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

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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 production networks might be an important propagation mechanism of monetary policy to the real economy.

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

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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 and try to influence households' consumption decisions and firms' investment decisions by influencing interest rates and risk premia.

Empirically, financial markets react immediately and strongly to central banks' actions. Bernanke and Kuttner (2005) show federal funds rate that is 25 basis points lower than expected leads to an increase in the CRSP value-weighted index of more than 1% within minutes of the FOMC announcement.[1]

The large reaction of broad stock market indices is difficult to rationalize with the amplification mechanisms proposed in standard models. 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 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 from 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 fed funds rates, the main policy instrument of the Fed. We sketch a simple model of production with intermediate inputs to guide our empirical analysis.

We decompose the overall effect of monetary policy shocks on stock returns in narrow

[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%.

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 constrained spatial-weighting matrices.

We interpret monetary policy shocks as demand shocks. We provide evidence that direct effects are larger for industries selling most of the industry output directly (or indirectly as intermediate inputs) 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 demands effect might account for a substantial fraction of the overall effect of monetary policy shocks on stock returns. Our baseline results for stock returns suggest we should see 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 stock returns across 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.[2]

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, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Gabaix (2011)). We construct a pseudo input-output matrix with those two characteristics. We find indirect effects account for only 18% compared to more than 80% in our baselines estimation.

Our findings indicate production networks might not only be important for the propagation of idiosyncratic shocks, but might also be a propagation mechanism of

[2]Stock prices are the present discounted value of future cash flows. Financial markets incorporate news about changes in future cash flows within minutes around macroeconomic news announcements (see, e.g., Andersen et al. (2003) and Rigobon and Sack (2003)).

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 changing 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 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). Acemoglu, Akcigit, and Kerr (2015) 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 joined 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.

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 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.

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 (2015), among others, show 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 firms with stickier output prices have more volatile cash flows and high conditional volatility in narrow event windows around FOMC announcements.

Standard transmission channels of monetary policy, such as the firm balance-sheet channel stemming from financial constraints, have ambiguous predictions regarding the effect of monetary policy shocks on stock returns. Looser monetary policy can increase the collateral value, and hence borrowing capacity of credit-constrained firms. The returns of constrained firms might, therefore, respond more strongly to monetary policy than the returns of unconstrained firms.[3] If, on the other hand, bankruptcy costs (trade-off model) or information costs (costly state-verification model) constrain firms, we might expect constrained firms to respond less than unconstrained firms, because they cannot borrow as much.[4] These opposing effects limit the ability of the credit channel to explain the large reaction of stock returns to monetary policy.

We make the following three contributions to the literature. First, we provide evidence that production networks are also an important propagation channel for aggregate shocks. The existing literature so far has focused exclusively on the propagation of micro shocks. Second, we show 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

[3]See, for example, Ehrmann and Fratzscher (2004). Ippolito, Ozdagli, and Perez (2015) provide an alternative mechanism based on the floating-rate nature of bank loans and the response of interest payments to changes in benchmark rates induced by monetary policy.

[4]See Ozdagli (2015) for recent evidence. Wieland and Yang (2015) provide a similar mechanism that shows how banks' deleveraging following a financial crisis leads to a lower effect of monetary policy on their credit supply.

finance.

II Framework

Firms have to increase their purchases of intermediate goods when they face increased demand for their production good in models with intermediate production. The 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. Production networks, therefore, lead to higher order demand effects of monetary policy shocks, 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). Section III shows how the SAR specification naturally arises 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 returns, v is a vector of monetary policy shocks, and W' is a row-normalized spatial-weighting matrix. W corresponds to the BEA input-output matrix, which we describe in 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 1,000 times for samples with the same number of events as our empirical sample.

B. Spatial Autoregressions: Parameter Interpretation

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^{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^{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, the $S(W')_{1,1}$ gives the reaction of industry 1 to the monetary policy shock, v, if it were the only industry affected by monetary policy shock. Similarly, $S(W')_{1,2}$ gives the reaction of industry 1 to the monetary policy shock if industry 2 were the only industry affected by the shock. 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 input-output matrix W governs the response of industry returns to monetary policy shocks via its effect on intermediate production, the parameter ρ, which determines the strength of spillover effects, and the parameter β. 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^{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 ι_n is a vector of ones. The average total impact is then defined as $\frac{1}{n}\iota_n' c_r$.

