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

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This version: May 2017

**Abstract**

Monetary policy shocks have a large impact on aggregate stock market returns in narrow event windows around press releases by the Federal Open Market Committee. We use spatial autoregressions to decompose the overall effect of monetary policy shocks into a direct (demand) effect and an indirect (network) effect. We attribute 50%–85% of the overall effect to indirect effects. The decomposition is robust to different sample periods, event windows, and types of announcements. Direct effects are larger for industries selling most of the industry output to end-consumers compared to other industries. We find similar evidence of large indirect effects using ex-post realized cash-flow fundamentals. A simple model with intermediate inputs guides our empirical methodology. Our findings indicate that production networks might be an important propagation mechanism of monetary policy to the real economy.

**JEL classification: E12, E31, E44, E52, G12, G14**

**Keywords: Input-output linkages, Spillover effects, Asset prices, High frequency identification**

*We thank David Baqaee (discussant), Susanto Basu, Daniele Bianchi (discussant), John Campbell, Vasco Carvalho, Anna Cieslak (discussant), Gabe Chodorow-Reich, Larry Christiano, Marty Eichenbaum, Mark Garmaise, Mark Gertler, Basile Grassi (discussant), Dan Greenwald, Lars Hansen, Sam Hartzmark, Bernard Herskovic (discussant), Simon Gilchrist, Narayana Kocherlakota, Oleksiy Kryvtsov, Sydney Ludvigson, Hanno Lustig, Emanuel Moench, Atif Mian, Rick Mishkin, Stefan Nagel, Lubos Pastor, Paolo Pasquariello (discussant), Carolin Pflueger (discussant), David Romer, Eric Swanson, Yinan Su, Alireza Tahbaz-Salehi (discussant), Stijn Van Nieuwerburgh (discussant), Paul Whelan (discussant), Toni Whited, and seminar participants at Adam Smith Asset Pricing Workshop 2016, Asset Prices and the Macro Economy Conference, Banco Central de Colombia, Bank of Canada, Bank for International Settlements, 2016 Barcelona Summer Forum, 2016 Cambridge-Inet Confernece on Firms in Macroeconomics, Chicago, Columbia University, Chinese University Hong Kong, City University Hong Kong, Duke–UNC Asset Pricing Conference, Econometric Society NASM 2016, 2016 Ghent Workshop on Empirical Macroeconomics, HKUST, ESMT/ HU Berlin, Insper, NBER Monetary Economics, NBER SI Impulse and Propagation, PUC-Rio, SED 2016, Texas Finance Festival, UCLA Anderson, University of Michigan, and Ozyegin University for valuable comments. Weber gratefully acknowledges financial support from the University of Chicago, the Neubauer Family Foundation, and the Fama–Miller Center. The views expressed in this paper are the authors and do not necessarily reflect those of the Federal Reserve Bank of Boston, the Federal Reserve System, or the Federal Open Market Committee (FOMC). We thank Will Cassidi, Menaka Hampole and Stephen Lamb for excellent research assistance.

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# I Introduction

*Understanding how monetary policy affects the broader economy necessarily entails understanding both how policy actions affect key financial markets, as well as how changes in asset prices and returns in these markets in turn affect the behavior of households, firms, and other decision makers.* Ben S. Bernanke (2003)

The objective of central banks around the world is to affect real consumption, investment, and GDP. Monetary policy can affect those real variables, but only indirectly. Central banks directly and immediately affect financial markets through interest rates, which then influences households' consumption decisions and firms' investment decisions.

Empirically, financial markets react immediately and strongly to central banks' actions. Bernanke and Kuttner (2005) show an unanticipated 25-basis-point decrease in the federal funds rate leads to an increase in the CRSP value-weighted index of more than 1% within minutes of the FOMC announcement.[1] Despite the consensus on the large and immediate impact of monetary policy on financial markets, we know very little about how the monetary policy actions propagate through the economy.

A growing literature in macroeconomics argues microeconomic shocks might propagate through the production network, and contribute to aggregate fluctuations. In this paper, we study theoretically and empirically whether the production network and the input-output structure of the U.S. economy are also an important propagation mechanism of aggregate monetary policy shocks. We merge data from the benchmark input-output tables of the Bureau of Economic Analysis (BEA) with stock price data for individual firms from NYSE Trade and Quote (taq) at the BEA industry level. We identify monetary policy shocks as changes in futures on the federal funds rates, the main policy instrument of the Fed. We sketch a simple model of production with intermediate inputs in the spirit of Acemoglu, Carvalho,

[1]Bjørnland and Leitemo (2009) use structural VARs to identify the effect of monetary policy shocks on stock returns, and find values as high as 2.25%.

Ozdaglar, and Tahbaz-Salehi (2012) to guide our empirical analysis.

Our approach allows us to decompose the overall effect of monetary policy shocks on stock returns in narrow time windows around press releases of the Federal Open Market Committee (FOMC) into direct effects and higher-order network effects using spatial autogressions. We attribute 50%–85% of the overall reaction of stock returns to monetary policy shocks to indirect network effects. The effect is robust to different sample periods, event windows, and types of announcements. Our results are similar for industry-demeaned returns and when we account for the possibility of other common shocks in the same event window.

Our model implies 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 shock, we find supportive evidence for the prediction. Firms in industries with average profitability have a sensitivity to monetary policy shocks that is reduced by 55% relative to our baseline analysis. Crucially, after we account for differences in the sensitivity to monetary policy shocks by profitability, we still find indirect effects constitute about 80% of the overall responsiveness of industry returns to monetary shocks.

We interpret monetary policy shocks as demand shocks. Consistent with this interpretation, we provide evidence that direct effects of monetary policy are larger for industries selling most of the industry output directly to end-consumers compared to other industries. The bigger importance of direct-demand effects for these industries is consistent with the intuition that indirect-demand effects should be less important for industries "close to end-consumers."

Our baseline findings indicate higher-order demand effects might account for a substantial fraction of the overall effect of monetary policy shocks on stock returns. We further support this argument by analyzing similar network effects in ex-post realized fundamentals, such as sales or operating income. Indirect effects make up 60% of the impact effect of monetary policy shocks on fundamentals, a result robust to different measures of fundamentals and weighting schemes. The indirect response increases up to seven quarters after the monetary policy shocks but loses statistical significance after eight quarters.

A major concern of our analysis is that we mechanically assign a large fraction of the overall effect of monetary policy shocks to indirect effects as we regress industry returns on a weighted average of industry returns. The empirical input-output matrix is sparse, and few big sectors are important suppliers to the rest of the economy (see Acemoglu et al. (2012) and Gabaix (2011)). We construct a pseudo input-output matrix with those two characteristics. We find that indirect effects account for only 18% compared to more than 80% in our baselines estimation, suggesting a mechanical correlation between industries does not drive our main results.

We show our empirical results on the relative importance of direct versus indirect effects are consistent with data we simulate from the model. Specifically, we simulate data from the model under different assumptions regarding deep parameters, run our baseline specifications on simulated data using the actual input-output matrix as spatial-weighting matrix, and perform the decomposition into indirect and direct effects. Across different specifications, we find indirect effects constitute 70% to 80% of the overall effect.

Our findings indicate production networks might not only be important for the propagation of idiosyncratic shocks, but might also be a propagation mechanism of monetary policy to the real economy. The network effects we document in firm and industry fundamentals indicate monetary policy shocks affect the real economy at least partially through demand effects and not only through changes in risk premia, consistent with findings in Bernanke and Kuttner (2005) and Weber (2015).

## *A.* Related Literature

A growing literature in macroeconomics argues microeconomic shocks might propagate through the production network and contribute to aggregate fluctuations.

