policy has a weaker

[4] We estimate a model with constant coefficients because we only have few events and hence industry observations for some of the sample cuts.

effect on stock returns compared to looser-than-expected monetary policy.[5] A federal funds rate that is 1 percentage point lower than expected leads to an average increase in industry returns of 3.5 percent, which is highly statistically significant, with 77 percent of the increase due to network effects. The effect of tighter monetary policy in column (3) is not statistically significant, a result that is likely not due to lower power because both sample sizes are similar.

[5]Bernanke and Kuttner (2005) obtain a similar result, with the exception that they bundle zero surprises with negative surprises by comparing positive surprises with the whole sample. See also Neuhierl and Weber (2017) for related findings.

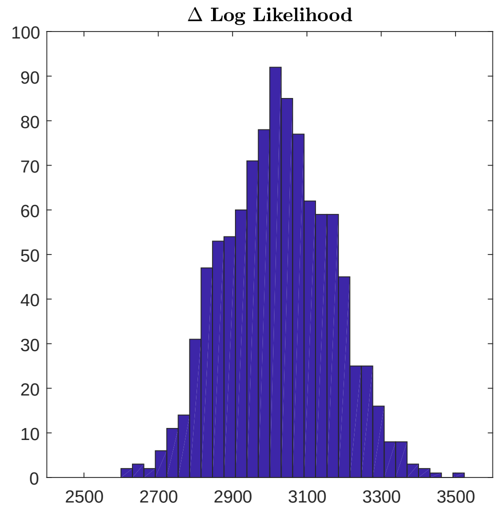
Figure A.1: **Time Series of Federal Funds Target Rate**



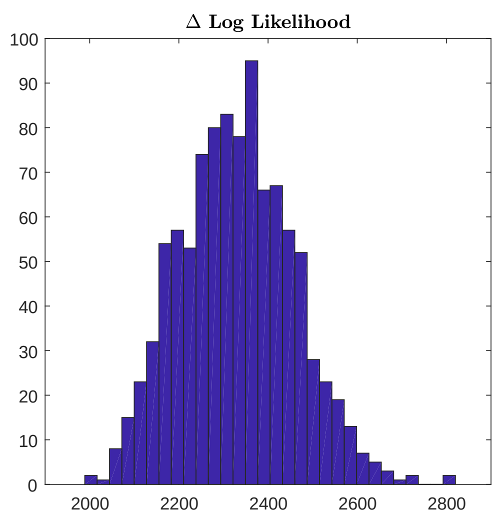
This figure plots the time series of the federal funds target rate from 1994 to 2009. Source: St. Louis Federal Reserve Economic Data (FRED).

Figure A.2: **Placebo log Likelihood Effects: Monte Carlo Simulation Industry-by-Industry**

Panel A: Matched Sparsity & First-order Outdegree Industry-by Industry



Panel B: Matched Sparsity & First- and Second-order Outdegree Industry-by Industry



This figure plots the histogram of the actual log likelihood estimated in Table 2 column (3) minus the log likelihood for different assumptions on simulated input-output matrices. Each simulation consists of 1,000 draws. Panel A matches the sparsity and first-order outdegree and draws entries for the pseudo input-output table from a fitted Pareto distribution but ensures for each simulation industries have sparsity and first-order outdegree as in the actual data. Panel B matches the sparsity, draws entries for the pseudo input-output table from a fitted Pareto distribution and matches the first-order and second-order outdegree of the actual input-output tables but ensures for each simulation industries have sparsity, first-order outdegree and second-order outdegrees as in the actual data.

Table A.1: **Response of Industry Returns to Monetary Policy Shocks (Conditional on Event Type)**

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t, and an input-output network-weighted average of industry returns (see equation (19)) for different event types. The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Bootstrapped standard errors are reported in parentheses.

