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 a laboratory. We decompose the overall effect of monetary policy shocks into a direct effect and a network effect and attribute 50 to 85 percent of the overall effect to the network effect. Large network effects are a robust feature of the data, and we document similar patterns in realized cash-flow fundamentals. A simple model with intermediate inputs predicts that 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 to the real economy.

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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 Gabaix (2011) and 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 50 to 80 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. Many canonical macroeconomic models ignore production networks for tractability. 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. This result might appear surprising because the production network in the United States is sparse; that is, most industries are not directly linked to each other (Figure 1). 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 that a random production network with the same sparsity as the one observed in the actual US network generates a network effect of less than 20%, which is less than a quarter of our baseline estimate. The large network effects we document stress the importance of the particular structure of the US input-output network as opposed to just the sparsity of the network, because sparsity ignores higher-order interconnections. An arbitrary input-output structure will not generate large network effects, which emphasizes how important it is to quantify these effects based on the actual structure in the data.

Quantifying the extent 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.[1] 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

[1] Bernanke and Kuttner (2005) and Gürkaynak, Sack, and Swanson (2005) show that an unanticipated 25-basis-point decrease in the federal funds rate leads to an increase in the Center for Research in Security Prices (CRSP) value-weighted index of more than 1 percent within minutes of the FOMC announcement.

spatial-weighting matrix is ad hoc, which makes the structural interpretation of the spillover effects difficult.[2]

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 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 effects 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. We find large network effects that are robust to different sample periods, event windows, and types of announcements.[3]

We also document substantial heterogeneity in the relative importance of direct and network effects of monetary policy across industries. Direct effects are larger for industries 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

[2]See LeSage and Pace (2009).

[3]There are two important advantages of focusing on industry returns rather than individual firms' returns. 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.

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, but loses statistical significance after eight quarters.

Our model implies that industries with higher average profitability should have lower sensitivities to monetary policy shocks due to a leverage effect. When we add measures of average industry profitability and their interaction with the monetary policy shocks, we find supportive evidence for this prediction. Firms in industries with an average level of profitability have a sensitivity to monetary policy shocks that is reduced by 55 percent relative to an industry with zero profitability. Crucially, after we account for differences in the sensitivity to monetary policy shocks due to profitability, we still find that network effects constitute about 80 percent of the overall responsiveness of industry returns to monetary shocks.

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. 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 (see Acemoglu et al. 2012), we construct a pseudo (random) input-output matrix with these two characteristics. Using this pseudo input-output matrix, we find network effects account for only 18 percent of the overall effect compared to more than 80 percent in our baseline estimation, suggesting that a mechanical correlation between industries does not drive our main results.

In our spatial autoregressions, we estimate a constant sensitivity for all industries conditional on their respective positions in the network, following Acemoglu et al.

(2016).[4] Imposing a constant sensitivity across industries might bias our estimate of network effects. We find in simulations that imposing a constant beta on monetary policy shocks across industries does not explain why monetary policy shocks result in large network effects. Our results are also similar for industry-adjusted returns and when we account for the possibility of other common shocks in the same event window. Crucially, we find network effects of similar magnitude for CAPM-adjusted returns. This latter result is important, because it shows that differences in the cyclicality and riskiness of industries do not explain our findings.[5]

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 matrix, and decompose the results into direct and network effects. Across different specifications, we find that network effects constitute 70–80 percent 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.

[4] 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.

[5] Bernanke and Kuttner (2005) show that the CAPM captures the differences in the response of industries to monetary policy shocks, and Weber (2015) and Savor and Wilson (2014) find similar evidence for individual stocks and several portfolios.

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 that 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 (2017a) extend the analysis of these papers to allow for heterogeneity in price stickiness across sectors and identify a frictional origin of aggregate fluctuations. Acemoglu, Akcigit, and Kerr (2016) and Barrot and Sauvagnat (2016) show that networks are empirically important for aggregate fluctuations as well as for the transmission of federal spending, trade, technology, and knowledge shocks. Oberfield (2017) 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 (2017), Ramirez (2017) and Gofman, Segal, and Wu (2017) study the asset-pricing implications. We build on this work and study the importance of production networks on 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.[6]

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

[6]Other recent contributions to this fast-growing literature are Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017); Atalay (2017); Baqaee (2016); Baqaee and Farhi (2017); Bigio and La'O (2016); Caliendo et al. (2017); Carvalho and Gabaix (2013); Carvalho and Grassi (2015); Foerster, Sarte, and Watson (2011); Gofman (2013); Grassi (2017); and Taschereau-Dumouchel (2017).

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 study 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 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 our findings.

II The Benchmark Network Model

This section develops a static model with intermediate inputs in which money has heterogeneous effects on firms' stock prices. 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. The producers of intermediate inputs 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 allows for labor as an input in production and adds money to the economy. We also introduce wage stickiness 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, a firm's net income determines its stock price. Moreover, a firm has a predetermined fixed nominal obligation. We are agnostic about the origin of the fixed costs, but these might include rent payments or repayments of nominal debt.

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:

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

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

In equations (1) and (2), y_i is the output of firm i, λ and α are the factor shares, and ω_{ij} is the share of input from firm j in the production of firm i 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,

$$\alpha\omega_{ij}R_i = p_j x_{ij}, \tag{3}$$
$$\lambda R_i = w l_i, \tag{4}$$

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

$$\pi_i = (1-\alpha-\lambda)R_i - f_i. \tag{5}$$

The representative consumer maximizes utility

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

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 that 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

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

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

The goods-market-clearing condition is

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

which simplifies to

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

Equation (10) shows that 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, $\alpha \times w_{ji}$.

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

$$(I - \alpha W')R = (1-\alpha) \begin{pmatrix} \left(\sum_{i=1}^{N} R_i\right)/N \\ \vdots \\ \left(\sum_{i=1}^{N} R_i\right)/N \end{pmatrix}_{N \times 1}. \qquad (11)$$

B. Money Supply and Equilibrium Network Effects

We assume that intermediate inputs are financed through trade credit between firms, whereas consumption goods are purchased with cash.[7] Therefore, money supply determines prices through the following cash-in-advance constraint:

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

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

$$(I - \alpha W')R = \begin{pmatrix} M/N \\ \vdots \\ M/N \end{pmatrix}_{N \times 1} \equiv m. \qquad (13)$$

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

$$\pi = (1 - \alpha - \lambda)R - f = (I - \alpha W')^{-1} (1 - \alpha - \lambda)m - f, \qquad (14)$$

which we can log-linearize to get

$$\bar{\pi}\hat{\pi} = (I - \alpha W')^{-1} (1 - \alpha - \lambda)\bar{m}\hat{M}.^{8} \qquad (15)$$

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

$$\beta_i = \frac{(1 - \alpha - \lambda)\bar{m}}{\bar{\pi}_i}. \qquad (16)$$

[7] See Cooley and Hansen (1989).

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

Then,

$$\hat{\pi} = (I - \alpha W')^{-1} \beta \hat{M}. \tag{17}$$

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

$$\hat{\pi} = \beta \times \hat{M} + \alpha \times W' \times \hat{\pi}. \tag{18}$$

The changes in net incomes, that is, the firms' stock prices, react to the monetary shock $\hat{M}$ and the reaction of its customers' net incomes to the shock, $W' \times \hat{\pi}$.

Equation (18) has the form of a spatial autoregression (SAR) which we introduce in the next section.

III Framework

Section II shows how the SAR specification arises naturally from a model of production networks. In this section, we first introduce SARs, define how we identify the direct and network effects and then discuss how we measure monetary policy shocks.[9]

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. The spatial autoregressive model is given by

$$r_t = \beta v_t + \rho W' r_t + \varepsilon_t, \tag{19}$$

which implies that the data-generating process is

$$\begin{aligned} r_t &= (\mathbb{I}_n - \rho W')^{-1} \beta v_t + (\mathbb{I}_n - \rho W')^{-1} \varepsilon_t \\ \varepsilon_t &\overset{N}{\sim} (0, \sigma^2 \mathbb{I}_n).^{10} \end{aligned}$$

In equation (19), r is a vector of n industry returns around FOMC press releases, v is a vector of monetary policy shocks, and W' is a row-normalized spatial-weighting matrix. W corresponds to the BEA input-output matrix, which we describe in

[9]Denbee et al. (2014) use SARs to study systemic liquidity risk in the sterling interbank market.

[10]We show that our results are robust to relaxing this assumption about error terms.