The standard view is that idiosyncratic shocks are irrelevant, because the law of large numbers applies (Lucas (1977)). However, recent work by Gabaix (2011) and Acemoglu et al. (2012) building on Long and Plosser (1983) and Horvath (1998) shows that the law of large numbers does not readily apply when the firm-size distribution or the importance of sectors as suppliers of intermediate inputs to the rest of the economy is fat-tailed (see Figure 1). Pasten, Schoenle, and Weber (2017a) extend their analysis to allow for heterogeneity in price stickiness across sectors and identify a frictional origin of aggregate fluctuations. Acemoglu, Akcigit, and Kerr (2015) and Barrot and Sauvagnat (2016) show networks are empirically important for aggregate fluctuations as well as for the propagation of federal spending, trade, technology, and knowledge shocks. Kelly, Lustig, and Van Nieuwerburgh (2013) study the joint dynamics of the firm-size distribution and stock return volatilities, and Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) and Herskovic (2015) study the asset-pricing implications.[2]

We also relate 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 to examine the effects of changes in the federal funds rate on bond rates using a daily event window. They show changes in the federal funds target rate are associated with changes in interest rates 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 increase in the CRSP value-weighted market index of about 1 percentage point. Gürkaynak, Sack, and Swanson (2005) focus on intraday event windows and find effects of similar magnitudes for the S&P500. Pasquariello and Vega (2007) study the importance of order flow on price formation in bond markets on FOMC and other macro announcement days. Neuhierl and Weber (2017) show that changes in

[2]Other recent contributions to this fast-growing literature are Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017); Atalay (2015); Baqaee (2016); Bigio and La'O (2016); Carvalho and Gabaix (2013); Carvalho and Grassi (2015); and Baqaee and Farhi (2017).

long-term federal funds futures relative to changes in short-term federal funds futures are powerful in moving markets.

Besides the effect on the level of the stock market, researchers have recently also studied cross-sectional differences in the response to monetary policy. Ehrmann and Fratzscher (2004) and Ippolito, Ozdagli, and Perez (2017), among others, show that firms with large bank debt and low cash flows, as well as small firms and firms with low credit ratings, high price-earnings multiples, and Tobin's q, show a higher sensitivity to monetary policy shocks, which is in line with bank-lending, balance-sheet, and interest-rate channels of monetary policy. Gorodnichenko and Weber (2016) show that firms with stickier output prices have more volatile cash flows and higher conditional volatility in narrow event windows around FOMC announcements.

We make the following three contributions to the literature. First, we provide evidence that production networks are also an important propagation channel for aggregate demand shocks. The existing literature so far has focused exclusively on the propagation of micro (supply) shocks. In production-based models, supply shocks travel downstream from suppliers to customers, whereas demand shocks travel upstream in the production network.[3] Second, we show that higher-order demand effects are responsible for a large part of the overall effect of monetary policy shocks on the stock market. Our findings open up novel avenues to develop asset-pricing theories based on the network feature of the economy. Third, we make a methodological contribution and use methods from spatial econometrics—spatial autoregressions—to study questions in macroeconomics and finance.

# II Framework

Firms increase their purchases of intermediate goods when they face increased demand for their production good in models with intermediate production. The

[3]See Acemoglu et al. (2015): "Networks may also be playing a role in the amplification of macroshocks – such as aggregate demand, monetary and financial shocks – which appears to be a generally understudied area."

input into production is the output of firms in other sectors. The producers of intermediate inputs themselves have to increase production to satisfy the increased demand for their goods, which results in higher demand for the output of other sectors.

Expansionary monetary policy shocks, therefore, 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, which can rationalize the large and cross-sectionally heterogenous effects of monetary policy shocks on stock market returns. This section demonstrates how we identify direct and indirect effects using spatial autoregressions (SARs).[4] Section III shows how the SAR specification arises naturally from a model of productions networks.

## *A.* Spatial Autoregressions

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

The spatial autoregressive model is given by

$$y = \beta v + \rho W' y + \varepsilon, \tag{1}$$

with data-generating process

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

$y$ is a vector of industry returns around FOMC press releases, $v$ is a vector of monetary policy shocks, and $W'$ is a row-normalized spatial-weighting matrix. $W$

[4]Denbee, Julliard, Li, and Yuan (2014) use SARs to study systemic liquidity risk in the Sterling interbank market.

corresponds to the BEA input-output matrix, which we describe in section IV. We estimate the model in equation (1) 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.* SARs: Parameter Interpretation and Decomposition

We can interpret parameter estimates in linear regression models as partial derivatives of the dependent variable with respect to the independent variable. The interpretation of parameters in a spatial model is less straightforward, because they incorporate information from related industries (or neighboring regions in a spatial application). We can see the complication more clearly when we re-write equation (1) as

$$\begin{aligned}(\mathbb{I}_n - \rho W')y &= \beta v + \varepsilon \\ y &= S(W')v + V(W')\varepsilon,\end{aligned}$$

where

$$S(W') = V(W')\mathbb{I}_n\beta \tag{2}$$

$$V(W') = (\mathbb{I}_n - \rho W')^{-1} = \mathbb{I}_n + \rho W' + \rho^2(W')^2 + \dots \tag{3}$$

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

$$\begin{pmatrix} y_1 \\ y_3 \\ y_3 \end{pmatrix} = \begin{pmatrix} S(W')_{11} & S(W')_{12} & S(W')_{13} \\ S(W')_{21} & S(W')_{22} & S(W')_{23} \\ S(W')_{31} & S(W')_{32} & S(W')_{33} \end{pmatrix} \times \begin{pmatrix} v \\ v \\ v \end{pmatrix} + V(W')\varepsilon,$$

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

We focus on industry 1,

$$y_1 = S(W')_{1,1}v + S(W')_{1,2}v + S(W')_{1,3}v + V(W')_1\varepsilon, \tag{4}$$

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

We see from equation (4) that the response of returns to a monetary policy shock $v$ in industry 1 ($y_1$) 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 indirect effect of monetary policy on industry 1 through intermediate input linkages, that is, the demand of industry 2 for goods 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 indirect effects due to industry 1's exposure to industry 2 and industry 3 through input-output networks.

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 $\rho$, which determines the strength of spillover effects; and the parameter $\beta$. The diagonal elements of $S(W')$ contain the direct effect of monetary policy shocks on industry returns, and the off-diagonal elements present indirect effects. We follow Pace and LeSage (2006) and define three scalars to measure the overall, direct, and indirect effects:

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

*Average indirect effect:* the difference between the average total effect and the average indirect effect.

The definition of average direct and indirect effects corresponds to average partial derivatives. The average direct effect also includes spillover effects of other industry returns on own industry returns and therefore results in conservative estimates of network effects.

## *C.* Monetary Policy Shocks

Identification of unanticipated, presumably exogenous shocks to monetary policy is central to our analysis. In standard macroeconomic contexts (e.g., 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 (e.g., real GDP or unemployment rate) within a month or a quarter. However, asset prices are likely to respond to changes in monetary policy within days, if not hours or 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 returns and 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

$$v_t = \frac{D}{D-t}(ff^0_{t+\Delta t^+} - ff^0_{t-\Delta t^-}), \tag{5}$$

where $t$ is the time when the FOMC issues an announcement, $ff^0_{t+\Delta t^+}$ is the federal funds futures implied rate shortly after $t$, $ff^0_{t-\Delta t^-}$ is the federal funds futures implied 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.

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

$$RET_t = \beta_0 + \beta_1 \times v_t + \rho \times W' \times RET_t + error_t, \tag{6}$$

where $RET_t$ is a vector of industry returns, $RET_t = (RET_{it})_1^N$ in the interval $[t - \Delta t^-, t + \Delta t^+]$ around event $t$, $v_t$ is the monetary policy shock defined above, and $W$ is the industry-by-industry input-output table from the BEA.