	Reversals	Large Shocks	Positive Shocks	Negative Shocks
	(1)	(2)	(3)	(4)
	Panel A. Point Estimates			
β	−0.99	−0.44***	−0.21	−0.50**
	(0.76)	(0.17)	(0.21)	(0.25)
ρ	0.85***	0.87***	0.87***	0.86***
	(0.04)	(0.02)	(0.01)	(0.02)
Constant	0.02	0.00	−0.03*	−0.02
	(0.04)	(0.01)	(0.01)	(0.01)
Adj R^2	62.06	25.82	9.81	8.12
Observations	529	2,061	3,163	4,121
Log-L	-208	-830	-1,026	-1,257
	Panel B. Decomposition			
Direct Effect 1	−1.56	−0.70***	−0.35	−0.79**
	(1.01)	(0.25)	(0.34)	(0.38)
Network Effect 1	−4.95***	−2.63***	−1.37	−2.70**
	(1.60)	(0.69)	(1.32)	(1.22)
Direct Effect 2	−0.99	−0.44***	−0.21	−0.50**
	(0.76)	(0.17)	(0.21)	(0.25)
Network Effect 2	−5.51***	−2.90***	−1.50	−2.99**
	(1.85)	(0.77)	(1.45)	(1.36)

Standard errors in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.2: **Response of Industry Returns to Monetary Policy Shocks (Robustness)**

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t*, and an input-output network-weighted average of industry returns (see equation (19)). The value of* β *is the average of* β_i *for individual industries and* ρ *is the average of the diagonal elements of* $D(\rho)$*. The full sample ranges from February 1994 through December 2008, excluding intermeeting policy decisions, for a total of 120 observations. Bootstrapped standard errors are reported in parentheses. Columns (1)-(3) use the balanced panel of industries for which we have observations on all event dates. Column (2) estimates the model with MLE as in Table 2 and Column 3 estimates the model with MCMC. Column (4) normalizes small entries of the input-output tables to 0 and ensures intermediate input shares add up to 1 and column (5) uses all industries rather than requiring at least three firms per event and date. Direct and Network Effects 1 follow Pace and LeSage (2014), Direct and Network Effects 2 follow Acemoglu et al. (2016), Direct Effect 3 refers to the total effect under autarky, and Network Effect 3 refers to amplification due to network effects, i.e. the difference between total effect under the empirical input-output matrix and the total effect under autarky.*

	Balanced Panel			SAR: 1992 Tables	
	OLS	MLE	MCMC	W(W<0.0001)=0	Min Firms = 1
	(1)	(2)	(3)	(4)	(5)
Panel A. Point Estimates					
β	−2.97∗∗∗	−0.47∗∗∗	−0.63∗∗∗	−0.50∗∗∗	−0.63∗∗∗
	(0.14)	(0.15)	(0.18)	(0.15)	(0.20)
ρ		0.86∗∗∗	0.81∗∗∗	0.83∗∗∗	0.79∗∗∗
		(0.01)	(0.02)	(0.01)	(0.02)
Constant	−0.11∗∗∗	−0.02∗∗	−0.02∗∗	−0.01	−0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Adj R^2	9.52	9.34	9.34	11.12	6.38
Observations	7,200	7,200	7,200	9,040	10,058
Log-L		-2,625	-13,085	-3,412	-5,617
Panel B. Decomposition					
Direct Effect 1		−0.61∗∗∗	−0.86∗∗∗	−0.61∗∗∗	−0.75∗∗∗
		(0.19)	(0.25)	(0.19)	(0.24)
Network Effect 1		−2.36∗∗∗	−2.11∗∗∗	−2.35∗∗∗	−2.28∗∗∗
		(0.70)	(0.64)	(0.67)	(0.67)
Direct Effect 2		−0.47∗∗∗	−0.63∗∗∗	−0.50∗∗∗	−0.63∗∗∗
		(0.15)	(0.18)	(0.15)	(0.20)
Network Effect 2		−2.50∗∗∗	−2.33∗∗∗	−2.46∗∗∗	−2.40∗∗∗
		(0.74)	(0.71)	(0.70)	(0.70)
Direct Effect 3		−1.32∗∗∗	−1.30∗∗∗	−1.37∗∗∗	−1.66∗∗∗
		(0.40)	(0.37)	(0.41)	(0.54)
Network Effect 3		−1.65∗∗∗	−1.66∗∗∗	−1.59∗∗∗	−1.37∗∗∗
		(0.53)	(0.56)	(0.47)	(0.44)

Standard errors in parentheses.
$*p < 0.10, **p < 0.05, ***p < 0.01$

Table A.3: **BEA Industries 1992**

This table reports the BEA industry codes as well as a description for the 1992 input-output tables.