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

The SAR model of equation (1) allows a simple way to calculate the average total impact for row stochastic W':

$$\frac{1}{n}\iota_n' S(W')\iota_n = (1-\rho)^{-1}\beta. \tag{5}$$

We calculate the direct, indirect, and total effects using traces of series expansions of $S(W)$ as the calculation of the inverse of $(\mathbb{I}_n - \rho W')$ is computationally inefficient. We use Bayesian Markov Chain Monte Carlo methods proposed by LeSage (1997) to get estimates for the standard deviation of the effects.

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. Identification

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 of the policy rate, we use federal funds futures, which provide a high-frequency market-based measure of the anticipated path of the fed funds rate.

We calculate the surprise component of the announced change in the federal funds rate as

$$v_t = \frac{D}{D-t}(ff^0_{t+\Delta t^+} - ff^0_{t-\Delta t^-}), \tag{6}$$

where t is the time when the FOMC issues an announcement, $ff^0_{t+\Delta t^+}$ is the fed funds futures rate shortly after t, $ff^0_{t-\Delta t^-}$ is the fed funds futures rate just before t, and D is the number of days in the month.[5] 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:

$$RET_t = \beta_0 + \beta_1 \times v_t + \rho \times W' \times RET_t + error_t, \tag{7}$$

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 Bureau of Economic Analysis.

III The Benchmark Network Model

This section develops a model with intermediate inputs in which money has a heterogeneous effect 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 to motivate our empirical specification. The model, however, also has important shortcomings. It implies monetary neutrality, because it does not have any nominal friction. We discuss in section I of the Online Appendix a simple extension with wage stickiness that has identical implications for the reaction of stock prices. The Cobb-Douglas production function implies the network structure does not affect the

[5]We implicitly assume in these calculations that the average effective rate within the month is equal to the federal funds target rate and that only one rate change occurs within the month. Due to changes in the policy target on unscheduled meetings, we have six observations with more than one change in a given month. Because these policy moves were not anticipated, they most likely have no major impact on our results. We nevertheless analyze intermeeting policy decisions separately in our empirical analyses. While constructing v_t, we have also implicitly assumed a potential risk premium does not change in the $[t-\Delta t^-, t+\Delta t^+]$ window, which is consistent with results in Piazzesi and Swanson (2008).

aggregate stock market reaction. We discuss an extension with wage stickiness and a CES production aggregator in the appendix, which breaks this result.

A. Firms and Consumers

Our setup follows closely Acemoglu et al. (2015) and Carvalho (2014). We have a one-period model with only 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 cost, but they might include rent payment, or payment of nominal debt.

The objective of the firm i is to maximize net income, π_i:

$$\max \pi_i = p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - f_i \tag{8}$$

subject to the production function

$$y_i = z_i \left(\prod_{j=1}^{N} x_{ij}^{\omega_{ij}} \right)^{\alpha} . \tag{9}$$

p_i denotes the output price of firm i; y_i the level of output; x_{ij} amount of input firm i purchases from firm j; and ω_{ij} the share of input j in the production of firm i such that $\sum_{j=1}^{N} \omega_{ij} = 1$.

The first-order condition of the firm's problem is

$$\begin{aligned} \alpha \omega_{ij} p_i y_i &= p_j x_{ij} && (10) \\ &\Longleftrightarrow && (11) \\ \alpha \omega_{ij} R_i &= p_j x_{ij}, \end{aligned}$$

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

$$\pi_i = (1 - \alpha) R_i - f_i . \tag{12}$$

The representative consumer maximizes utility subject to the budget constraint

$$\max \sum_{i=1}^{N} \log(c_i) \quad s.t. \ \sum_{i=1}^{N} p_i c_i = \sum_{i=1}^{N} \pi_i + \sum_{i=1}^{N} f_i,$$

where we assume fixed costs are simply a transfer from the firms to consumers.

The first-order condition is given by

$$\begin{aligned} c_i &= \frac{\sum_{i=1}^{N} (\pi_i + f_i)}{N p_i} && (13) \\ &= \frac{(1-\alpha)\sum_{i=1}^{N} R_i}{N p_i}, && (14) \end{aligned}$$

where the second equality follows from equation (12).