# III The Benchmark Network Model

This section develops a static model with intermediate inputs in which money has heterogeneous effects on stock prices of firms. The simplicity of the model allows us to focus on the propagation of (demand) shocks to the real economy via input-output linkages and motivates our empirical specification. We discuss in section VI a dynamic version of the model and estimate our baseline empirical specification on model-simulated data.

## *A.* Firms and Consumers

Our setup follows closely Acemoglu et al. (2015) and Carvalho (2014) but allows for labor in production and adds money to the economy. We also introduce wage stickiness to get 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, net income determines the stock price. Moreover, the firm has a predetermined fixed nominal obligation. We are agnostic about the origin of the fixed costs, but they might include rent payments, or payments of nominal debt.

Firm $i$'s objective is to maximize profits $\pi_i$, by choosing homogeneous labor, $l$, and intermediate inputs, $x_{ij}$ from firms $i = 1 \ldots N$, given prices, $\{p_i\}_{i=1}^N$ for the goods produced by these firms, and the overall wage rate, $w$,

$$\pi_i = \max p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - w l_i - f_i \qquad \text{with} \tag{7}$$

$$y_i = z_i l_i^{\beta} \left( \prod_{j=1}^{N} x_{ij}^{\omega_{ij}} \right)^{\alpha}, \tag{8}$$

where $y_i$ is the output of firm $i$, $z_i$ is a sector-specific technology shocks, $\beta$ and $\alpha$ are the factor shares, and $\omega_{ij}$ is the share of input from firm $j$ in the production of firm $i$ such that $\sum_{j=1}^N \omega_{ij} = 1$.

The first-order conditions of the firm's problem are

$$\alpha \omega_{ij} R_i = p_j x_{ij}, \tag{9}$$

$$\beta R_i = w l_i. \tag{10}$$

$R_i \equiv p_i y_i$ is the revenue of the firm, and $\omega_{ij}$ corresponds to the entries of the input-output matrix, $W$. A substitution of the first-order condition into the objective function gives

$$\pi_i = (1 - \alpha - \beta) R_i - f_i. \tag{11}$$

The representative consumer maximizes utility

$$\max \sum_{i=1}^{N} \log(c_i) \tag{12}$$

subject to the budget constraint

$$\sum_{i=1}^{N} p_i c_i = w \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} \pi_i + \sum_{i=1}^{N} f_i. \tag{13}$$

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

The first-order condition is

$$c_i = \frac{w \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} (\pi_i + f_i)}{N p_i} = \frac{(1-\alpha) \sum_{i=1}^{N} R_i}{N p_i}, \tag{14}$$

where the second equality follows from equations ((10 and 11)).

The goods-market-clearing condition is

$$y_i = c_i + \sum_{j=1}^{N} x_{ji} \Rightarrow y_i = \frac{(1-\alpha) \sum_{i=1}^{N} R_i}{N p_i} + \frac{\alpha \sum_{j=1}^{N} \omega_{ji} p_j y_j}{p_i}, \tag{15}$$

which simplifies to

$$R_i = (1-\alpha) \frac{\sum_{i=1}^{N} R_i}{N} + \alpha \sum_{j=1}^{N} \omega_{ji} R_j. \tag{16}$$

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

$$(I - \alpha W')R = (1-\alpha) \begin{pmatrix} \left(\sum_{i=1}^{N} R_i\right)/N \\ \vdots \\ \left(\sum_{i=1}^{N} R_i\right)/N \end{pmatrix}_{N\times 1}. \tag{17}$$

## *B.* Money Supply and Equilibrium Network Effects

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

$$\sum_{i=1}^{N} p_i c_i = (1-\alpha)\sum_{i=1}^{N} R_i = M, \tag{18}$$

where $M$ is money supply. Combining equation (18) with the goods-market-clearing condition (17), we get

$$(I - \alpha W')R = \begin{pmatrix} M/N \\ \vdots \\ M/N \end{pmatrix}_{N\times 1} \equiv m. \tag{19}$$

Define $\pi \equiv (\pi_1, ..., \pi_N)'$ and $f \equiv (f_1, ..., f_N)'$. We get

$$\pi = (1-\alpha)R - f = (I - \alpha W')^{-1}(1-\alpha)m - f, \tag{20}$$

which we can log-linearize to get

$$\bar{\pi}\hat{\pi} = (I - \alpha W')^{-1}(1-\alpha)\bar{m}\hat{M}.^{5} \tag{21}$$

Define $\beta \equiv (\beta_1, ..., \beta_N)'$ with

$$\beta_i = \frac{(1-\alpha)\bar{m}}{\bar{\pi}_i}. \tag{22}$$

Then,

$$\hat{\pi} = (I - \alpha W')^{-1}\beta\hat{M}. \tag{23}$$

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

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

$$\hat{\pi} = \beta \times \hat{M} + \alpha \times W' \times \hat{\pi}, \tag{24}$$

which has the form of a spatial autoregression (see equation 1).

The changes in net income, that is, the stock returns of firms, react to money shocks $\hat{M}$ and the reaction of its customers, $W' \times \hat{\pi}$.

# 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 United States Department of Commerce publishes, as well as how we employ these tables to create an industry-to-industry matrix of dollar trade flows.[6]

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 commodities each industry produces. Looking across columns for a given row, we see all commodities a given industry produces. The sum of the entries adds up to the industry's output. Looking across rows for a given column, we see all industries producing a given commodity. The sum of the entries adds up to the output of that commodity.

The use table contains the uses of commodities by intermediate and final users.

[6]Pasten, Schoenle, and Weber (2017b) use similar data.

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 output of that commodity. The columns document the products each industry uses as inputs and the three components of "value added": compensation of employees, taxes on production and imports less subsidies, and gross operating surplus. The sum of the entries in a column adds up to industry 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 baselines analysis to create industry-by-industry trade flows at the four-digit IO industry aggregation. Results are similar if we use the detailed data.

### *A.1* Industry Aggregations

The 1992 IO tables are based on the 1987 SIC codes, the 1997 IO tables are based on the 1997 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 with minor modifications to create our industry classifications for the subsequent estimation. We account for duplicates when SIC and NAICS codes are not as detailed as the IO codes. In some cases, different IO industry codes are defined by an identical set of SIC or NAICS codes. For example, for the 2002 IO tables, a given NAICS code maps to both Dairy farm products (010100) and Cotton (020100). We aggregate industries with overlapping SIC and NAICS codes to remove duplicates.

### *A.2* Identifying Supplier-to-Customer Relationships

We combine the make and use tables to construct an industry-by-industry matrix that details how much of an industry's inputs 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 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 III and the empirical counterpart of section II.

## *B.* Federal Funds Futures

Federal funds futures started trading on the Chicago Board of Trade 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 face limited counterparty risk due to daily marking to market and collateral requirements by the exchange.

The FOMC has eight scheduled meetings per year and, starting with the first meeting in 1995, most press releases are issued around 2:15 p.m. ET. Table A.1 in the online appendix reports event dates, time stamps of the press releases, actual target rates changes, and expected and unexpected changes for a tight (30 minutes) and wide (60 minutes) event windows. We obtained these statistics from Gorodnichenko and Weber (2016).

## *C.* Event Returns

We sample returns for all common stock trading on 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 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 observations after the end of the event window to calculate event returns. For the five event dates for which the press release was issued before the start of the 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 closing prices of the previous trading day and prices at 10:00 a.m. of the event day.[7] We exclude 0 event returns to make sure 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 SIC or NAICS codes for the aggregation. We calculate both equally 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 ranges from February 2, 1994, the first FOMC press release in 1994, to December 16, 2008, the last announcement in 2008, for a total of 129 FOMC meetings. We exclude the rate cut of September 17, 2001—the first trading

[7]Intermeeting policy decisions are special in several respects, as we discuss later. Markets might therefore need additional time to incorporate fully 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. Result do not change materially.

day after the terrorist attacks of September 11, 2001. Our sample starts in 1994 because our tick-by-tick stock price data are not available before 1993, and 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 of 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 the first meeting in 1994, the FOMC started to communicate its decision by issuing press releases after every meeting and policy decision. Therefore, the start of our sample eliminates almost all timing ambiguity (besides the nine intermeeting policy decisions). The increased transparency and predictability makes the use of our intraday identification scheme more appealing, because our identification assumptions are more likely to hold.