BEA Industry code	Industry Description	Industry Sector
05	Ferroalloy ores mining	MINING
06	Nonferrous metal ores mining	MINING
09	Nonmetallic minerals mining	MINING
13	Ordnance and accessories	MANUFACTURING
14	Food and kindred products	MANUFACTURING
15	Tobacco products	MANUFACTURING
16	Broad and narrow fabrics, yarn and thread mills:	MANUFACTURING
17	Miscellaneous textile goods and floor coverings	MANUFACTURING
18	Apparel	MANUFACTURING
19	Miscellaneous fabricated textile products	MANUFACTURING
20	Lumber and wood products	MANUFACTURING
22	Furniture	MANUFACTURING
23	Furniture and Fixtures	MANUFACTURING
24	Paper and allied products, except containers	MANUFACTURING
25	Paperboard containers and boxes	MANUFACTURING
26A	Newspapers and periodicals	MANUFACTURING
26B	Other printing and publishing	MANUFACTURING
27A	Industrial and other chemicals	MANUFACTURING
27B	Agricultural fertilizers and chemicals	MANUFACTURING
28	Plastics and synthetic materials	MANUFACTURING
29A	Drugs	MANUFACTURING
29B	Cleaning and toilet preparations	MANUFACTURING
30	Paints and allied products	MANUFACTURING
31	Petroleum refining and related products	MANUFACTURING
32	Rubber and miscellaneous plastics products	MANUFACTURING
34	Footwear, leather, and leather products	MANUFACTURING
35	Glass and glass products	MANUFACTURING
36	Stone and clay products	MANUFACTURING
37	Primary iron and steel manufacturing	MANUFACTURING
38	Primary nonferrous metals manufacturing	MANUFACTURING
39	Metal containers	MANUFACTURING
40	Heating, plumbing, and fabricated structural metal	MANUFACTURING
41	Screw machine products and stampings	MANUFACTURING
42	Other fabricated metal products	MANUFACTURING
43	Engines and turbines	MANUFACTURING
46	Materials handling machinery and equipment	MANUFACTURING
47	Metalworking machinery and equipment	MANUFACTURING
48	Special industry machinery and equipment	MANUFACTURING
49	General industrial machinery and equipment	MANUFACTURING
50	Miscellaneous machinery, except electrical	MANUFACTURING
51	Computer and office equipment	MANUFACTURING
52	Service industry machinery	MANUFACTURING
53	Electrical industrial equipment and apparatus	MANUFACTURING
54	Household appliances	MANUFACTURING
55	Electric lighting and wiring equipment	MANUFACTURING
56	Audio, video, and communication equipment	MANUFACTURING
57	Electronic components and accessories	MANUFACTURING
58	Miscellaneous electrical machinery and supplies	MANUFACTURING
59A	Motor vehicles (passenger cars and trucks)	MANUFACTURING
59B	Truck and bus bodies, trailers, and motor parts	MANUFACTURING
60	Aircraft and parts	MANUFACTURING
61	Other transportation equipment	MANUFACTURING
62	Scientific and controlling instruments	MANUFACTURING
63	Ophthalmic and photographic equipment	MANUFACTURING
64	Miscellaneous manufacturing	MANUFACTURING
65A	Railroads and related services; passenger ground transportation	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
65B	Motor freight transportation and warehousing	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
65C	Water transportation	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
65D	Air transportation	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
65E	Pipelines, freight forwarders, and related services	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
66	Communications, except radio and TV	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
67	Radio and TV broadcasting	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
68A	Electric services (utilities)	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
68C	Water and sanitary services	TRANSPORTATION, COMMUNICATIONS, & UTILITIES
69A	Wholesale trade	WHOLESALE AND RETAIL TRADE
69B	Retail trade	WHOLESALE AND RETAIL TRADE
70A	Finance	FINANCE, INSURANCE, AND REAL ESTATE
70B	Insurance	FINANCE, INSURANCE, AND REAL ESTATE
71A	Owner-occupied dwellings	FINANCE, INSURANCE, AND REAL ESTATE
72A	Hotels and lodging places	SERVICES
72B	Personal and repair services (except auto)	SERVICES
73A	Computer and data processing services	SERVICES
73B	Legal, engineering, accounting, and related services	SERVICES
73C	Other business and professional services, except medical	SERVICES
73D	Advertising	SERVICES
74	Eating and drinking places	SERVICES
75	Automotive repair and services	SERVICES
76	Amusements	SERVICES
77A	Health services	SERVICES
77B	Educational and social services, and membership organizations	SERVICES
A1	Agricultural forestry and fisheries	OTHERS
A2	Construction	OTHERS
A3	Other mining	OTHERS
A4	Gas production and distribution	OTHERS
A8	Farm, construction, and mining	OTHERS