The goods-market-clearing condition is given by

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

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 factor shares and $R = (R_{1,\ldots}, R_N)'$ as the vector of revenues,

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

B. Money Supply and Determination of Equilibrium Prices

We assume intermediate inputs are financed through trade credit, whereas consumption goods are purchased with cash. Therefore, the 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 the money supply. Combining equation (18) with the goods-market-clearing condition (17), we get

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

The model features monetary neutrality because no nominal rigidity exists. If money supply doubles, prices double as well, leaving real variables unaffected. As a result, the operating profits of the firm, defined as the difference between sales and cost of goods sold, is proportional to money supply. Without fixed nominal obligations, the net income is equal to operating profits, and the stock price reaction of all firms is the same regardless of the level of revenues, and hence, network structure. However, fixed nominal obligations create a leverage effect, which makes the level of revenues matter for stock prices. Because the network structure determines how the money supply is distributed among firms, it will also determine the reaction of individual stock prices through the level of revenues.

Any model with monetary neutrality would lead to the same stock price reaction due to the leverage effect as long as it produces the same distribution of revenues (similar to Hulten (1978)). The network structure determines how the money is distributed to different firms/sectors in terms of revenues, which in turn determines the reaction of stock prices due to nominal obligations. Because the model is static, the stock price reaction is the same as the reaction of net income.

Let $\pi \equiv (\pi_1,...,\pi_N)'$ 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

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

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

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

Then,

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

Note we can rewrite the reaction 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 appendix shows how a model with labor, wage stickiness, and CES production functions results in similar testable implications.

IV Data

A. Bureau of Economic Analysis Input and Output Tables

This section discusses the benchmark input-output (IO) tables published by the Bureau of Economic Analysis (BEA) at the United States Department of Commerce, as well as how we employ these tables to create an industry-to-industry matrix of dollar trade flows. Pasten, Schoenle, and Weber (2015) use similar data to study the importance of heterogeneity of price rigidities, sector size, and sector inputs for the real effects of monetary policy on consumption.

The BEA produces benchmark input-output tables, which detail the dollar flows between all producers and purchasers in the U.S. 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 produced by a given industry. 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. 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 and report robustness results using the detailed accounts.[6]

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.

[6] We have 89 sectors for the summary accounts and 350 sectors for the detailed accounts using the 1992 IO tables.

A.2 Identifying Supplier to Customer Relationships

We combine the make and use tables to construct an industry-by-industry matrix which 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, which is an industry-by-commodity matrix. We define the market share of industry i's production of commodity c as

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

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 $SUPPSHARE$:

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

$SUPPSHARE$ corresponds to the theoretical W matrix of section III and the empirical counterpart of section II.

A.3 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 fed 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. We acquired tick-by-tick data of the federal funds futures trading on the Chicago Mercantile Exchange (CME) Globex electronic trading platform (as opposed to the open-outcry market) directly from the CME. Using Globex data has the advantage that trading in these contracts starts on the previous trading day at 6:30 p.m. ET (compared to 8:20 a.m. ET in the open-outcry market). We are therefore able to calculate the monetary policy surprises for all event days including the intermeeting policy decisions occurring outside of open-outcry trading hours. To provide some insights into the quality of the data and the adequacy of our high-frequency identification strategy, we plot the futures-based expected federal funds rate for three event dates in Figure 2.[7] These plots show two general patterns in the data: high trading activity around FOMC press releases and immediate market reaction following press releases.

On August 8, 2006, the FOMC decided to stop increasing the federal funds target rate. Until then, the FOMC had been increasing the policy target for more than two years for a total of 17 increases of 25 bps. This streak of increases had been the longest since the change in market communication in 1994. The FOMC had clearly signalled a pause in previous press releases and, according to the financial press around the event, the market also expected this break. Still, the federal funds futures indicate market participants saw a small chance—potentially due to statements of Jeffrey Lacker, then President of the Federal Reserve Bank of Richmond, who was opposing the pause—of a further increase resulting in a negative monetary policy surprise of 4.77 bps. This episode shows policy surprises do not necessarily require changes in the policy rate.

On September 18, 2007, the FOMC cut the target rate by 50 bps, the first cut since 2003. Market participants expected a monetary policy easing. Motivated by weakening economic growth and turmoil in the subprime housing sector, the FOMC considered this step necessary to prevent a credit crunch. The aggressiveness of this decision, though, seemed to surprise the market, resulting in an unexpected change in the federal funds rate of about 20 bps.

The FOMC has eight scheduled meetings per year and, starting with the first meeting

[7] Similar plots for the earlier part of our sample can be found in Gürkaynak et al. (2005).