Section IV.

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 (19) as

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

where we omit time subscripts for brevity and where

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

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

To illustrate our method, we focus on a simple example with three industries. We can expand the data-generating process to

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

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

We focus on industry 1,

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

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

We see from equation (22) that 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. In particular, $S(W')_{1,1}$ gives the reaction of industry 1 to the monetary policy shock, v, as if it were the only industry directly affected by the monetary policy shock. $S(W')_{1,2}$, instead, gives the reaction of industry 1 to the monetary policy shock as if industry 2 were the only industry directly affected by the shock. This entry of the matrix measures the spillover or network 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. Similarly, $S(W')_{1,3}$ measures the higher-order demand effect originating from industry 3. Therefore, $S(W')_{1,1}$ gives the direct effect of the monetary policy shock, v, whereas $S(W')_{1,2}$ and $S(W')_{1,3}$ give the network effects due to industry 1's exposure to industry 2 and industry 3 through input-output linkages.

Hence, 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 parameter ρ, which determines the strength of spillover effects; and the parameter β. The diagonal elements of $S(W')$ contain the direct effects of monetary policy shocks on industry returns, and the off-diagonal elements present network effects. We follow Pace and LeSage (2014) and define three scalars to measure the overall, direct, and network effects separately:

Average direct effect: the average of the diagonal elements of $S(W')$: $\frac{1}{n}tr(S(W'))$, where tr is the trace of a matrix.

Average total effect: the sum across the i^{th} row of $S(W')$ represents the total impact on industry i from the monetary policy shock. Overall, n of these sums exist, which we represent by the column vector $c_r = S(W')\iota_n$, where ι_n is a vector of ones. We define the average total impact then as $\frac{1}{n}\iota_n' c_r$.

Average network effect: the difference between the average total effect and the average direct effect.

The definitions of average direct effect and average network effect correspond to average partial derivatives. The average direct effect also includes the feedback effect, whereby an industry's immediate response can travel back to itself through the network, and therefore results in conservative estimates of network effects.

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

$$r_t = \beta_0 + \beta_1 \times v_t + \rho \times W' \times r_t + \varepsilon_t, \tag{23}$$

where r_t is a vector of industry returns, $r_t = (r_{it})_1^N$ in the interval $[t - \Delta t^-, t + \Delta t^+]$ around event t, v_t is the monetary policy shock which we will introduce below, and W is the industry-by-industry input-output table from the BEA. We estimate the model using maximum likelihood. 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. 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 the tradition of Cook and Hahn (1989) and more recently 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 as

$$v_t = \frac{D}{D-t}(ff^0_{t+\Delta t^+} - ff^0_{t-\Delta t^-}), \tag{24}$$

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

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.[11]

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 and ending with the most recent tables in 2012.

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.

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 baseline analysis to

[11] Ahern and Harford (2014) and Pasten, Schoenle, and Weber (2017b) use similar data.

create industry-by-industry trade flows at the four-digit IO industry aggregation. Our results are similar if we use the detailed data.

A.1 Industry Aggregations

The 1992 IO tables are based on the 1987 Standard Industrial Classification (SIC) codes, the 1997 IO tables are based on the 1997 North American Industry Classification System (NAICS) codes, and the 2002 IO tables are based on the 2002 NAICS codes. The BEA provides concordance tables between SIC and NAICS codes and IO industry 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 intermediate inputs are produced by other industries.

We use the make table ($MAKE$) to determine the share of each commodity c that each industry i produces. We call this matrix share ($SHARE$), which is an industry-by-commodity matrix. We define the market share of industry i's production of commodity c as

$$SHARE = MAKE \odot (\mathbb{I} \times MAKE)^{-1}_{i,j}, \tag{25}$$

where $\mathbb{I}$ is a matrix of ones with suitable dimensions.

We multiply the share and use table (USE) to calculate the total dollar amount that industry i sells to industry j. We label this matrix revenue share ($REVSHARE$), which is a supplier industry-by-consumer industry matrix:

$$REVSHARE = (SHARE \times USE). \tag{26}$$

We use the revenue-share matrix to calculate the percentage of industry j's inputs purchased from industry i, and label the resulting matrix $SUPPSHARE$:

$$SUPPSHARE = REVSHARE \odot ((MAKE \times \mathbb{I})^{-1}_{i,j})^{\top}. \tag{27}$$

$SUPPSHARE$ 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.1 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).

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. For the five event dates for which the press release was issued before the start of the day's trading session (all intermeeting releases in the easing cycle starting in 2007; see Table A.1 in the Online Appendix), we calculate event returns using the closing prices from the previous trading day and prices as of 10:00 a.m. Eastern time on the event day.[12] 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. We have on average 61–71 industries, depending on whether we use the SIC or NAICS codes for the aggregation. We calculate both equal-weighted and value-weighted industry returns. We use the market cap at the end of the previous trading day or calendar month.

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, for a total of 129 FOMC meetings. We exclude the emergency rate cut of September 17, 2001—the first trading day after the September 11, 2001, terrorist attacks. 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 start of our sample eliminates almost all timing ambiguity (apart from the nine intermeeting policy decisions). 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

A. Aggregate Stock Market

We first document the effects of monetary policy shocks on the return of the CRSP value-weighted index. Table 1 reports the results from regressing returns of the

[12]Intermeeting policy decisions are special in several respects, as we shall discuss later. Markets might therefore need additional time fully to incorporate the information contained in the FOMC press release into prices. In a robustness check, we calculate event returns using opening prices on the event date. There is no material change in the results.

CRSP value-weighted index in the 30-minute event window surrounding the FOMC press releases on monetary policy surprises for different sample periods. Column (1) shows that 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 somewhat muted compared with the previous results reported in the literature, and the explanatory power is rather weak. Restricting our sample period to 1994–2004, we can replicate the results of Bernanke and Kuttner (2005), Gürkaynak, Sack, and Swanson (2005), and others: a 25 basis point (bp) unexpected cut in interest rates leads to an increase of the CRSP value-weighted index of more than 1.4 percent. Monetary policy shocks explain close to 50 percent of the variation in stock returns within a 30-minute event window for this sample period. In column (3), the results indicate a lower responsiveness of stock returns to monetary policy shocks for a sample ending in 2000, but this sample includes only 50 observations. Most of our analysis will focus on the 1994–2004 sample to compare our results with previous results in the literature and to sidestep any concerns related to the Great Recession and the zero-lower bound episode on nominal interest rates. We discuss the robustness of our findings to different sample periods below in Section *E.*

B. Baseline Results

Panel A of Table 2 presents results for equation (23), the baseline specification in which we regress event returns at the industry level on monetary policy surprises (column (1)) and on a weighted average of industry stock returns (columns (2)–(4)). We report bootstrapped standard errors in parentheses. Federal funds rate decisions that are 25 bps higher than expected lead to an average drop in industry returns of 1 percentage point (column (1)), consistent with the result for the overall market. We see in column (2) that the estimate for β as well as for ρ are highly statistically significant for equally weighted 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. Magnitudes of point estimates are similar for value-weighted returns (columns (3) and (4)), independent of whether we use the previous month's or previous trading day's market capitalization to determine the weights. In the following analysis, we use value-weighted returns with market capitalizations from the end of the last month before a policy announcement as weights.

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. Panel B of Table 2 decomposes the overall effect of monetary policy shocks on stock returns into direct and network effects according to the decomposition outlined in Section III. Network effects are an important driver of the overall effect of –3.5 percent to –4.4 percent; they account for roughly 80 percent of the overall effect of monetary policy shocks on stock returns.

C. Additional Results

We used the 1992 BEA input-output tables in Table 2 to construct the spatial-weighting matrix, because it is fully predetermined. In Table 3, we also use the 1997 and 2002 BEA tables. Column (1) only uses the 1997 input-output tables, and column (2) only uses the 2002 input-output tables, whereas column (3) employs a time-varying spatial-weighting matrix. We use the 1992 tables until 1997, the 1997 tables until 2002, and the 2002 tables afterwards. Point estimates for the networks parameter ρ are highly statistically significant and vary between 0.60 and 0.67. Economically, the estimates of Table 3 imply that between 53 percent and 61 percent of the overall effect from monetary policy shocks stems from higher-order demand effects. In the following tables, we will focus on a constant spatial-weighting matrix, using the 1992 input-output tables, which is fully predetermined with respect to our empirical sample.