Table A.4: **Monetary Policy Surprises**

This table reports the days of the FOMC press releases with exact time stamps as well as the actual changes in the federal funds rate further decomposed into an expected and an unexpected part. The latter component is calculated as the scaled change of the current month federal funds future in a 30-minute (tight) window and a 60-minute (wide) window, bracketing the release time according to equation (5) in the main body of the paper.

		Unexpected Change (bps)		Expected Change (bps)		
Release Date	Release Time	Tight Window	Wide Window	Tight Window	Wide Window	Actual Change (bps)
04-Feb-94	11:05:00	16.30	15.20	8.70	9.80	25.00
22-Mar-94	14:20:00	0.00	0.00	25.00	25.00	25.00
17-May-94	14:26:00	11.10	11.10	38.90	38.90	50.00
06-Jul-94	14:18:00	−5.00	−3.70	5.00	3.70	0.00
16-Aug-94	13:18:00	12.40	14.50	37.60	35.50	50.00
27-Sep-94	14:18:00	−9.00	−9.00	9.00	9.00	0.00
15-Nov-94	14:20:00	12.00	12.00	63.00	63.00	75.00
20-Dec-94	14:17:00	−22.60	−22.60	22.60	22.60	0.00
01-Feb-95	14:15:00	6.20	6.20	43.80	43.80	50.00
28-Mar-95	14:15:00	−1.00	0.00	1.00	0.00	0.00
23-May-95	14:15:00	0.00	0.00	0.00	0.00	0.00
06-Jul-95	14:15:00	−11.20	−7.40	−13.80	−17.60	−25.00
22-Aug-95	14:15:00	3.40	3.40	−3.40	−3.40	0.00
26-Sep-95	14:15:00	3.00	4.00	−3.00	−4.00	0.00
15-Nov-95	14:15:00	4.00	5.00	−4.00	−5.00	0.00
19-Dec-95	14:15:00	−9.00	−10.30	−16.00	−14.70	−25.00
31-Jan-96	14:15:00	−3.00	−3.00	−22.00	−22.00	−25.00
26-Mar-96	11:39:00	1.00	1.00	−1.00	−1.00	0.00
21-May-96	14:15:00	0.00	0.00	0.00	0.00	0.00
03-Jul-96	14:15:00	−7.20	−6.60	7.20	6.60	0.00
20-Aug-96	14:15:00	−2.80	−2.80	2.80	2.80	0.00
24-Sep-96	14:15:00	−12.00	−12.00	12.00	12.00	0.00
13-Nov-96	14:15:00	−1.80	−1.80	1.80	1.80	0.00
17-Dec-96	14:15:00	1.10	0.00	−1.10	0.00	0.00
05-Feb-97	14:15:00	−3.70	−3.00	3.70	3.00	0.00
25-Mar-97	14:15:00	4.00	4.00	21.00	21.00	25.00
20-May-97	14:15:00	−9.90	−9.90	9.90	9.90	0.00
02-Jul-97	14:15:00	−2.10	−1.10	2.10	1.10	0.00
19-Aug-97	14:15:00	0.00	0.00	0.00	0.00	0.00
30-Sep-97	14:15:00	0.00	0.00	0.00	0.00	0.00
12-Nov-97	14:15:00	−4.20	−4.20	4.20	4.20	0.00