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 the tight and wide event windows. We obtained these statistics for the period up to 2004 from Gürkaynak et al. (2005). The FOMC Freedom of Information Service Act Service Center provided the time stamps of the press releases in the later part of the sample. The release times are based on the timing of the first FOMC statement-related story appearing in the press.

Panel A of Table 1 reports descriptive statistics for surprises in monetary policy for all 129 event dates between 1994 and 2008, as well as separately for turning points in monetary policy and intermeeting policy decisions. Turning points are target-rate changes in the direction opposite to previous changes. Jensen et al. (1996) argue the Fed is operating under the same fundamental monetary policy regime until the first change in the target rate in the opposite direction. This assertion is in line with the observed level of policy inertia and interest rate smoothing (cf. Piazzesi (2005), as well as Figure 5). Monetary policy reversals therefore contain valuable information on the future policy stance.

The average monetary policy shock is approximately zero. The most negative shock, with more than -45 bps, is about three times larger in absolute value than the most positive shock. Policy surprises on intermeeting event dates and turning points are more volatile than surprises on scheduled meetings. Andersen et al. (2003) point out that whether the announcement is known in advance matters. Lastly, the monetary policy shocks are almost perfectly correlated across a 30-minute event window and a longer event window of 60 minutes. Figure 3 visually confirms this finding in a scatterplot of monetary policy shocks in the tight event window on the x-axis and the wide event window on the y-axis. Almost all 129 observations line up perfectly along the 45° line. August 17, 2007, and December 16, 2008, are the only two exceptions. The first observation is an intermeeting event day on which the FOMC unexpectedly cut the discount rate by 50 bps at 8:15 a.m. ET just before the opening of the open-outcry futures market in Chicago. The financial press reports heavy losses for the August futures contract on that day and a very volatile market environment. The second observation, December 16, 2008, is the day on which the FOMC cut the federal funds rate to a target range between 0% and 0.25%. We focus our empirical analysis on a 30-minute event window.

A.4 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.[8] 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 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

[8]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.

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.

Panel B of Table 1 reports descriptive statistics for the percentage returns of the value-weighted CRSP index for all 129 event dates between 1994 and 2008, turning points, and intermeeting policy decisions. We use the event returns of the individual stocks, which we use in our empirical analysis to calculate index returns using the market capitalization of the previous trading day as weights. The average return is close to zero with an event standard deviation of about 1%. The large absolute values of the event returns are remarkable. Looking at the columns for intermeeting press releases and turning points, we see that the most extreme observations occur on non-regular release dates. Figure 4, a scatterplot of CRSP index event returns versus monetary policy shocks, highlights this point. Specifically, 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. (2004a) argue that intermeeting policy decisions are likely to reflect new information about the state of the economy; hence, the stock market reacts to this new information rather than changes in monetary policy. This logic calls for excluding intermeeting announcements, because our predictions are only for exogenous monetary policy shocks.

Faust et al. (2004b) show FOMC announcements do not contain superior information about the state of the economy. Professional forecasters do not systematically change their forecasts for a wide range of macroeconomic variables following FOMC press releases, and these forecasts are efficient given the announcement. The only exception is industrial production, an index actually produced by the Fed. Faust et al. (2004a) 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.

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 2 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 one percentage point higher than expected leads to a drop in stock prices of roughly three 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 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.

B. Baseline

Panel A of Table 3 presents results for the baseline specification (equation (7)) in which we regress event returns at the industry level on monetary policy surprise (column (1)) and a weighted average of industry returns (columns (2)–(4)). We report bootstrapped standard errors in parentheses. Fed 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 β as well as for ρ are highly statistically significant for equally-weighted industry returns. Economically, a negative estimate of β means tighter-than-expected monetary policy leads to a drop in stock returns. The positive estimate of ρ means this effect is amplified and propagated through the production network: higher-than-expected fed 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.

The positive and statistically significant point estimates of ρ indicate part of the responsiveness of stock returns to monetary policy shocks might be due to higher-order network effects. Panel B of Table 3 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 -3.6% to -4.4%. Indirect effects account for roughly 80% of the overall impact.