Figure 2 is a scatterplot of CRSP index event returns versus monetary policy shocks for a 30 minutes event window.[8] This figure shows a clear negative relation between monetary policy shocks and stock returns on regular FOMC meetings and on policy reversal dates in line with Bernanke and Kuttner (2005) and Gürkaynak et al. (2005). The scatterplot, however, also documents anything that goes on intermeeting announcement days: negative (positive) monetary policy shocks induce positive and negative stock market reactions with about equal probabilities. Faust et al. (2004) find monetary policy surprises do have predictive power for industrial production on intermeeting announcement days. They argue the FOMC must have strong incentives to pursue a policy action on unscheduled meetings, because the maximum time span to the next regular meeting is only six weeks. They conclude the FOMC might have superior information on intermeeting event days. The stock market reaction to monetary policy announcements is therefore less of a reaction to monetary policy shocks than it is to news about the state of the economy. We control for intermeeting policy actions in section V because our predictions are only for exogenous monetary policy shocks.

[8] All results are identical for a event window of 60 minutes.

# 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 results from regressing returns of the CRSP value-weighted index in the 30-minute event window around the FOMC press releases on monetary policy surprises for different sample periods. Column (1) shows 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 returns to monetary policy shocks is somewhat muted compared to the results 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 et al. (2005), and others: a 25 bps unexpected cut in interest rates leads to an increase of the CRSP value-weighted index of more than 1.4%. Monetary policy shocks explain close to 50% of the variation in stock returns in a 30-minute event window for this sample period. In column (3), we find a lower responsiveness of stock returns on monetary policy shocks for a sample ending in 2000, but this sample also only includes 50 observations. We will focus for most of our analysis on the 1994–2004 sample to compare our results with results in the literature and sidestep any concerns related to the Great Recession and the zero-lower bounds on nominal interest rates. We discuss the robustness of our findings to different sample periods below.

## *B.* Baseline

Panel A of Table 2 presents results for the baseline specification (equation (6)) in which we regress event returns at the industry level on monetary policy surprises (column (1)) and a weighted average of industry returns (columns (2)–(4)). We report bootstrapped standard errors in parentheses. Federal funds rates that are 25 bps higher than expected lead to an average drop in industry returns of 1 percentage point, consistent with the result for the overall market (column (1)). We see in column (2) that the estimates for $\beta$ as well as for $\rho$ are highly statistically significant for equally weighted industry returns. Economically, a negative estimate of $\beta$ means tighter-than-expected monetary policy leads to a drop in stock returns. The positive estimate of $\rho$ means this effect is propagated through the production network: higher-than-expected federal funds rates result in a drop in industry returns, which leads to an additional drop in industry returns through spillover effects. Magnitudes of point estimates are similar for value-weighted returns, independent of whether we use the previous month or previous trading day market capitalization to determine the weights. In the following, we use value-weighted returns with market capitalizations from the end of the previous months as weights.

The positive and statistically significant point estimates of $\rho$ indicate part of the responsiveness of stock 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 indirect effects according to the decomposition of section II. Network effects are an important driver of the overall effect of -3.5% to -4.4%. Indirect effects account for roughly 80% of the overall effect of monetary policy shocks on stock returns.

## *C.* Additional Results

We only used the 1992 BEA input-output tables in Table 2 to construct the spatial-weighting matrix. 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 $\rho$ are highly statistically significant and vary between 0.59 and 0.67. Economically, the estimates of Table 3 imply that between 57% and 65% of the overall effect of monetary policy shocks comes 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 returns to monetary policy shocks varies across types of events and shocks and might influence the importance of higher-order demand effects. Table 4 contains results for different event types. Column (1) focuses on reversals in monetary policy, such as the first increase in federal funds rates after a series of decreasing or constant rates. We see that reversals lead to a larger impact of monetary policy shocks on stock returns. The point estimate for $\beta$ almost triples compared to the overall sample (see column (3) of Table 2) with a similar point estimate for $\rho$ of 0.77. A federal funds rate that is 1 percentage point higher than expected leads to an average drop in industry returns of 6.9%. Higher-order demand effects account for more than 70% of this overall sensitivity.

We see in column (2) that monetary policy has no effect on stock returns on unscheduled intermeetings, consistent with Figure 2 and results in the literature. Changes in target rates on unscheduled meetings might contain news about the state of the economy. The stock market might react to the news component rather than the monetary policy surprise.

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 3). Many policy shocks are small in size. To ensure these observations do not drive the large effects of higher-order demand effects, we restrict our sample to events with shocks larger than 5 basis points in absolute value in column (3). Economic significance remains stable when we exclude small policy surprises. Statistical significance is sparse for the estimate of $\beta$, which might be due to reduced power as we lose more than 70% of our sample. Nevertheless, the indirect effect still constitutes about 80% of the total effect.

We see 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. A federal funds rate that is 1 percentage point lower than expected leads to an average increase in industry returns of more than 5%, which is highly statistically significant, with 80% due to network effects. The effect of tighter monetary policy in column (4) is not statistically significant, which is unlikely due to lower power, because both sample sizes are similar in size.

## *E.* Robustness

We focus on industry returns, and the empirical input-output matrix has non-zero entries on the diagonal, which means, for example, that a car manufacturer uses tires in the production process. One concern is that those within-industry demand effects are largely responsible for 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 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 stocks returns of 4% with direct demand effects (see series expansion in equation (3)). However, indirect effects still make up more than 50% 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 effects.

We constrain the sensitivity of different industries to monetary policy shocks to be equal across industries. 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 on an industry dummy and then use the industry-demeaned returns as the left-handside variable in equation (6). The adjustment has little impact on point estimates, overall response to monetary policy shocks, and relative importance of direct and indirect effects.

In column (3), we study market-adjusted returns. By construction, we now no longer find a statistically significant reaction of average industry returns to monetary policy shocks ($\beta$ is no longer statistically significant), because all industries together constitute the market. However, we do find that industries whose customers are more responsive to monetary policy shocks relative to the overall response of the market are also more responsive to monetary policy shocks. In fact, the estimate for $\rho$ is close to the estimate in our baseline analysis.

We estimate our baseline model for a sample of scheduled events from 1994 to 2008 in column (4). The point estimate for $\rho$ is identical to the estimate for a sample ending in 2004, and the overall responsiveness of the stock market to monetary policy shocks is similar as well. Indirect effects contribute more than 80% to the overall effect of 4.27%.

We also estimated specifications allowing for heteroskedastic error terms. Estimates of $\rho$ are around 0.70, and we assign 70% of the overall effect of monetary policy shocks to indirect effects. For the sake of brevity, we do not report these results.

## *F.* Placebo Test

Empirically, we find networks are important for the propagation of monetary policy shocks to the stock market. The effect survives a series of robustness checks, such as looking at industry-adjusted returns and focusing on different event types and sample periods. One major concern, however, is that we mechanically find a large estimate of $\rho$, and hence, 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 mechanically attribute large parts of the stock market 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 economy (see Figure 1 and Acemoglu et al. (2012) and Gabaix (2011)). We create a pseudo input-output matrix with those 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 and estimated distribution function using the 1992 input-output matrix .

We see in column (1) of Table 6 that part of the effect of monetary policy shocks on stock returns that we attribute to indirect effects might be due to a bias in our estimation. However, we also see this bias is most likely small. We estimate a $\rho$ 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 indirect effects assigns only 17% of the total effect of monetary policy shocks on the stock market to indirect effects, compared to more than 80% for our baseline estimate (see column (3) Table 2).