continued on next page

Table A.4: **Continued from Previous Page**

Release Date	Release Time	Unexpected Change (bps) Tight Window	Unexpected Change (bps) Wide Window	Expected Change (bps) Tight Window	Expected Change (bps) Wide Window	Actual Change (bps)
16-Dec-97	14:15:00	0.00	0.00	0.00	0.00	0.00
04-Feb-98	14:12:00	0.00	0.00	0.00	0.00	0.00
31-Mar-98	14:15:00	−1.00	−1.00	1.00	1.00	0.00
19-May-98	14:15:00	−2.60	−2.60	2.60	2.60	0.00
01-Jul-98	14:15:00	−0.50	−0.50	0.50	0.50	0.00
18-Aug-98	14:15:00	1.20	1.20	−1.20	−1.20	0.00
29-Sep-98	14:15:00	5.00	6.00	−30.00	−31.00	−25.00
17-Nov-98	14:15:00	−6.90	−5.80	−18.10	−19.20	−25.00
22-Dec-98	14:15:00	0.00	−1.70	0.00	1.70	0.00
03-Feb-99	14:12:00	0.60	0.60	−0.60	−0.60	0.00
30-Mar-99	14:12:00	−1.00	0.00	1.00	0.00	0.00
18-May-99	14:11:00	−1.20	−1.20	1.20	1.20	0.00
30-Jun-99	14:15:00	−3.00	−4.00	28.00	29.00	25.00
24-Aug-99	14:15:00	3.50	3.00	21.50	22.00	25.00
05-Oct-99	14:12:00	−4.20	−4.20	4.20	4.20	0.00
16-Nov-99	14:15:00	7.50	9.60	17.50	15.40	25.00
21-Dec-99	14:15:00	1.60	1.60	−1.60	−1.60	0.00
02-Feb-00	14:15:00	−5.90	−5.90	30.90	30.90	25.00
21-Mar-00	14:15:00	−4.70	−4.70	29.70	29.70	25.00
16-May-00	14:15:00	4.10	3.10	45.90	46.90	50.00
28-Jun-00	14:15:00	−2.50	−2.00	2.50	2.00	0.00
22-Aug-00	14:15:00	−1.70	0.00	1.70	0.00	0.00
03-Oct-00	14:12:00	0.00	−0.60	0.00	0.60	0.00
15-Nov-00	14:12:00	−1.00	−1.00	1.00	1.00	0.00
19-Dec-00	14:15:00	6.50	6.50	−6.50	−6.50	0.00
31-Jan-01	14:15:00	3.50	4.00	−53.50	−54.00	−50.00
20-Mar-01	14:15:00	7.10	5.60	−57.10	−55.60	−50.00
15-May-01	14:15:00	−9.70	−7.80	−40.30	−42.20	−50.00
27-Jun-01	14:12:00	10.50	11.00	−35.50	−36.00	−25.00
21-Aug-01	14:15:00	1.60	1.60	−26.60	−26.60	−25.00
02-Oct-01	14:15:00	−3.70	−3.70	−46.30	−46.30	−50.00
06-Nov-01	14:20:00	−15.00	−15.00	−35.00	−35.00	−50.00
11-Dec-01	14:15:00	−0.80	0.00	−24.20	−25.00	−25.00

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Table A.4: **Continued from Previous Page**