D. Subsample Analysis

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 4 presents the results for different event types. 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 almost triples compared to the overall sample (see column (3) of Table 2), with a similar point estimate for ρ of 0.77. A federal funds rate that is 1 percentage point higher than expected leads to an average decline in industry returns of 6.9 percent. The network effects account for more than 70 percent of this overall sensitivity.

We see in column (2) that monetary policy has no effect on stock returns on unscheduled intermeeting dates, consistent with Figure A.1 in the Online Appendix and results in the literature. Changes in the target rate on days of unscheduled meetings are usually a reduction in the rate, which might signal news about the state of the economy, thereby offsetting the policy change's typical expansionary effects on the stock market.

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.2 in the Online Appendix and discussion in Neuhierl and Weber (2017b)). 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 (3) presents the findings when we restrict our sample to events with shocks larger than 5 basis points in absolute value. The economic significance remains stable when we exclude small policy surprises. The statistical significance is sparse for the estimate of β, which might be due to reduced power, as we lose more than 70 percent of our sample. Nevertheless, the network effect still constitutes about 80 percent of the total effect.

We see in columns (4) and (5) that the response of stock returns to monetary policy shocks is asymmetric. Tighter-than-expected monetary policy has a weaker effect on stock returns compared to looser-than-expected monetary policy.[13] A federal funds rate that is 1 percentage point lower than expected leads to an average increase in industry returns of more than 5 percent, which is highly statistically

[13]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 (2017a) for related findings.

significant, with 80 percent of the increase due to network effects. The effect of tighter monetary policy in column (4) is not statistically significant, a result that is likely not due to lower power because both sample sizes are similar.

E. Robustness

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 the importance of network effects. In column (1) of Table 5, we constrain the diagonal entries of the input-output matrix to zero but ensure that the intermediate input shares still add up to 1. By construction, we now associate a larger part of the overall effect of monetary policy shocks on stock returns with direct demand effects (see series expansion in equation (21)). However, network effects still make up more than 50 percent of this overall effect. 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.

While we constrain the sensitivity of different industries to monetary policy shocks to be equal across industries conditional on network effects, in reality, industries might differ in their sensitivities because of differences in their cyclicality of demand or durability of output (see D'Acunto, Hoang, and Weber (2017)). In column (2) of Table 5, we look at industry-adjusted returns to control for those systematic differences. We first regress industry returns within our 30-minutes event window for all FOMC announcements on industry dummies and then use the industry-demeaned returns in the SAR (see equation (23)). 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.

For an additional robustness check, we use CAPM-adjusted industry returns. Bernanke and Kuttner (2005) show CAPM betas capture the differences in the response of industries to monetary policy shocks and Weber (2015) and Savor and Wilson (2014) find similar evidence for individual stocks and several portfolios.

Therefore, adjusting for CAPM-betas should absorb any differences across industries due to different degrees of cyclicality and riskiness. We first regress event returns at the industry level on the market return on our event days to obtain estimates of CAPM betas. We then calculate CAPM-adjusted returns by subtracting the CAPM predicted industry reaction from the industry event return and use these adjusted returns in the SAR. The results are in column (3). By construction, we no longer find a statistically significant reaction of average industry returns to monetary policy shocks (β is no longer statistically significant), because all industries together constitute the aggregate stock market underlying the CAPM adjustment. But we still find large network effects with a point estimate of ρ similar to our baseline estimate. Hence, while industries exhibit different sensitivities to monetary policy shocks, these different sensitivities do not explain the large network effects we document.

Focusing on CAPM-adjusted returns does not allow us to study the overall effect of monetary policy shocks on stock returns. A simple way around this issue is to demean CAPM loadings at the industry level using the average loading across industries and then perform an estimation as before on CAPM-adjusted returns. This time, we subtract the market response to the monetary policy shock times the industry CAPM loadings relative to the average industry loading. We report the results of this estimation in column (4). We find a β estimate that is very similar to our baseline estimate in Table 2. More importantly, the estimate of ρ is in fact identical to our baseline estimate. In Panel B, we find network effects comprise 79% of the total effect of monetary policy on stock returns. So even after controlling for differences in cyclicality and riskiness across industries, we still find large and economically important network effects in the response of industry returns to monetary policy shocks.

Column (5) presents our estimate of the baseline model for a sample of scheduled events from 1994 to 2008. The point estimate for ρ is very close to the estimate for the sample ending in 2004, and the overall responsiveness of the stock market to monetary policy shocks is similar as well. Network effects contribute more than 73 percent to the overall effect of 4.27 percent.

We also estimate specifications allowing for heteroskedastic error terms.

Estimates of ρ are around 0.70, and we assign 70 percent of the overall effect of monetary policy shocks to network effects. For the sake of brevity, we do not report these results.

F. Placebo Test

Empirically, we find that networks are important for the transmission of monetary policy shocks to the stock market. The effect survives a series of robustness checks, such as looking at industry- and CAPM-adjusted returns and focusing on different event types and sample periods. One major concern, however, is that we mechanically find a large estimate of ρ, and hence, large network effects, as we regress industry returns on a weighted average of industry returns. We construct a pseudo input-output matrix to see whether we are mechanically attributing large parts of the stock market's sensitivity to monetary policy shocks to network effects.

The empirical input-output matrix is sparse and few sectors are important suppliers to the rest of the industries in the economy (see Figure 1 and Acemoglu et al. (2012)). We create a pseudo input-output matrix with these two features. 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 2.94068 and a scale parameter of 0.000100821. 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.

The results in column (1) of Table 6 indicate that part of the effect of monetary policy shocks on stock returns that we attribute to network effects might be due to a bias in our estimation. However, we also see that this bias is most likely small. We estimate a ρ of 0.21, which is more than four times smaller than our baseline estimate of 0.87. The decomposition of the overall effect into direct and network effects assigns only 17 percent of the total effect of monetary policy shocks on the stock market to network effects, compared to more than 80 percent for our baseline estimate (see column (3) Table 2). Recall that we bootstrap standard errors; that is, we construct 500 random weighting matrices, estimate 500 βs and ρs, and report the standard deviations of these estimates in parentheses. We see that standard deviations are small, suggesting that large network effects due to pure chance are unlikely.

Constructing a pseudo-spatial-weighting matrix by drawing random numbers from a fitted distribution might alter the sector-size distribution or destroy linkages across sectors. Columns (2) and (3) of Table 6 therefore take the actual input-output matrix and only permute the columns and rows, respectively. Even in cases in which we keep economic linkages across sectors intact, we still find point estimates of ρ that are only 40 percent of our baseline estimate and network effects constituting less than 40 percent of the overall response of industry returns to monetary policy shocks. These results suggest that the particular structure of the input-output linkages is the main factor resulting in large network effects of monetary policy.

G. Model-Implied Sensitivities and Heterogeneity

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). Industries might have heterogeneous sensitivities to changes in interest rates. In fact, the model we develop in Section II predicts a lower sensitivity of stock returns for industries that are on average more profitable: $\beta_i = \frac{(1-\alpha-\lambda)\bar{m}}{\bar{\pi}_i}$. In addition to the robustness checks in Section *E.* addressing the issue of heterogeneity in industry sensitivities, we now want to test the model's prediction directly but also check whether imposing a constant β_i across industries biases our baseline findings.

Using annual balance sheet data from Compustat, we first calculate firm-level measures of profitability as net sales minus the cost of goods sold scaled by total assets. We then value-weight each firm-level observation by the firm's market capitalization at the end of the previous calendar year to get an annual measure of total industry profitability. Last, we take the average profitability across the years in our sample to arrive at the empirical counterpart of the average profitability that the model implies.

To see whether we indeed find that industries with higher average profitability have stock prices that are less sensitive to monetary policy shocks, we add the level of profitability and its interaction with the monetary policy shock to our baseline estimation,

$$r_{it} = \beta_0 + \beta_1 \times v_t + \beta_2 \times prof_i + \beta_3 \times prof_i \times v_t + \rho \times W' \times r_t + \varepsilon_{it}.$$

The results presented in column (1) of Table 7 show that contractionary monetary policy shocks result in a decline in industry returns ($\beta_1 < 0$) and that this reduction is transmitted through the production network ($\rho > 0$). We also see that the response of stock returns to monetary policy shocks is less pronounced for industries with higher average profitability ($\beta_3 > 0$). The average industry profitability is not associated with stock price changes occurring in a 30-minute window around FOMC press releases ($\beta_2 = 0$). The network effect is still the main driver of the overall sensitivity to monetary policy shocks (Panel B). We report only the decomposition for the sensitivity to monetary policy shocks, which means the results in Panel B hold for an industry with an average profitability of zero. In unreported results, we find that an industry with the mean average industry profitability of 16.67 percent in our sample has a 55.3 percent reduced exposure to monetary policy shocks compared with the results in Panel B.