C. Additional Results

We only used the 1992 BEA input-output tables in Table 4 to construct the spatial-weighting matrix. In Table 4, we also use the 1997 and 2002 BEA tables. Column (1) only uses the 1997 input-output tables and column (2) only uses the 2002 input-output tables, whereas column (3) employs a time-varying spatial-weighting matrix. We use the 1992 tables until 1997, the 1997 tables until 2002, and the 2002 tables afterwards. Point estimates for the networks parameter ρ are highly statistically significant and vary between 0.59 and 0.67. Economically, the estimates of Table 4 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. Neuhierl and Weber (2015) show changes in long-term fed funds futures relative to changes in short-term fed funds futures are powerful in moving markets. Table 5 contains results for different event types. Column (1) focuses on reversals in monetary policy, such as the first increase in fed funds rates after a series of decreasing or constant rates. We see reversals lead to a larger impact of monetary policy shocks on stock returns. The point estimate for β almost triples compared to the overall sample (see column (4) of Table 3) with a similar point estimate for ρ of 0.77. A fed fund rate that is one-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 4. We see in Panel B that higher-than-expected fed funds rates lead to an *increase* in the stock market, which is, however, not statistically significant. 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 5). Many policy shocks are small in size. To ensure these observations do not drive the large effects of higher-order demand effect, we restrict our sample to events with shocks larger than 0.05 in absolute value in column (3). Economic significance remains stable when we exclude small policy surprises. Statistical significance is sparse for the estimate of β, which might be due to reduced power as we lose more than 70% of our sample.

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 fed fund rate that is one 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 and Placebo Test

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 6, we constrain the diagonal entries of the input-output matrix to zero. By construction, we now associate a larger part of the overall effect of monetary policy shocks on stocks returns of 4% to direct demand effects. 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 (2015)). In column (2) of Table 6, 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-hand-side variable in equation (7). The adjustment has little impact on point estimates, overall response to monetary policy shocks, and relative importance of direct and indirect effects.

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 ρ 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 of the rest of the economy (see Figure 1 and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (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 from the 1992 input-output matrix by minimizing the squared distance between the empirical and estimated distribution function.

We see in column (3) of Table 6 that part of the effect of monetary policy shocks on stock returns which 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 ρ of 0.19, which is almost five times smaller than our baseline estimate. The decomposition of the overall effect into direct and indirect effect assigns less than 20% 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 (4) Table 3).

We estimate our baseline model for a sample from 1994 to 2008 in column (4). The point estimate for ρ is identical to the estimate for a sample ending in 2004, but the overall responsiveness of the stock market to monetary policy shocks is somewhat reduced. Indirect effects contribute more than 80% to the overall effect of 2.66%.

F. 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, and Carvalho (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.[9] 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 7 reports our decomposition in direct and indirect effects for both sets of industries. Column (1) reports our baseline decomposition for convenience. In column (2), we re-estimate our SAR model of equation (7) for industries close to end-consumers and report the decomposition. Column (3) uses the estimates from our baseline estimation to calculate direct and indirect effects for the relevant submatrix of matrix S (see equation 3). Columns (4) and (5) repeat the analysis for industries far from end-consumers. We assign only 30% of the effect of monetary policy shocks on stock returns to direct effects in our baseline estimation. The share of direct effects increases to about 50% 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.

[9] Section III in the online appendix details the procedure.

G. Fundamentals

Our baseline findings in Table 3 indicate higher-order network effects might be responsible for up to 80% of the reaction of stock returns to monetary policy shocks. We argue 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 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 of demand. 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 8). 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 monetary policy shocks affect the real economy at least partially through demand effects and not only through changing risk premia, consistent with findings in Bernanke and Kuttner (2005) and Weber (2015).

VI Concluding Remarks

Monetary policy has a large and prompt effect on financial markets. A fed 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 higher-order demand effects are responsible for a large fraction of the overall effect. 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 a large source of aggregate fluctuations. In particular, Acemoglu, Akcigit, and Kerr (2015) empirically document networks are important for aggregate fluctuations originating at the micro level. So far, however, no evidence exists on whether networks are also important for the propagation of macro shocks, such as monetary policy shocks.