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 $\rho$ that are only 40% of our baseline estimate and indirect effects constituting less than 40% of the overall response of industry returns to monetary policy shocks. These results suggest the particular structure of the input-output linkages is the main factor resulting in high indirect 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. Industries might have heterogeneous sensitivities to changes in interest rates. In fact, the model we develop in section III predicts a lower sensitivity of industry returns for industries that are on average more profitable: $\beta_i = \frac{(1-\alpha)\bar{m}}{\bar{\pi}_i}$. In addition to the robustness checks we report above addressing the issue of heterogeneity in industry sensitivities, we now want to test the prediction of the model directly and check whether imposing a constant beta across industries biases our baseline findings.

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

To see whether we indeed find a lower sensitivity of returns to monetary policy shocks for industries with on-average higher profitability, we add the level of profitability and the interaction of it with our monetary policy shock to our baseline estimation,

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

We see in column (1) of Table 7 that contractionary monetary policy shocks result in a drop in industry returns ($\beta_1 < 0$), which gets propagated through the production network ($\rho > 0$), but we also see the response of 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 returns in a 30-minutes window around FOMC press releases ($\beta_2 = 0$). The indirect effect is still the main driver of the overall sensitivity to monetary policy shocks (Panel B). We only report 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 0. In unreported results, we find that an industry with the mean average industry profitability in our sample of 16.67% has an exposure to monetary policy shocks that is reduced by 55.30% compared to the results in Panel B.

Imposing a constant beta across industries might bias upwards our estimate of $\rho$. 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 $\beta$ 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 $\rho$. 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 the residuals are normally distributed with a mean of 0 and standard deviation 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 downwards ($\beta$), but crucially for us, has no impact on the estimate of $\rho$. The results from this simulation suggest imposing a constant beta to monetary policy shocks across industries can hardly explain large indirect effects of monetary policy shocks on industry returns.

## *H.* Identification through Heteroskedasticity

Section V.*G.* allows for potential heterogeneity in the sensitivity of monetary policy shocks across industries, but it still ignores shocks other than monetary policy shocks that can generate cross-sectional correlation of returns. Our 30-minute event window is sufficiently narrow, alleviating concerns of another shock occurring contemporaneously.

Nevertheless, we perform an additional robustness check using a heteroskedasticity-based estimator in the spirit of Rigobon and Sack (2003) and Rigobon and Sack (2004) and returns in the same 30-minutes window on the day before an FOMC meeting. Because these pre-event dates are in the FOMC blackout period, monetary policy is unlikely to drive any movements in stock prices during the 30-minute window on the pre-event dates.

If we denote $r_t$ as the vector of returns on the event date t and $r_{t-}$ as 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 in event and pre-event dates (see Rigobon and Sack (2003)), the following moment restrictions identify $\rho$ and $\beta$:

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

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

If we were to use all these moment conditions, we could not estimate the two-step GMM approach, because the second step would require inverting a singular covariance matrix.[9] Therefore, we follow a more parsimonious approach and take the

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

cross-sectional average for each of the two equations, giving us an exactly identified model.

We see in column (3) of Table 7 that our baseline finding remains the same. Industry returns decrease in response to contractionary monetary policy shocks, and this decrease is propagated through the production network. We see in Panel B that higher-order network effects are responsible for 85% of the total effect.

## *I.* Closeness to End-Consumers

We interpret monetary policy shocks as demand shocks. Our theory has predictions for the relative importance of direct and indirect effects as a function of closeness to end-consumers. The response of industries that sell most of their output directly to consumers should have most of their overall responsiveness to monetary policy shocks coming from direct effects. On the contrary, the sensitivity of input producers, such as the oil sector, should mainly originate due to indirect effects. We follow Saito, Nirei, Carvalho, and Tahbaz-Salehi (2015) and Su (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.[10] We assign an industry to layer 1 if it sells more than 90% of its output to consumers. Layer 2 consists of industries not in layer 1 and selling more than 90% of their output to consumers directly or indirectly through industries using the output of industries in layer 2 as input in the production of their output. The higher-order layers are defined accordingly. 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 in direct and indirect effects for both sets of industries. In column (1), we re-estimate our SAR model of equation (6) 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 assign only 30% of the effect of monetary policy shocks on stock returns to direct effects.

[10]Section II in the online appendix details the procedure.

The share of the direct effect increases to about 55% for industries that sell most of the output directly (or indirectly via inputs in production) to end-consumers. The direct share drops to only 25% for industries whose outputs are mainly used as intermediate inputs. The higher relevance of direct effects for industries closer to end-consumers provides supportive evidence for monetary policy affecting stock returns through changes in demand and intermediate production.

## *J.* Fundamentals

Our baseline findings in Table 2 indicate that higher-order network effects might be responsible for up to 80% of the reaction of stock returns to monetary policy shocks. We argue that demand effects account for the propagation of monetary policy shocks through the production network. Demand effects suggest we should see similar network effects in ex-post realized fundamentals such as sales or operating income. For a sample similar to ours, Bernanke and Kuttner (2005) find 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 fundamentals might be difficult. We add 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 with $\tilde{v}_t$. We also construct the following measure of change in profitability 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 $H$ can be interpreted as the horizon of the response. We create similar measures for operating income $OI$. We use four quarters before and after the 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 and value-weighting cash-flow fundamentals and total assets. Using these measures of profitability, we estimate the following modification of our baseline specification:

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

Higher-order network effects correspond to about 60% of the impact effect of monetary policy shocks on stock returns across different measures of fundamentals and weightings (Horizon $H = 0$, Table 9).[11] The indirect response increases up to seven quarters ($H = 3$) after the monetary policy shock and loses statistical significance after eight quarters.

The network effects we document in firm and industry fundamentals indicate that monetary policy shocks affect the real economy at least partially through demand effects, consistent with findings in Bernanke and Kuttner (2005) and Weber (2015).

# VI Dynamic Model: Simulation

Our static benchmark model predicts a SAR structure in stock returns around monetary policy announcements and we empirically attribute a large fraction of the overall stock market response to indirect effects. Although we cannot completely rule out potentially confounding factors, fundamentals, or other shocks driving our findings, we can abstract from these factors in a theoretical model and assess whether the size of the indirect effect is quantitatively rationalizable in a calibrated model in which the network structure is the only source of comovement across sectors. We sketch the central differences between the static model of section III and the dynamic model that we bring to the data and provide details in section I of the online appendix.

[11] The impact response includes the quarter of the monetary policy shocks and the following three quarters relative to the four quarters before the FOMC meeting.

## *A.* Economic Environment

Firms produce goods using labor and intermediate inputs with a 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 $\theta_i$ is the share of intermediate inputs in production.

This model breaks the linear 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 $\theta_i$.

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 and we can interpret $\psi$ as a degree of wage stickiness.

Money-supply growth is mean-reverting as in Cooley and Hansen (1989),

$$\Delta \hat{m}_t = \rho \Delta \hat{m}_{t-1} + u_t. \tag{31}$$

The deviations of net income are

$$\hat{R}_i = \frac{\bar{m}}{\bar{R}_i}\hat{m} + \sum_{j=1}^{N} \frac{\bar{p}_i \bar{x}_{ji}}{\bar{p}_i \bar{y}_i}\left(\hat{\theta}_j + \hat{R}_j\right), \tag{32}$$

where $\bar{p}_i \bar{x}_{ji}/\bar{p}_i \bar{y}_i$ is the share of industry $j$'s revenues from industry $i$.

We can rewrite this equation as a function of the state variables of this system, $\hat{m}_t$ and $\hat{w}_t$, after solving for $\hat{\theta}$ as a function of $\hat{R}_t$.