Imposing a constant beta across industries might bias our estimate of ρ upward. Simulations are a simple way to see whether our assumption biases the point estimates. Specifically, we assume industries have a heterogeneous sensitivity to monetary policy shocks, which is constant over time. We take our baseline estimate for β of around –0.60 (see Table 2), assume industry betas are equally distributed on an interval from –0.80 to –0.40, that is, $\beta_{1,i} \sim U[-0.80, -0.40] \quad \forall i$, and impose the baseline estimate for ρ. We then simulate industry returns to monetary policy shocks as

$$r_{it} = \beta_0 + \beta_{1,i} \times v_t + \rho \times W' \times r_t + \varepsilon_{it},$$

taking the actual input-output matrix as given. We assume that the residuals are normally distributed with a mean of zero and that the standard deviation is equal to the standard deviation of the residual of a regression of market returns on monetary policy shocks on the event days.

Column (2) of Table 7 reports the results of estimating our baseline SAR model on simulated data. Imposing a constant beta across industries seems to bias the estimated monetary policy shock exposure (β) downwards, but crucially for us, this has no impact on the estimate of ρ. The results from this simulation suggest that imposing a constant beta on monetary policy shocks across industries does not explain why monetary policy shocks impart large network effects on industry returns.

H. Heteroskedasticity-based Identification

We discuss in Section V.*E.* that our results do not change when we allow different standard deviations of errors across industries, and Section V.*G.* allows for potential heterogeneity in the sensitivity of monetary policy shocks across industries. These results ignore the possibility that shocks other than monetary policy shocks can generate cross-sectional correlations of returns.

The 30-minute event window is sufficiently narrow making this alternative explanation unlikely but to alleviate any remaining concerns, we perform an additional robustness check applying a heteroskedasticity-based estimator in the spirit of Rigobon and Sack (2003) and Rigobon and Sack (2004). We use returns occurring in the same 30-minute window on the day before an FOMC policy announcement. Because these pre-event dates occur within the FOMC's blackout period, monetary policy changes are unlikely to drive any movements in stock prices during the 30-minute window on the pre-event dates.

If we denote with r_t the vector of returns on the event date t and r_{t-} the vector of returns on the pre-event date, we can rewrite the SAR model as

$$\begin{aligned} r_t &= \beta v_t + \rho W' r_t + \varepsilon_t \\ r_{t-} &= \rho W' r_{t-} + \varepsilon_{t-}. \end{aligned}$$

Under the assumption that the covariance of the shocks attributable to news other than monetary policy remains the same on event and pre-event dates (see Rigobon and Sack (2003)), the following moment restrictions identify ρ and β:

$$\begin{aligned} E\left[\varepsilon_t \varepsilon_t^{'}\right] &= E\left[\varepsilon_{t-} \varepsilon_{t-}^{'}\right], \\ E\left[\varepsilon_t v_t\right] &= 0. \end{aligned}$$

The first equation yields $N(N+1)/2$ moment restrictions and the second equation yields N moment restrictions for a total of $N(N+3)/2$ moment restrictions for N industries.

If we were to use all these moment conditions, we could not estimate the two-step generalized method of moments (GMM) approach, because the second step would require inverting a singular covariance matrix.[14] Therefore, we follow a more parsimonious approach and take the cross-sectional average for each of the two equations, resulting in an exactly identified model.

In column (3) of Table 7, we show that our baseline finding remains unchanged. Industry returns decrease in response to contractionary monetary policy shocks, and this decrease is transmitted through the production network. Panel B shows that higher-order network effects are responsible for 85 percent of the total effect. Therefore, our results are robust even if we allow for sources of correlation between returns other than monetary policy in the narrow event windows.

I. Closeness to End-Consumers

Our model interprets monetary policy shocks as demand shocks and thereby suggests that the relative importance of direct and network effects is a function of how close an 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. We follow Carvalho, Saito, Nirei, and Tahbaz-Salehi (2016) 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.[15]

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 but 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

[14] The weighting matrix in the second stage is the inverse of the square matrix with dimension $N(N+3)/2$ and rank equal to $\min(N(N+3)/2, T) = T$, where T is the number of time periods.

[15] Section II in the Online Appendix details the procedure.

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 8 reports our decomposition into direct and network effects for both sets of industries. In column (1), we re-estimate our SAR model of equation (23) for industries close to end-consumers and report the decomposition. Column (2) repeats the analysis for industries far from end-consumers. In our baseline analysis, we attribute only 30 percent of the effect of monetary policy shocks on stock returns to direct effects. The share of the direct effect increases to almost 50 percent for industries that sell most of their output directly (or indirectly via inputs in production) to end-consumers. The direct share drops to only 25 percent for industries whose output is mainly used as intermediate inputs in other industries. The higher relevance of direct effects for industries closer to end-consumers provides evidence consistent with the notion that monetary policy affects stock returns through changes in demand and intermediate production.

J. Fundamentals

Our baseline findings presented in Table 2 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) 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). 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:

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

Higher-order network effects correspond to about 60 percent of the impact effect that monetary policy shocks have on different measures of fundamentals and weightings (see Horizon $H = 0$, Table 9).[16] The network effect increases in size up to seven quarters ($H = 3$) after the monetary policy shock and then loses statistical significance after eight quarters.

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 by Bernanke and Kuttner (2005) and Weber (2015).

VI Dynamic Model: Simulation

Our static benchmark model predicts that around monetary policy announcements, stock returns are characterized by a SAR structure. 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

[16] 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.

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 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 I 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 profit function of firms 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:

$$R_i \;=\; (M/N) + \sum_{j=1}^{N} \left[\alpha\theta_j\omega_{ji}R_j\right],$$

where θ_i is the share of intermediate inputs in 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 net income are

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

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 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 $\hat{\theta}$ as a function of $\hat{R}_t$.

Preferences are

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

which results 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, 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 that 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 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, α, to a value of 0.85, using the operating profit margin, $1-\alpha$, of 0.15 in Compustat data (EBITDA / Sales ratio). We set the autocorrelation and standard deviation of money growth to $\rho = 0.5$ and $\sigma = 0.01$, 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 $r = -0.5$ 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 all z_i to 1, and we set m/w in steady state to a value of 1.

C. Simulation Results

Table 10 presents point estimates for β and ρ as well as the fraction of the network effect from running our baseline SAR regression on simulated data from the dynamic model. We estimate the model both for industry sales and stock prices.

In our benchmark calibration, a contractionary monetary policy shock results in a drop in sales and 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 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.