We use the stock market response of industries to monetary policy shocks as a laboratory to test whether 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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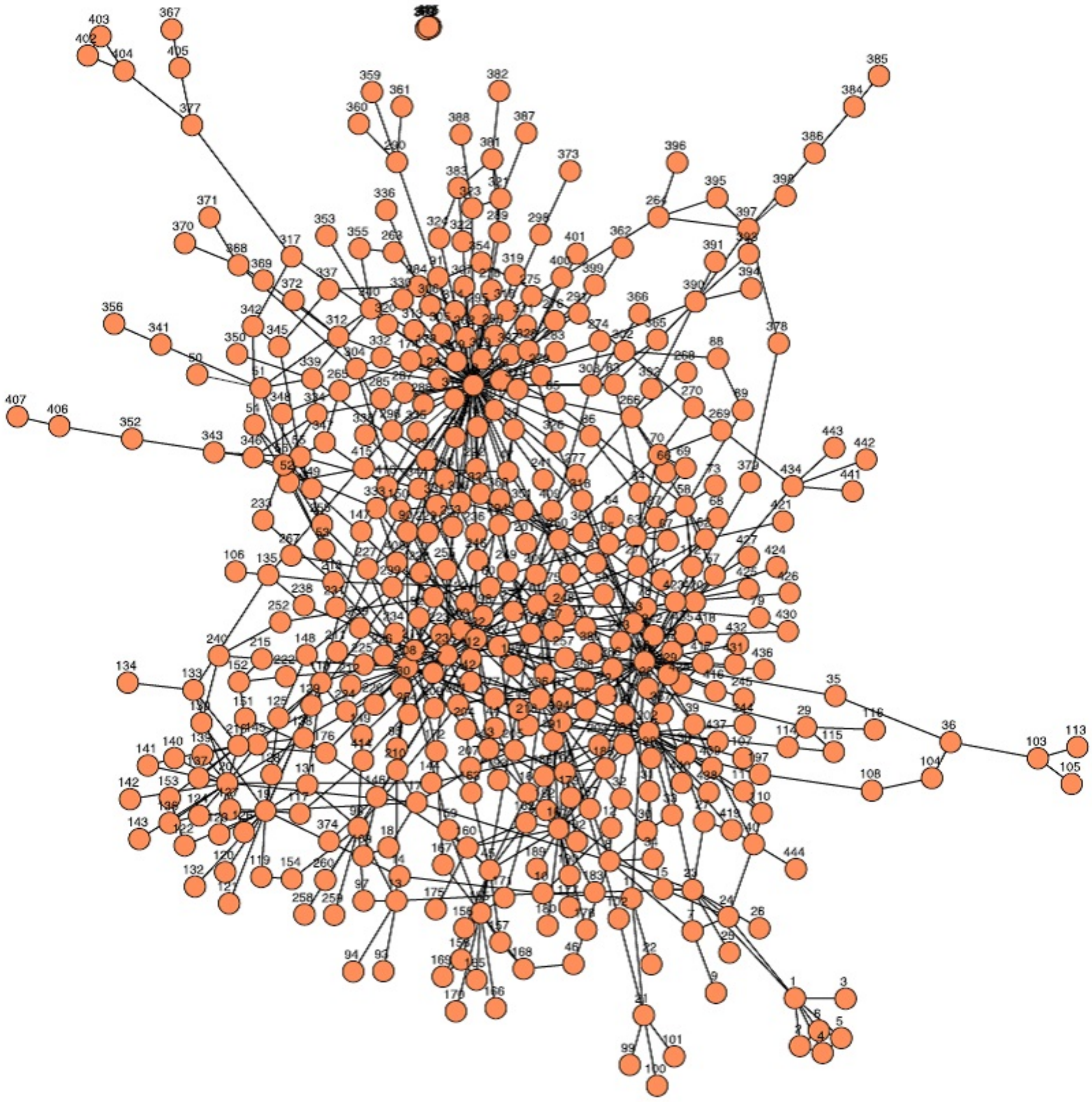
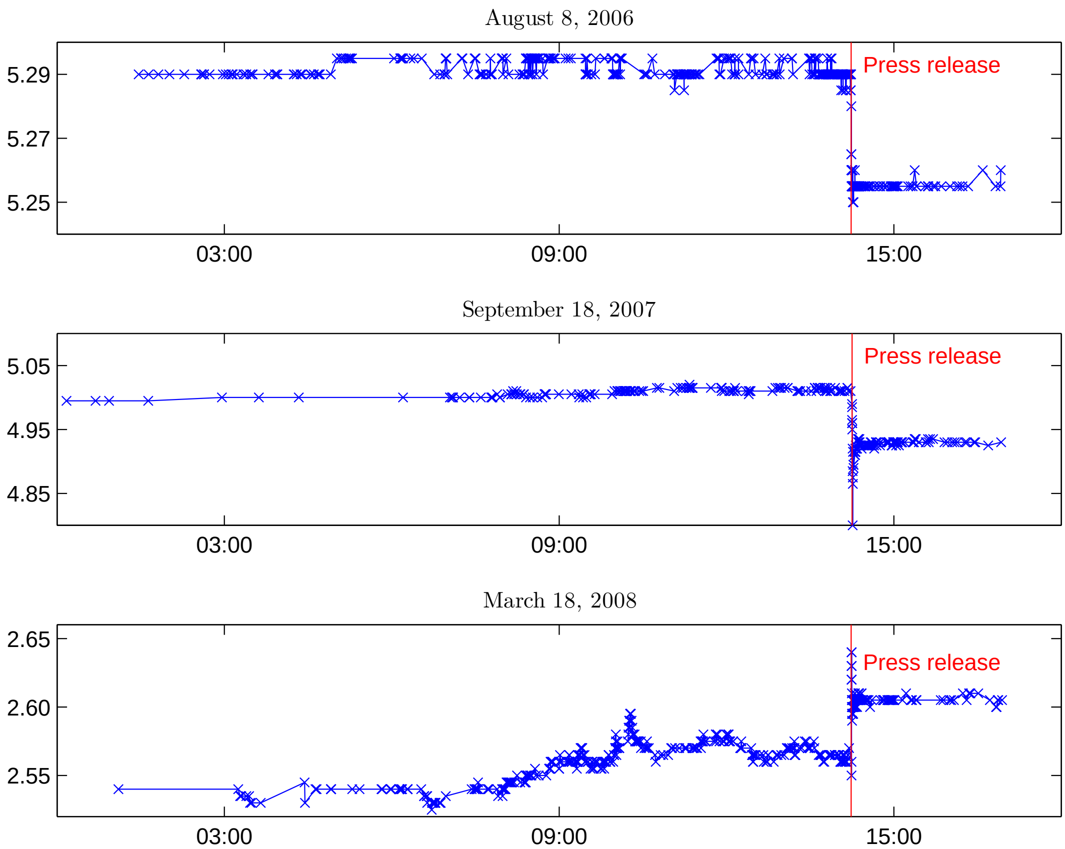
Figure 1: **Production Network corresponding to US Input-Output Data**