Preferences are

$$U\left(\{c_{i,t+s}\}\right) = E_t\left(\sum_{s=0}^{\infty}\delta^s\sum_{i=1}^{N}\log\left(c_{i,t+s}\right)\right), \tag{33}$$

which results in the "nominal stochastic discount factor" (see Campbell (2000)),

$$SDF_{t+s} = \delta\frac{c_{i,t}}{c_{i,t+s}}\frac{p_{i,t}}{p_{i,t+s}} = \delta\frac{m_t}{m_{t+1}}, \tag{34}$$

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

$$V_{i,t} = E_t\left(\sum_{s=0}^{\infty}\delta^s\frac{m_t}{m_{t+s}}\pi_{i,t+s}\right). \tag{35}$$

We show in the online appendix that stock prices have a spatial structure that is closely tied to the one for revenues. We solve for the log-linearized version of the market values using the method of undetermined coefficients.

## *B.* Calibration

We calibrate the model to the data and perform a battery of robustness checks. $\delta = 0.99$, which corresponds to a 1 percent interest rate per quarter. We calibrate the parameter for the curvature of the production function, $\alpha$, 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 $\sigma = 0.01$ following Cooley and Hansen (1989). We calibrate the parameter for wage stickiness, $\psi$, to a value of 0.2 to capture the autocorrelation of nominal wage growth during the time period 1964 - 2016 (see discussion in 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 1.

### *C.* Simulation Results

Table 10 presents point estimates for $\beta$ and $\rho$ as well as the fraction of the indirect 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 sales and stock prices ($\beta < 0$). This drop is propagated through the production network ($\rho > 0$). Interestingly, the point estimate for $\rho$ and the fraction of of indirect effect are very similar to our empirical estimates across specifications. The findings are robust across 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 indirect effect. The robustness of the measured indirect effect to various parameterizations suggests our SAR framework is robust to relaxing the assumptions in the benchmark static model, and indirect effects originating from intermediate input linkages are an important driver of the sensitivity of industry returns to monetary policy shocks.

## VII Concluding Remarks

Monetary policy has a large and immediate effect on financial markets. A federal funds rate that is 25 basis points lower than expected leads to an increase in the aggregate stock market of more than 1%. We document that intermediate input linkages across sectors introduce higher-order demand effects that are responsible for a large fraction of the overall effect of monetary policy on financial markets. We motivate our empirical analysis in a simple model of production in which firms use intermediate inputs as a production factor.

A recent literature in macroeconomics shows idiosyncratic shocks are important for aggregate fluctuations. So far, however, no evidence exists on whether networks are also important for the propagation of macro shocks, such as monetary policy shocks and demand shocks more generally.

We use the stock market response of industries to monetary policy shocks as a laboratory to test whether production networks matter for the propagation of monetary shocks. Around 70% of the responsiveness of the stock market to monetary shocks comes from higher-order demand effects. The effects are robust to different sample periods, event types, and alternative robustness tests. Direct effects are larger for industries selling most of the industry output directly to end-consumers compared to other industries, consistent with the intuition that indirect demand effects should be less important for industries "close to end-consumers." We document similar network effects in ex-post realized fundamentals such as sales or operating income.

Our findings indicate production networks might not only be important for the propagation of idiosyncratic shocks, but might also be a propagation mechanism of monetary policy to the real economy. The importance of networks for the propagation of monetary policy shocks raises interesting questions for future research: Which are the central sectors for the propagation of monetary policy shocks? How does optimal monetary policy look in this framework? Can monetary policy fully stabilize the economy? Should monetary policy target specific sectors?

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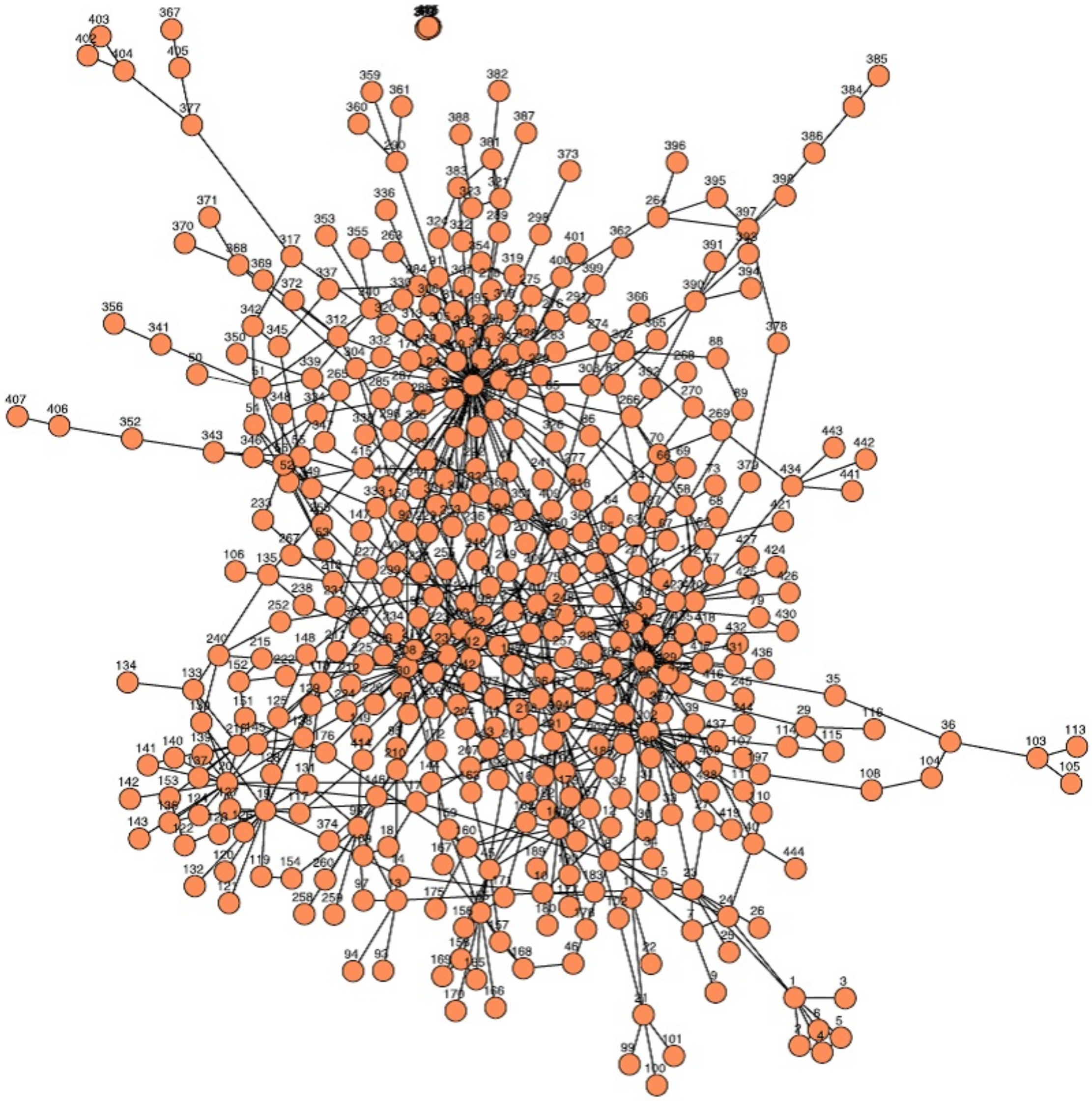
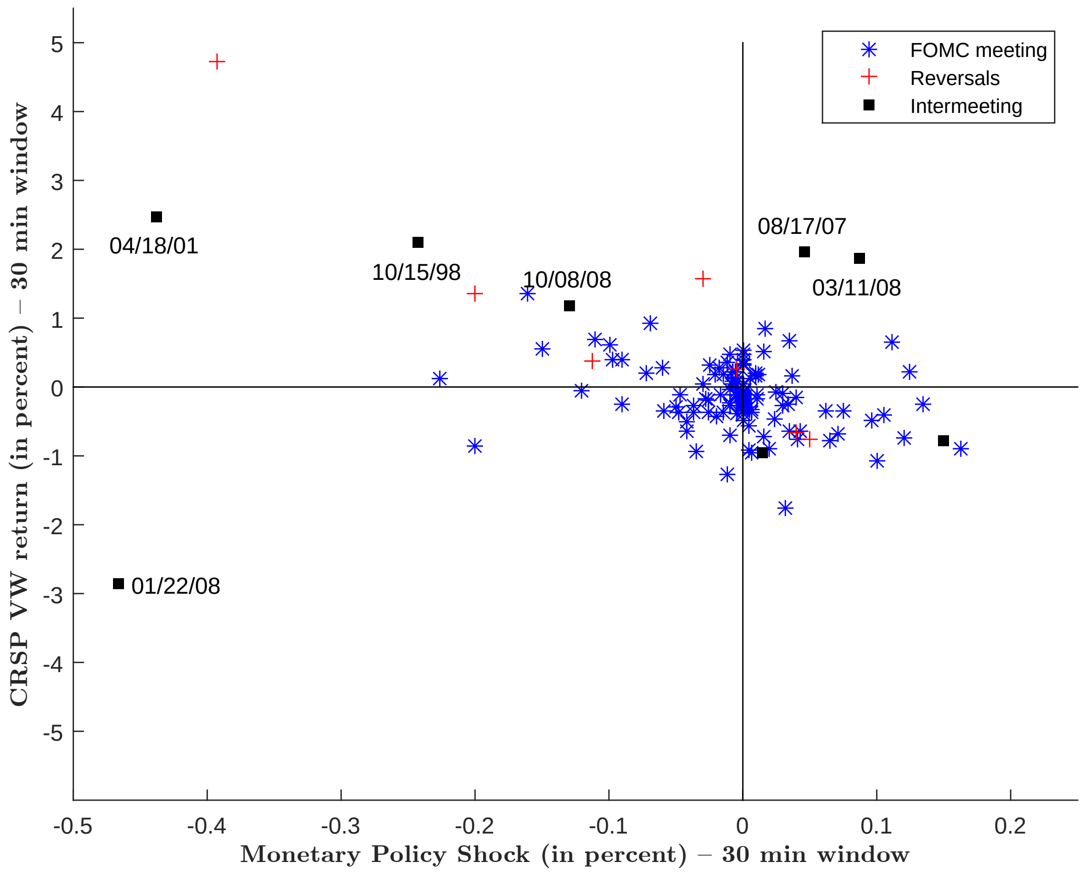
Figure 1: **Production Network corresponding to US Input-Output Data**