VII Concluding Remarks

Financial markets reflect the impact of monetary policy decisions within minutes. 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 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, no 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 varies 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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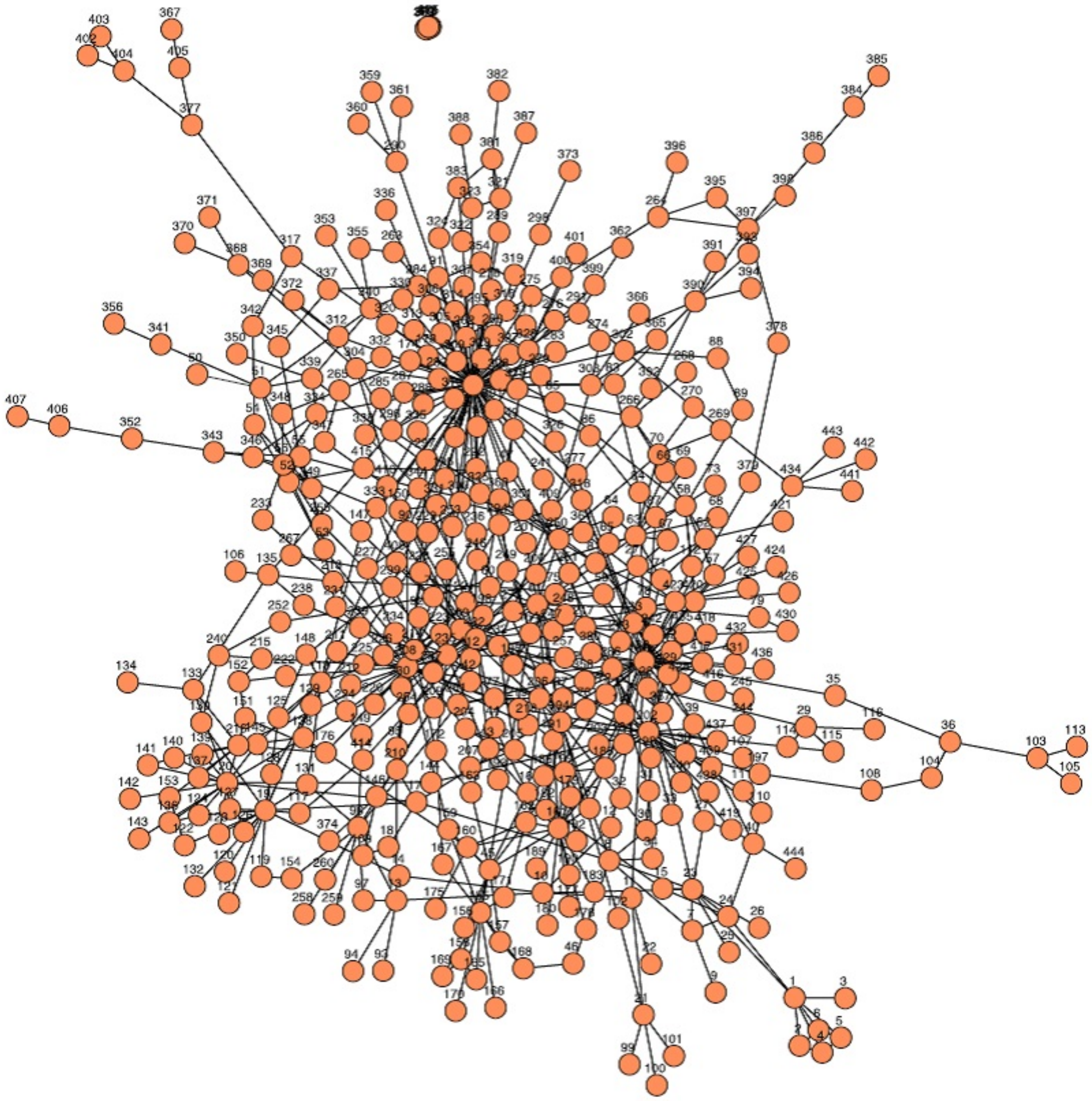
Figure 1: **Production Network Corresponding to U.S. Input-Output Data**



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 1997. Source: Figure 3 of Acemoglu et al. (2012).

Table 1: **Response of the CRSP Value-Weighted Index to Monetary Policy Shocks**

This table reports the results of regressing returns of the CRSP value-weighted (VW) index in a 30-minute event window bracketing the FOMC press releases on the federal-funds-futures-based measure of monetary policy shocks, v_t*. The return of the CRSP value-weighted index is calculated as a weighted average of the constituents' return in the respective event window, where the market capitilization of the previous trading day is used to calculate the weights. The full sample ranges from February 1994 through December 2008, excluding the release of September 17, 2001, for a total of 129 observations. Standard errors are reported in parentheses.*

	Full Sample	'Til 2004	'Til 2000
	(1)	(2)	(3)
Constant	–0.08	–0.12**	–0.05
	(0.07)	(0.06)	(0.07)
v_t	–3.28***	–5.64***	–3.54***
	(0.72)	(0.64)	(0.94)
R^2 (Percent)	13.83	45.10	22.31
Observations	129	92	50

Standard errors in parentheses.

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

Table 2: **Response of Industry Returns to Monetary Policy Shocks**

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)–(4)) (see equation (23)). The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations. Standard errors are reported in parentheses.

	OLS	SAR: 1992 Tables		
		Equally Weighted	Previous Month Mcap	Previous Day Mcap
	(1)	(2)	(3)	(4)
		Panel A. Point Estimates		
β	−3.96***	−0.63***	−0.58***	−0.60***
	(0.11)	(0.23)	(0.18)	(0.20)
ρ		0.82***	0.87***	0.86***
		(0.04)	(0.03)	(0.03)
Constant	−0.07***	−0.01	−0.01	−0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Adj R^2 (Percent)	14.39	7.20	14.43	14.23
Observations	7,873	7,873	7,873	7,873
Log-L		–7,361	–4,732	–4,714
		Panel B. Decomposition		
Direct Effect		−0.92***	−0.90***	−0.91***
		(0.30)	(0.27)	(0.27)
Network Effect		−2.60***	−3.46***	−3.41***
		(0.70)	(0.78)	(0.78)
Total Effect		−3.52***	−4.35***	−4.32***
		(0.95)	(0.99)	(0.98)

Standard errors in parentheses.

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

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

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 (23)). The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations. Standard errors are reported in parentheses.

	SAR: 1997 Tables	SAR: 2002 Tables	SAR: Time-Varying
	(1)	(2)	(3)
	Panel A. Point Estimates		
β	-1.67***	-1.18***	-1.42***
	(0.39)	(0.31)	(0.37)
ρ	0.60***	0.67***	0.67***
	(0.06)	(0.05)	(0.07)
Constant	-0.04**	-0.03**	-0.03**
	(0.02)	(0.01)	(0.01)
Adj R^2 (Percent)	10.77	7.14	12.43
Observations	9,153	9,130	8,771
Log-L	–9,416	–10,211	–8,091
	Panel B. Decomposition		
Direct Effect	-1.94***	-1.39***	-1.74***
	(0.45)	(0.36)	(0.43)
Network Effect	-2.23***	-2.18***	-2.53***
	(0.72)	(0.56)	(0.80)
Total Effect	-4.17***	-3.56***	-4.27***
	(1.09)	(0.86)	(1.10)

Standard errors in parentheses.

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

Table 4: **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 (23)) for different event types. The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations. Standard errors are reported in parentheses.

	Reversals (1)	Intermeetings (2)	Large Shocks (3)	Positive Shocks (4)	Negative Shocks (5)
Panel A. Point Estimates					
β	−1.57∗∗∗	0.10	−0.61∗	−0.24	−0.80∗∗∗
	(0.42)	(0.56)	(0.21)	(0.21)	(0.28)
ρ	0.77∗∗∗	0.91∗∗∗	0.86∗∗∗	0.91∗∗∗	0.85∗∗∗
	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)
Constant	0.03	0.08	0.00	−0.01	−0.03∗
	(0.04)	(0.11)	(0.02)	(0.02)	(0.02)
Adj R^2 (Percent)	54.71	–1.91	28.22	1.19	20.54
Observations	676	681	2,230	2,995	3,600
Log-L	–581	–755	–1,645	–1,580	–2,374
Panel B. Decomposition					
Direct Effect	−2.18∗∗∗	0.13	−0.93∗∗	−0.40	−1.19∗∗∗
	(0.54)	(0.88)	(0.29)	(0.31)	(0.39)
Network Effect	−4.76∗∗∗	0.96	−3.43∗∗∗	−2.28	−4.11∗∗∗
	(0.73)	(3.94)	(0.70)	(1.91)	(1.09)
Total Effect	−6.94∗∗∗	1.13	−4.36∗∗∗	−2.69	−5.30∗∗∗
	(1.16)	(4.79)	(0.94)	(2.13)	(1.45)

Standard errors in parentheses.

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

Table 5: **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 (23)). The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations unless specified otherwise. Standard errors are reported in parentheses.

	Zero Diagonal W (1)	Industry-Demeaned (2)	CAPM-Adjusted (3)	CAPM-Adjusted 2 (4)	1994–2008 (5)
		Panel A. Point Estimates			
β	-1.92***	-0.62***	-0.05	-0.55***	-0.79***
	(0.53)	(0.18)	(0.06)	(0.17)	(0.22)
ρ	0.52***	0.85***	0.83***	0.87***	0.82***
	(0.06)	(0.03)	(0.05)	(0.03)	(0.01)
Constant	-0.03			-0.01	-0.02
	(0.02)			(0.01)	(0.01)
Adj R^2 (Percent)	14.59	14.30	0.03	16.20	14.81
Observations	7,873	7,873	7,873	7,873	10,166
Log-L	–6,882	–4,719	–4,110	-4,155	–3,907
		Panel B. Decomposition			
Direct Effect	-1.95***	-0.94***		-0.85***	-1.14***
	(0.53)	(0.25)		(0.24)	(0.31)
Network Effect	-2.02***	-3.27***		-3.28***	-3.13***
	(0.57)	(0.72)		(0.75)	(0.79)
Total Effect	-3.97***	-4.21***		-4.12***	-4.27***
	(1.00)	(0.93)		(0.94)	(1.09)

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

Table 6: **Response of Industry Returns to Monetary Policy Shocks (Pseudo)**

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 (23)). The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations. Standard errors are reported in parentheses.