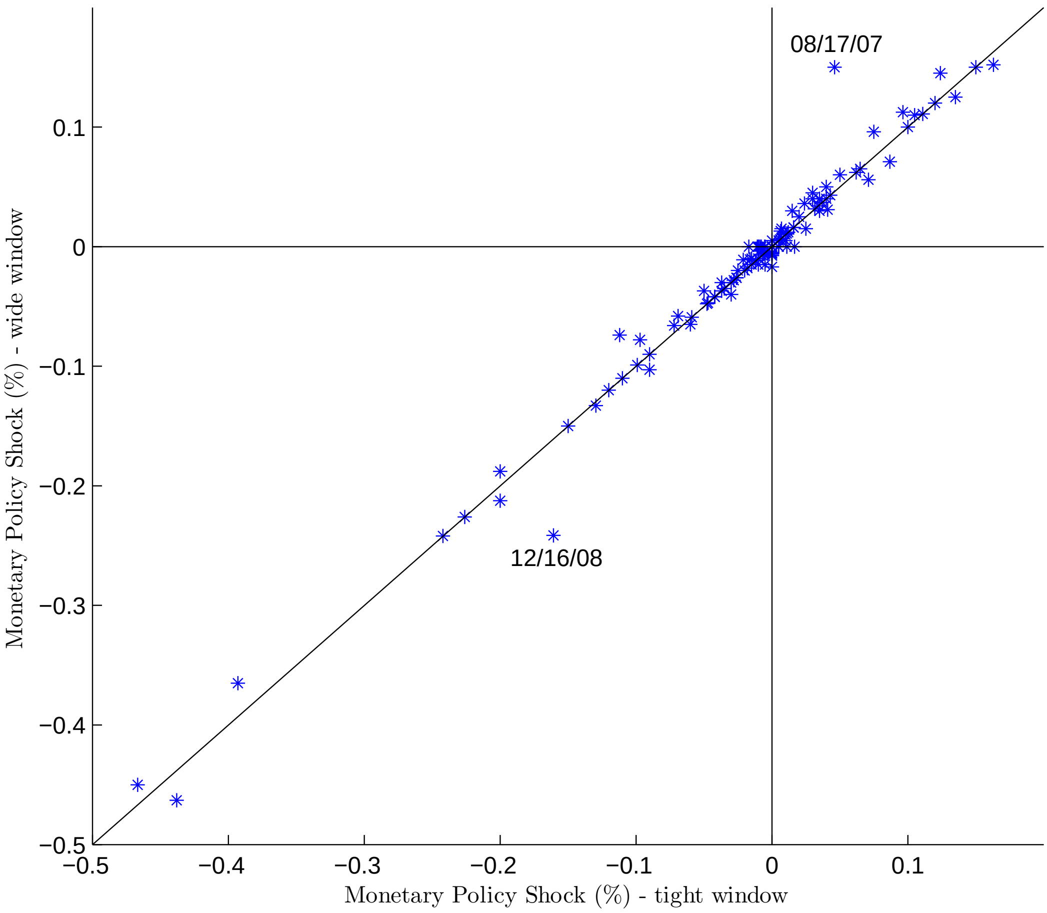
This figure plots the empirical input-output relationship in the U.S. using data from the benchmark input-output tables of the Bureau of Economic Analysis for the year 2002.