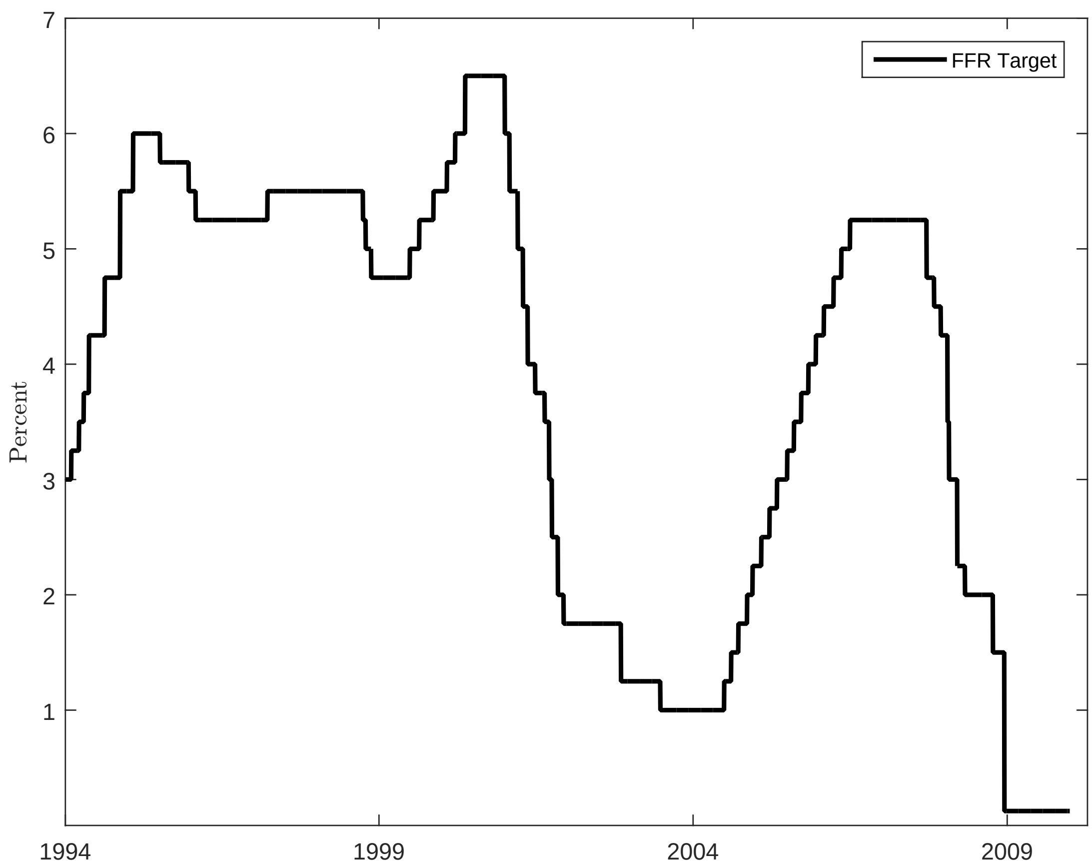


*This figure plots the empirical input-output relationship in the U.S. using data from the benchmark input-output tables of the Bureau of Economic Analysis for the year 1997. Source: Figure 3 of Acemoglu et al. (2012).*

Figure 2: **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 (5) for a 30 minutes 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.*




*This figure plots the time series of the federal funds target rate from 1994 to 2009.*

Table 1: **Response of the CRSP VW Index to Monetary Policy Shocks**

*This table reports the results of regressing returns of the CRSP value-weighted 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 | till 2004 | till 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) |
| $R^2$ | 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 shock, $v_t$ (column (1)), and an input-output network-weighted average of industry returns (columns (2)–(4)) (see equation (6)). 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** | | | | |
| $\beta$ | $-3.96$*** | $-0.63$*** | $-0.58$*** | $-0.60$*** |
| | (0.11) | (0.23) | (0.18) | (0.20) |
| $\rho$ | | 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 $R^2$ | 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) |
| Indirect 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**