	Pseudo W (1)	Permute Columns (2)	Permute Rows (3)
	Panel A. Point Estimates		
β	-3.16***	-2.52***	-2.34***
	(0.84)	(0.72)	(0.68)
ρ	0.21***	0.37***	0.41***
	(0.04)	(0.07)	(0.07)
Constant	-0.06*	-0.05*	-0.04*
	(0.03)	(0.03)	(0.02)
Adj R^2 (Percent)	14.59	14.59	14.59
Observations	7,873	7,873	7,873
Log-L	–7,180	–7,027	–7,009
	Panel B. Decomposition		
Direct Effect	-3.17***	-2.54***	-2.36***
	(0.85)	(0.72)	(0.68)
Network Effect	-0.84***	-1.48***	-1.63***
	(0.24)	(0.42)	(0.47)
Total Effect	-4.00***	-4.02***	-4.00***
	(1.01)	(1.01)	(1.01)

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

Table 7: **Response of Industry Returns to Monetary Policy Shocks (Heterogeneity)**

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 (23)). The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations. Standard errors are reported in parentheses. The GMM estimation requires a balanced panel of industries.

	Model-Implied Heterogeneity (1)	Simulation (2)	GMM Estimate (3)
	Panel A. Point Estimates		
β_1	−1.37***	−1.31***	−0.37***
	(0.45)	(0.27)	(0.12)
ρ	0.86***	0.78***	0.91***
	(0.03)	(0.01)	(0.03)
β_2	−0.01		
	(0.12)		
β_3	4.56***		
	(1.71)		
Constant	−0.01	−0.06**	−0.02*
	(0.02)	(0.02)	(0.01)
Adj R^2 (Percent)	14.73	3.07	
Observations	7,863	7,873	6,900
Log-L	–4,673	–10,545	
	Panel B. Decomposition		
Direct Effect	−2.08***	−1.82***	−0.64***
	(0.65)	(0.37)	(0.17)
Network Effect	−7.59***	−4.09***	−3.65***
	(2.58)	(0.79)	(0.90)
Total Effect	−9.68***	−5.91***	−4.30***
	(3.11)	(1.16)	(0.97)

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

Table 8: **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 (23)) for industries sorted on closeness to consumers. The full sample ranges from February 1994 through December 2004, excluding the release of September 17, 2001, for a total of 92 observations. Bootstrapped standard errors are reported in parentheses.

	Close to End-Consumer (1)	Far from End-Consumer (2)
Direct Effect	-2.37^{***}	-1.08^{***}
	(0.66)	(0.29)
Network Effect	-2.74^{***}	-3.07^{***}
	(0.80)	(0.70)
Total Effect	-5.10^{***}	-4.12^{***}
	(1.39)	(0.97)
Direct Effect (Percent)	46.32	26.11
Network Effect (Percent)	53.68	73.89

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

Table 9: **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 2004 for a total of 60 observations. Standard errors are reported in parentheses.

Horizon	0	1	2	3	4	5	6	7	8
				Panel A. Value-Weighted Sales					
Direct Effect	1.28**	1.45*	1.76**	1.82*	1.68	1.43	1.36	1.31	1.46
	(0.61)	(0.75)	(0.87)	(0.99)	(1.13)	(1.26)	(1.36)	(1.49)	(1.66)
Network Effect	1.87**	2.13*	2.38**	2.61*	2.35	2.18	1.94	1.86	2.25
	(0.89)	(1.10)	(1.18)	(1.42)	(1.57)	(1.91)	(1.95)	(2.11)	(2.56)
				Panel B. Equally Weighted Sales					
Direct Effect	0.96**	1.08**	1.23**	1.25*	1.10	0.95	0.88	0.83	0.74
	(0.42)	(0.48)	(0.57)	(0.68)	(0.74)	(0.83)	(0.91)	(0.98)	(1.07)
Network Effect	1.65**	1.86**	2.02**	2.02*	1.80	1.55	1.42	1.28	1.15
	(0.72)	(0.83)	(0.95)	(1.10)	(1.21)	(1.35)	(1.46)	(1.53)	(1.65)
				Panel C. Value-Weighted Operating Income					
Direct Effect	0.36**	0.43***	0.46**	0.43**	0.39*	0.32	0.25	0.30	0.35
	(0.14)	(0.16)	(0.19)	(0.21)	(0.23)	(0.26)	(0.28)	(0.29)	(0.33)
Network Effect	0.57**	0.68***	0.70**	0.65**	0.57*	0.48	0.39	0.45	0.54
	(0.23)	(0.26)	(0.30)	(0.32)	(0.33)	(0.39)	(0.44)	(0.44)	(0.51)
				Panel D. Equally Weighted Operating Income					
Direct Effect	0.31***	0.35***	0.36***	0.34**	0.32**	0.25	0.24	0.19	0.18
	(0.10)	(0.12)	(0.14)	(0.15)	(0.16)	(0.17)	(0.19)	(0.20)	(0.22)
Network Effect	0.59***	0.65***	0.67***	0.60**	0.58**	0.51	0.45	0.37	0.33
	(0.20)	(0.22)	(0.26)	(0.26)	(0.29)	(0.35)	(0.35)	(0.38)	(0.38)

Standard errors in parentheses.

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

Table 10: **Direct and Network Effects from Simulated Data**

This table reports estimates from estimating our baseline specification on simulated data from the dynamic model of Section VI (see equation (23)). 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 1,000 quarters and report the mean and standard deviations.

		Results for Stock Prices			Results for Sales		
Benchmark	Variation	β	ρ	% Network	β	ρ	% Network
		–0.16	0.84	75.45	–0.14	0.86	78.14
		(0.01)	(0.01)		(0.01)	(0.01)	
$\eta = 0.1$	$\eta = 0.2$	–0.11	0.89	81.17	–0.11	0.89	81.89
		(0.00)	(0.00)		(0.00)	(0.00)	
$\alpha = 0.85$	$\alpha = 0.7$	–0.16	0.84	75.00	–0.15	0.85	77.12
		(0.01)	(0.01)		(0.01)	(0.01)	
$r = -0.5$	$r = -0.25$	–0.23	0.77	66.94	–0.12	0.88	80.02
		(0.01)	(0.01)		(0.01)	(0.01)	
$m/w = 1$	$m/w = 2$	–0.16	0.84	75.82	–0.14	0.86	78.32
		(0.01)	(0.01)		(0.01)	(0.01)	
$\rho = 0.5$	$\rho = 0.75$	–0.16	0.84	75.57	–0.13	0.87	78.72
		(0.01)	(0.01)		(0.00)	(0.00)	
$\sigma = 0.01$	$\sigma = 0.02$	–0.16	0.84	75.39	–0.14	0.86	78.11
		(0.01)	(0.01)		(0.01)	(0.01)	
$\psi = 0.2$	$\psi = 0.4$	–0.16	0.84	75.39	–0.14	0.86	77.56
		(0.01)	(0.01)		(0.01)	(0.01)	
$\delta = 0.99$	$\delta = 0.98$	–0.16	0.84	75.54	–0.14	0.86	78.05
		(0.01)	(0.01)		(0.01)	(0.01)	

Online Appendix:

Monetary Policy through Production Networks: Evidence from the Stock Market

Ali Ozdagli and Michael Weber

Not for Print Publication

I Dynamic Model

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

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

$$X_i = \prod_{j=1}^{N} x_{ij}^{\omega_{ij}}, \tag{A.2}$$

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

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

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

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

$$p_i \frac{\partial y_i}{\partial x_{ij}} = p_j \Rightarrow \omega_{ij} \alpha \frac{\eta X_i^r}{\eta X_i^r + (1-\eta) l_i^r} p_i y_i = p_j x_{ij} \tag{A.3}$$

$$\Rightarrow \omega_{ij} \alpha \theta_i p_i y_i = p_j x_{ij}, \tag{A.4}$$

where

$$\theta_i \equiv \frac{\eta X_i^r}{\eta X_i^r + (1-\eta) l_i^r} \tag{A.5}$$

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

Also note that the marginal product of labor is

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

which leads to the FOC with respect to labor

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

Using these FOCs, the profit function then becomes

$$\pi_i = p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - w l_i - f_i = (1-\alpha) p_i y_i - f_i, \tag{A.6}$$