		Unexpected Change (bps)		Expected Change (bps)		
Release Date	Release Time	Tight Window	Wide Window	Tight Window	Wide Window	Actual Change (bps)
30-Jan-02	14:15:00	2.50	1.50	−2.50	−1.50	0.00
19-Mar-02	14:15:00	−2.60	−2.60	2.60	2.60	0.00
07-May-02	14:15:00	0.70	0.70	−0.70	−0.70	0.00
26-Jun-02	14:15:00	0.00	0.00	0.00	0.00	0.00
13-Aug-02	14:15:00	4.30	4.30	−4.30	−4.30	0.00
24-Sep-02	14:15:00	2.00	2.50	−2.00	−2.50	0.00
06-Nov-02	14:15:00	−20.00	−18.80	−30.00	−31.20	−50.00
10-Dec-02	14:15:00	0.00	0.00	0.00	0.00	0.00
29-Jan-03	14:15:00	1.00	0.50	−1.00	−0.50	0.00
18-Mar-03	14:15:00	2.40	3.60	−2.40	−3.60	0.00
06-May-03	14:15:00	3.70	3.70	−3.70	−3.70	0.00
25-Jun-03	14:15:00	13.50	12.50	−38.50	−37.50	−25.00
12-Aug-03	14:15:00	0.00	0.00	0.00	0.00	0.00
16-Sep-03	14:15:00	1.10	1.10	−1.10	−1.10	0.00
28-Oct-03	14:15:00	−0.50	−0.50	0.50	0.50	0.00
09-Dec-03	14:15:00	0.00	0.00	0.00	0.00	0.00
28-Jan-04	14:15:00	0.50	0.00	−0.50	0.00	0.00
16-Mar-04	14:15:00	0.00	0.00	0.00	0.00	0.00
04-May-04	14:15:00	−1.20	−1.20	1.20	1.20	0.00
30-Jun-04	14:15:00	−0.50	−1.50	25.50	26.50	25.00
10-Aug-04	14:15:00	0.70	1.50	24.30	23.50	25.00
21-Sep-04	14:15:00	0.00	0.00	25.00	25.00	25.00
10-Nov-04	14:15:00	−0.80	0.00	25.80	25.00	25.00
14-Dec-04	14:15:00	−0.90	0.00	25.90	25.00	25.00
02-Feb-05	14:17:00	−0.54	0.00	25.54	25.00	25.00
22-Mar-05	14:17:00	0.00	−0.50	25.00	25.50	25.00
03-May-05	14:16:00	0.00	−0.56	25.00	25.56	25.00
30-Jun-05	14:15:00	−0.50	0.00	25.50	25.00	25.00
09-Aug-05	14:17:00	−0.71	−0.71	25.71	25.71	25.00
20-Sep-05	14:17:00	3.00	4.50	22.00	20.50	25.00
01-Nov-05	14:18:00	−0.52	−0.52	25.52	25.52	25.00
13-Dec-05	14:13:00	0.00	0.00	25.00	25.00	25.00
31-Jan-06	14:14:00	0.50	0.50	24.50	24.50	25.00
28-Mar-06	14:17:00	0.50	0.50	24.50	24.50	25.00
10-May-06	14:17:00	0.00	−0.75	25.00	25.75	25.00
29-Jun-06	14:16:00	−1.00	−1.50	26.00	26.50	25.00

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Table A.4: **Continued from Previous Page**

Release Date	Release Time	Unexpected Change (bps) Tight Window	Unexpected Change (bps) Wide Window	Expected Change (bps) Tight Window	Expected Change (bps) Wide Window	Actual Change (bps)
08-Aug-06	14:14:00	−4.77	−4.77	4.77	4.77	0.00
20-Sep-06	14:14:00	−1.50	−1.50	1.50	1.50	0.00
25-Oct-06	14:13:00	−0.50	−0.50	0.50	0.50	0.00
12-Dec-06	14:14:00	0.00	0.00	0.00	0.00	0.00
31-Jan-07	14:14:00	0.00	−0.50	0.00	0.50	0.00
21-Mar-07	14:15:00	1.67	0.00	−1.67	0.00	0.00
09-May-07	14:15:00	0.00	−0.71	0.00	0.71	0.00
28-Jun-07	14:14:00	0.00	0.00	0.00	0.00	0.00
07-Aug-07	14:14:00	0.65	1.30	−0.65	−1.30	0.00
18-Sep-07	14:15:00	−20.00	−21.25	−30.00	−28.75	−50.00
31-Oct-07	14:15:00	−2.00	−2.00	−23.00	−23.00	−25.00
11-Dec-07	14:16:00	3.16	3.16	−28.16	−28.16	−25.00
30-Jan-08	14:14:00	−11.00	−11.00	−39.00	−39.00	−50.00
18-Mar-08	14:14:00	10.00	10.00	−85.00	−85.00	−75.00
30-Apr-08	14:15:00	−6.00	−6.50	−19.00	−18.50	−25.00
25-Jun-08	14:09:00	−1.50	−1.00	1.50	1.00	0.00
05-Aug-08	14:13:00	−0.60	−0.50	0.60	0.50	0.00
16-Sep-08	14:14:00	9.64	11.25	−9.64	−11.25	0.00
29-Oct-08	14:17:00	−3.50	−3.50	−46.50	−46.50	−50.00
16-Dec-08	14:21:00	−16.07	−24.15	−83.93	−75.85	−100.00