*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 shock, $v_t$, and an input-output network-weighted average of industry returns (see equation (6)). 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 (1) | SAR: 2002 tables (2) | SAR: time-varying (3) |
|---|---|---|---|
| | **Panel A. Point Estimates** | | |
| $\beta$ | $-1.67$*** | $-1.18$*** | $-1.42$*** |
| | (0.39) | (0.31) | (0.37) |
| $\rho$ | 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 $R^2$ | 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) |
| Indirect 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 shock, $v_t$, and an input-output network-weighted average of industry returns (see equation (6)) 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 | Intermeetings | Large Shocks | Positive Shocks | Negative Shocks |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A. Point Estimates** | | | | | |
| $\beta$ | $-1.57$*** | 0.10 | $-0.61$* | $-0.24$ | $-0.80$*** |
| | (0.42) | (0.56) | (0.21) | (0.21) | (0.28) |
| $\rho$ | 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 $R^2$ | 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) |
| Indirect 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 shock, $v_t$, and an input-output network-weighted average of industry returns (see equation (6)). 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.*

| | zero diagonal $W$ (1) | industry-demeaned (2) | market-demeaned (3) | 1994–2008 (4) |
|---|---|---|---|---|
| | **Panel A. Point Estimates** | | | |
| $\beta$ | $-1.92^{***}$ | $-0.62^{***}$ | 0.23 | $-0.79^{***}$ |
| | (0.53) | (0.18) | (0.14) | (0.22) |
| $\rho$ | $0.52^{***}$ | $0.85^{***}$ | $0.84^{***}$ | $0.82^{***}$ |
| | (0.06) | (0.03) | (0.04) | (0.01) |
| *Constant* | $-0.03$ | | | $-0.02$ |
| | (0.02) | | | (0.01) |
| adj $R^2$ | 14.59% | 14.30% | 3.47% | 14.81% |
| Observations | 7,873 | 7,873 | 7,873 | 10,166 |
| Log-L | -6,882 | -4,719 | -4,702 | -3,907 |
| | **Panel B. Decomposition** | | | |
| Direct Effect | $-1.95^{***}$ | $-0.94^{***}$ | | $-1.14^{***}$ |
| | (0.53) | (0.25) | | (0.31) |
| Indirect Effect | $-2.02^{***}$ | $-3.27^{***}$ | | $-3.13^{***}$ |
| | (0.57) | (0.72) | | (0.79) |
| Total Effect | $-3.97^{***}$ | $-4.21^{***}$ | | $-4.27^{***}$ |
| | (1.00) | (0.93) | | (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 shock, $v_t$, and an input-output network-weighted average of industry returns (see equation (6)). 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 $W$ | permute rows | permute rows |
|---|---|---|---|
| | (1) | (2) | (3) |
| | **Panel A. Point Estimates** | | |
| $\beta$ | $-3.16$∗∗∗ | $-2.52$∗∗∗ | $-2.34$∗∗∗ |
| | (0.84) | (0.72) | (0.68) |
| $\rho$ | 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 $R^2$ | 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) |
| Indirect 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 shock, $v_t$, and an input-output network-weighted average of industry returns (see equation (6)). 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** | | | |
| $\beta_1$ | $-1.37$*** | $-1.31$*** | $-0.37$*** |
| | (0.45) | (0.27) | (0.12) |
| $\rho$ | 0.86*** | 0.78*** | 0.91*** |
| | (0.03) | (0.01) | (0.03) |
| $\beta_2$ | $-0.01$ | | |
| | (0.12) | | |
| $\beta_3$ | 4.56*** | | |
| | (1.71) | | |
| *Constant* | $-0.01$ | $-0.06$** | $-0.02$* |
| | (0.02) | (0.02) | (0.01) |
| adj $R^2$ | 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) |
| Indirect 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 shock,* $v_t$*, and an input-output network-weighted average of industry returns (see equation (6)) 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) |
| Indirect Effect | $-2.74$*** | $-3.07$*** |
| | (0.80) | (0.70) |
| Total Effect | $-5.10$*** | $-4.12$*** |
| | (1.39) | (0.97) |
| Direct Effect [%] | 46.32% | 26.11% |
| Indirect Effect [%] | 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, $v_t$ 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) |
| Indirect 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) |
| Indirect 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) |
| Indirect 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) |
| Indirect 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 Indirect Effects from Simulated Data**

*This table reports estimates from estimating our baseline specification on simulated data from the model (see equation (6)). 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 shocks. We simulate each model calibration 50 times and report the means and standard deviations.*

| Benchmark | | Results for Stock Prices | | | Results for Sales | | |
|---|---|---|---|---|---|---|---|
| Value | Variation | $\beta$ | $\rho$ | % Indirect | $\beta$ | $\rho$ | % Indirect |
| | | -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) | |
| $\beta = 0.99$ | $\beta = 0.98$ | -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

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*Not for 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 indirect 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 FOC w.r.t. 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 w.r.t. 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, together with the cash-in-advance constraint for consumption goods, gives the following equation:

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

To summarize, the solution of this model 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):

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

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 $\theta_1, ..., \theta_N$.

Note that this model differs from the benchmark model in an important way. In the benchmark model, the aggregate net income is of the form $\sum_{i=1}^N \pi_i = \kappa \sum_{i=1}^N R_i - \sum_{i=1}^N f_i$ where $\kappa$ is a constant and $\sum_{i=1}^N R_i$ is proportional to money supply due to the cash-in-advance constraints. Therefore, in the benchmark model, the network structure does not play a direct role for the reaction of aggregate revenue, $\sum_{i=1}^N R_i$, and hence the aggregate stock market, $\sum_{i=1}^N \pi_i$, to monetary policy. However, in this model, $\sum_{i=1}^N (1-\alpha\theta_i) R_i = M$, and therefore doubling money supply, $M$, does not double each revenue $R_i$ because $\theta_i$ responds to money supply due to wage stickiness. As a result, the linear relationship between $\sum_{i=1}^N R_i$ and $M$ breaks down and the network structure affects the reaction of the aggregate stock market to monetary policy through $\theta_i$.

## *A.* Dynamic Wages, Monetary Policy, and Simulation Equations

Throughout the equations below, let $\bar{x}$ be the deterministic steady state and $\hat{x}$ be the log-devation 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 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 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 mean-reverting money supply, we get the following:

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

$D(\bar{x})$ denotes a diagonal matrix of which 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 that $\bar{p}_i \bar{x}_{ji}/\bar{p}_i \bar{y}_i$ is the share of industry $j$'s revenues from industry $i$. The greater this value is, the more important industry $j$ is for industry $i$. In terms of how the effect of monetary policy on industry $j$ impacts on industry $i$, there are two channels. The first one is the effect of higher revenues of industry $j$, $\hat{R}_j$. The second one is the additional effect from $\hat{\theta}_j$, which captures the change in 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

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

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 network effect because $r < 0$, that is, the elasticity of substitution between 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 $\alpha$ 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 indirect effects due to these additional complications, we use the SAR regressions on this simulated model.

## *B.* Reaction of Stock Prices to Policy Surprises

Now, the 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)), i.e., 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 the industry $i$, with profit stream $\{\pi_{i,t}\}$, will be given by

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

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 $V_t' = (V_{i,t})_{i=1}^N$:

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

where the first component gives the expected present value of profits and the second term gives the expected present value of nominal obligations. Stock prices have a spatial-weighting matrix structure that is closely tied to the one for revenues. In particular, for the benchmark model where $S(W;\theta_t) = S(W)$, 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 $\bar{\pi}\hat{\pi}_{i,t} = (1-\alpha)\bar{R}_i\hat{R}_{i,t}$,

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

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 in 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, $\psi$

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,

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

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

After some algebra, the equations become

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

We can simplify further to

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

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 in the data, $var\left(\Delta \hat{m}_t\right) = 0.01/\left(1-0.5^2\right) = 0.013$ and $var\left(\Delta \hat{w}_t\right) = 0.01$ in the data, we get

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

which gives $\psi = 0.2$.

# II Closeness to End-Consumer

The section details the construction of our empirical proxy for 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

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

where $\mu$ is dollar amount of household consumption spending and $\gamma$ is defined as dollar amount of intermediate input purchases from industry $i$ to industry $j$. In order to construct $\mu$, 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 $\Gamma$ as an $n \times n$ matrix of intermediate input purchases that industry $j$ makes from industry $i$. $\Gamma$ corresponds to the REVSHARE matrix in Section IV (see equation 26).

Next, we column normalize $C$ in order to obtain sales shares.

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

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

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

The first step, $\hat{\mu}$, is the percentage of sales from $i$ to the household as a percentage of total industry $i$'s sales. The second step, $\hat{\Gamma}^\top \hat{\mu} + \hat{\mu}$, is the percentage of sales from industry $i$ to $j$ then to the household. In the limit, the expansion approaches 1.

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 an half hour (tight) window and one hour (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 |