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

$$c_i = \frac{\sum_{i=1}^{N} (\pi_i + w l_i + f_i)}{N p_i} = \frac{\sum_{i=1}^{N} (1-\alpha\theta_i) R_i}{N p_i}. \tag{A.7}$$

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

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

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

$$R_i = (M/N) + \sum_{j=1}^{N} \left[\alpha \theta_j \omega_{ji} R_j\right].$$

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 $i \in \{1, ..., N\}$:

$$\begin{aligned}
R_i &= (M/N) + \sum_{j=1}^{N} [\alpha\theta_j\omega_{ji}R_j] \text{ (one of these N conditions redundant due to Walras's Law)}, \\
\theta_i &\equiv \frac{\eta X_i^r}{\eta X_i^r + (1-\eta)l_i^r}, \\
X_i &= \prod_{j=1}^{N} x_{ij}^{\omega_{ij}}, \\
x_{ij} &= \frac{\omega_{ij}\alpha\theta_i R_i}{p_j} = \frac{\omega_{ij}\alpha\theta_i R_i}{R_j} y_j \text{ (FOC)}, \\
l_i &= \frac{\alpha(1-\theta_i)R_i}{w} \text{ (FOC)}, \\
y_i &= z_i[\eta X_i^r + (1-\eta)l_i^r]^{\alpha/r} = z_i\theta_i^{-\alpha/r}\eta^{\alpha/r}X_i^{\alpha}.
\end{aligned}$$

We can rewrite the first equation in matrix form as before

$$(I - \alpha W' D(\theta))R = \begin{pmatrix} M/N \\ \vdots \\ M/N \end{pmatrix}_{N\times 1} = m, \tag{A.8}$$

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

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 $x_t = \bar{x}\exp(\hat{x}_t) \approx \bar{x}(1+\hat{x}_t)$.

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

$$w_t = \psi w_{t-1} + (1-\psi) w_t^*, \tag{A.9}$$

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),

$$\Delta\hat{m}_t = \rho\Delta\hat{m}_{t-1} + u_t. \tag{A.10}$$

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

$$\begin{aligned}D\left(\frac{\bar{R}}{\bar{m}}\right)\hat{R}_t - \alpha W' D\left(\frac{\bar{\theta}\bar{R}}{\bar{m}}\right)\hat{R}_t &= \hat{m}_t + \alpha W' D\left(\frac{\bar{\theta}\bar{R}}{\bar{m}}\right)\hat{\theta}_t \\ \hat{\theta}_t + D\left(1-\bar{\theta}\right) r\left(\hat{l}_t - \hat{X}_t\right) &= 0 \\ \hat{X}_t - \hat{\theta}_t - W\hat{y}_t - (I-W)\,\hat{R}_t &= 0 \\ \hat{y}_t + \frac{\alpha}{r}\hat{\theta}_t - \alpha\hat{X}_t &= 0 \\ \left(\hat{w}_t + \hat{l}_t\right) - \hat{R}_t + D\left(\frac{\bar{\theta}}{(1-\bar{\theta})}\right)\hat{\theta}_t &= 0 \\ \hat{w}_t - (1-\psi)\,\hat{m}_t &= \psi\hat{w}_{t-1} \\ \Delta\hat{m}_t &= \rho\Delta\hat{m}_{t-1} + u_t.\end{aligned}$$

$D\left(\bar{x}\right)$ denotes a diagonal matrix where the diagonal elements are the elements of vector $\bar{x} = (\bar{x}_i)_{i=1}^N$. 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

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

which is quite intuitive. Note $\bar{p}_i \bar{x}_{ji}/\bar{p}_i \bar{y}_i$ is the share of industry j's revenues from industry i. 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 the monetary policy affects the relative importance of intermediate inputs in industry j's production.

The last equation can be written in matrix form as

$$
\hat{R} = \tilde{W}\hat{R} + \beta\hat{m} + \tilde{W}\hat{\theta}, \tag{A.11}
$$

where $\beta_i = \bar{m}/\bar{R}_i$ 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

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

which leads to

$$\begin{aligned}\hat{R} &= \tilde{W}\left[I-\frac{(1-\alpha)\,r}{(1-r)}D\left(1-\bar{\theta}\right)\left(I-\alpha WD\left(\bar{\theta}\right)\right)^{-1}W\right]\hat{R}\\ &\quad+\beta\hat{m}+\frac{(1-\alpha)\,r}{(1-r)}\tilde{W}D\left(1-\bar{\theta}\right)\left(I-\alpha WD\left(\bar{\theta}\right)\right)^{-1}\hat{w}_t.\end{aligned}$$

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 $r<0$, 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 α or for values of r sufficiently close to zero, it should provide a reasonable approximation. In order to see how far our estimates of indirect 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

$$U\left(\{c_{i,t+s}\}\right)=E_t\left(\sum_{s=0}^{\infty}\delta^s\sum_{i=1}^{N}\log\left(c_{i,t+s}\right)\right), \tag{A.12}$$

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

$$SDF_{t+s}=\delta\frac{c_{i,t}}{c_{i,t+s}}\frac{p_{i,t}}{p_{i,t+s}}=\delta\frac{m_t}{m_{t+1}}, \tag{A.13}$$

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

$$\begin{aligned}V_{i,t} &= E_t\left(\sum_{s=0}^{\infty}\delta^s\frac{m_t}{m_{t+s}}\pi_{i,t+s}\right)\\ &= E_t\left[\sum_{s=0}^{\infty}\delta^s\frac{m_t}{m_{t+s}}\left((1-\alpha)\,R_{i,t+s}-f\right)\right].\end{aligned}$$

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

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

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

$$V_t = \frac{1-\alpha}{1-\delta}S\left(W\right)m_t - E_t\left[\sum_{s=0}^{\infty}\delta^s\frac{m_t}{m_{t+s}}f\right]. \tag{A.14}$$

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 $\pi_{i,t} = (1-\alpha)\,R_{i,t} - f$, which gives $\bar{\pi}\hat{\pi}_{i,t} = (1-\alpha)\,\bar{R}_i\hat{R}_{i,t}$,

$$\bar{V}_i\hat{V}_{i,t} = (1-\alpha)\,\bar{R}_i\hat{R}_{i,t} + E_t\left(\delta\bar{V}_i\left(\hat{V}_{i,t+1}-\Delta\hat{m}_{t+1}\right)\right). \tag{A.15}$$

By the method of undetermined coefficients, we have

$$\hat{V}_{i,t} = s_{mi}\hat{m}_t + s_{\Delta mi}\Delta\hat{m}_t + s_{wi}\hat{w}_{,t}\,, \tag{A.16}$$

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

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

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

$$\hat{V}_{i,t} - E_{t-1}\left(\hat{V}_{i,t}\right) = \left(s_{mi} + s_{\Delta mi} + (1-\psi)\,s_{wi}\right)u_t. \tag{A.17}$$

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

$$cov\,(y_t, y_{t-1}) = \psi var\,(y_t) + \frac{1}{\psi}var\,(y_t) - cov\,(y_t, y_{t-1}) - \frac{(1-\psi)^2}{\psi}var\,(x_t)\,. \tag{A.18}$$

We can simplify further to obtain

$$corr\left(y_t, y_{t-1}\right) = \frac{cov\left(y_t, y_{t-1}\right)}{var\left(y_t\right)} = \frac{1}{2}\left(\psi + \frac{1}{\psi} - \frac{\left(1-\psi\right)^2}{\psi}\frac{var\left(x_t\right)}{var\left(y_t\right)}\right). \tag{A.19}$$

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

$$0.47 = \frac{1}{2}\left(\psi + \frac{1}{\psi} - \frac{\left(1-\psi\right)^2}{\psi}\frac{4}{3}\right), \tag{A.20}$$

which gives $\psi = 0.2$.

II Closeness to End-Consumer

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

$$D = \begin{bmatrix} 0 & \mu^{\top} \\ 0 & \Gamma \end{bmatrix}, \tag{A.21}$$

where μ is 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 buys from industry i,

$$\mu = (MAKE * P) * \frac{1}{\sum_{i=1}^{C} C_i}. \tag{A.22}$$

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 (26)).

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

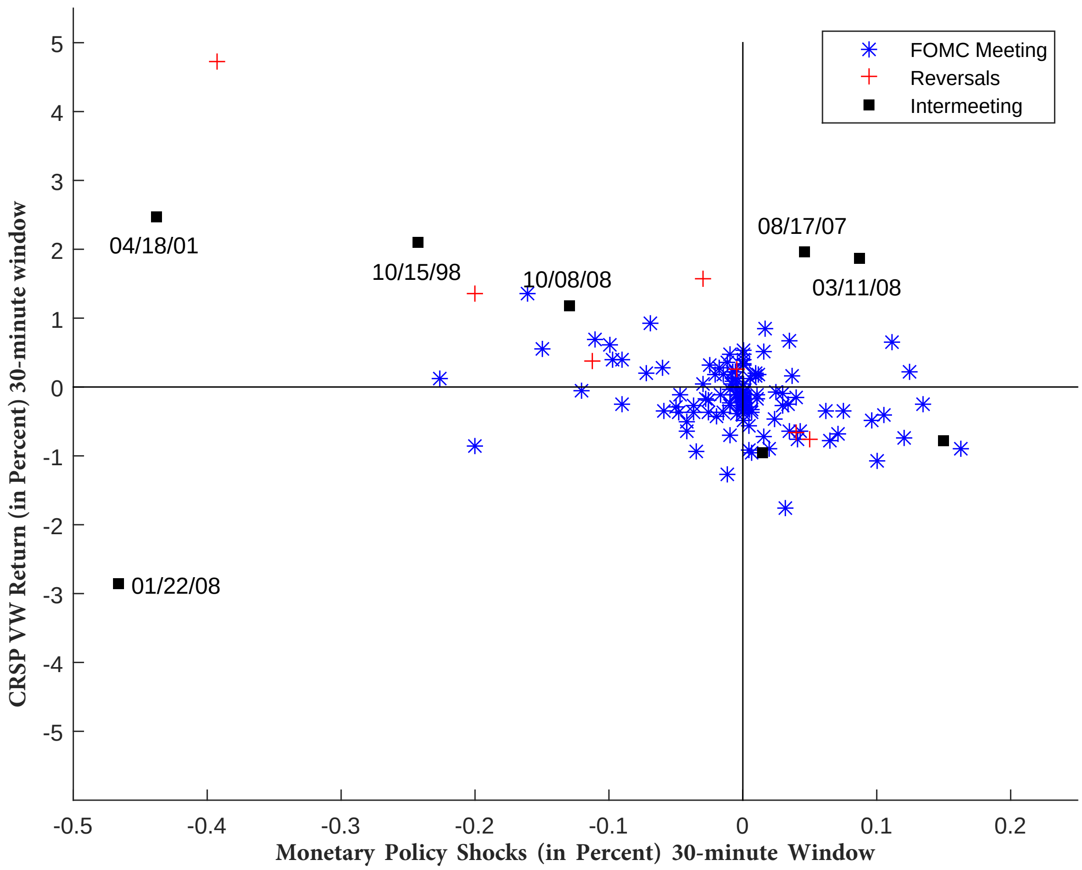
$$D^{c.n} = D * diag(D * 1)^{-1} = \begin{bmatrix} 0 & \hat{\mu}^{\top} \\ 0 & \hat{\Gamma} \end{bmatrix}. \tag{A.23}$$

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

$$
\begin{aligned}
S &= (1 - \hat{\Gamma}^\top)^{-1}\hat{\mu} \\
&= .... + (\hat{\Gamma}^\top)^2\hat{\mu} + \hat{\Gamma}^\top\hat{\mu} + \hat{\mu} \qquad \text{(A.24)} \\
&= 1.
\end{aligned}
$$

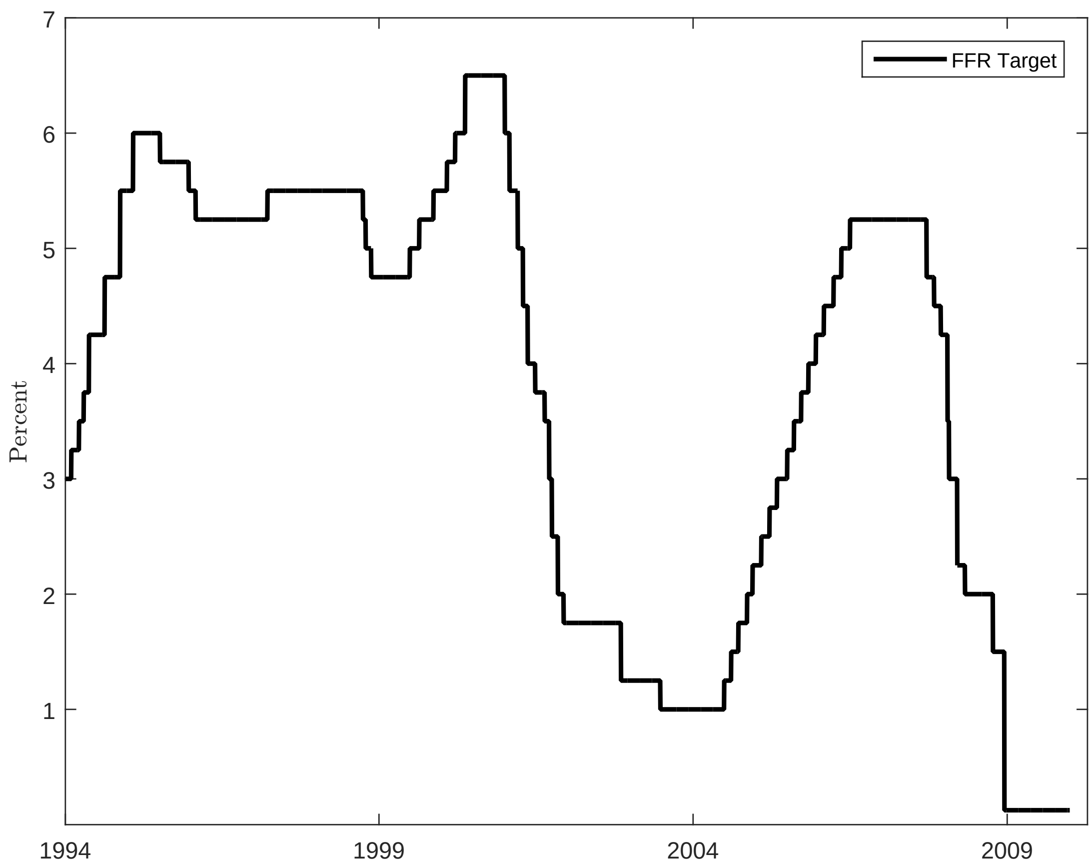
The first step, $\hat{\mu}$, is the percentage of sales from industry i to the household sector as a percentage of industry i's total sales. The second step, $\hat{\Gamma}^\top\hat{\mu} + \hat{\mu}$, is the percentage of sales from industry i to households, both directly and via other industries. In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

Figure A.1: **Return of the CRSP Value-Weighted Index versus Monetary Policy Shocks (Tight Window)**



This figure is a scatterplot of the percentage returns on the CRSP value-weighted index versus the federal-funds-futures-based measure of monetary policy shocks, calculated according to equation (24) for a 30-minute event window. The full sample ranges from February 1994 through December 2008, excluding the release of September 17, 2001, for a total of 129 observations. We distinguish between regular FOMC meetings, turning points in monetary policy, and intermeeting press releases. Source: authors' calculations.

Figure A.2: **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).

Table A.1: **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
18-Apr-94	10:06:00	15.00	15.00	10.00	10.00	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

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Table A.1: **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
15-Oct-98	15:15:00	−24.20	−24.20	−0.80	−0.80	−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
03-Jan-01	13:13:00	−39.30	−36.50	−10.70	−13.50	−50.00
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
18-Apr-01	10:54:00	−43.80	−46.30	−6.20	−3.70	−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.1: **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)
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.1: **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
10-Aug-07	09:15:00	1.50	3.00	−1.50	−3.00	0.00
17-Aug-07	08:15:00	4.62	15.00	−4.62	−15.00	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
22-Jan-08	08:21:00	−46.67	−45.00	−28.33	−30.00	−75.00
30-Jan-08	14:14:00	−11.00	−11.00	−39.00	−39.00	−50.00
11-Mar-08	08:30:00	8.68	7.11	−8.68	−7.11	0.00
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
08-Oct-08	07:00:00	−12.95	−13.30	−37.05	−36.70	−50.00
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