Figure 2: **Intraday Trading in Globex Federal Funds Futures**



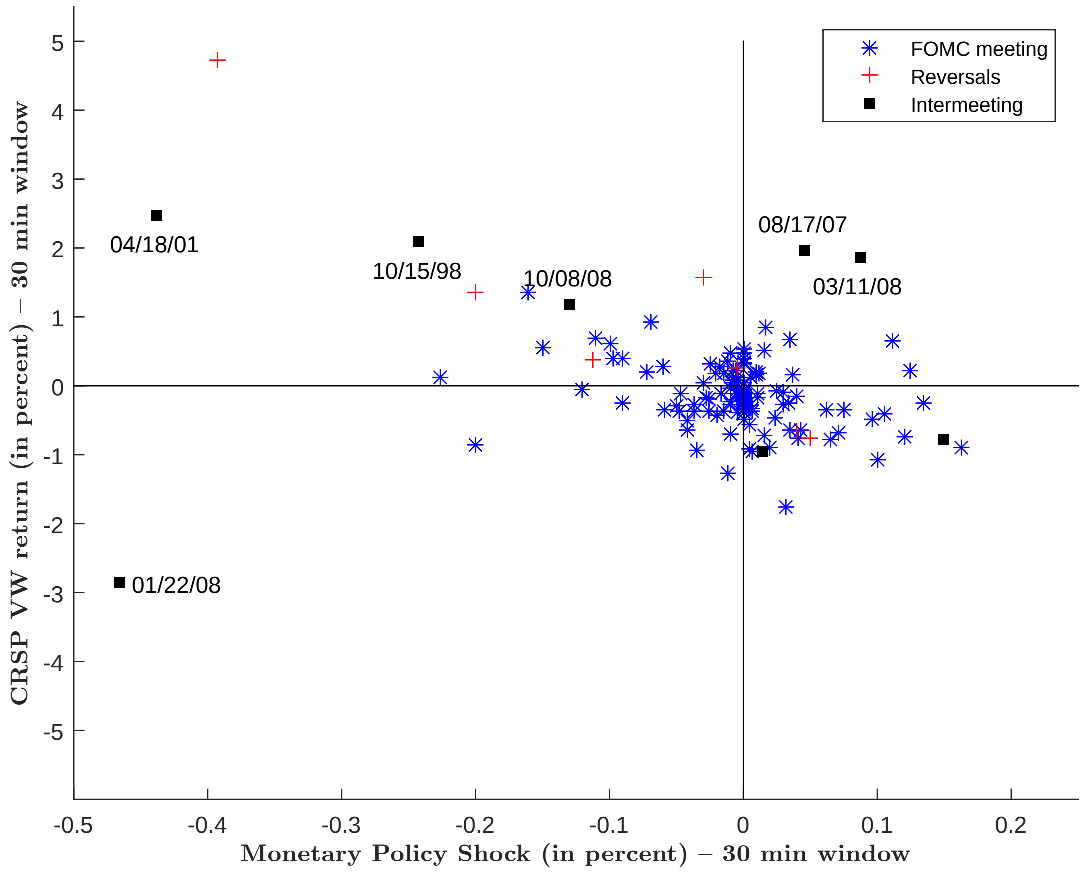
This figure plots the tick–by–tick trades in the Globex Federal funds futures for three different FOMC press release dates with release times at 2:14 p.m. on August 8, 2006; 2:15 p.m. on September 18, 2007; and 2:14 p.m. on March 18, 2008; respectively.

Figure 3: **Futures–based Measure of Monetary Policy Shocks**



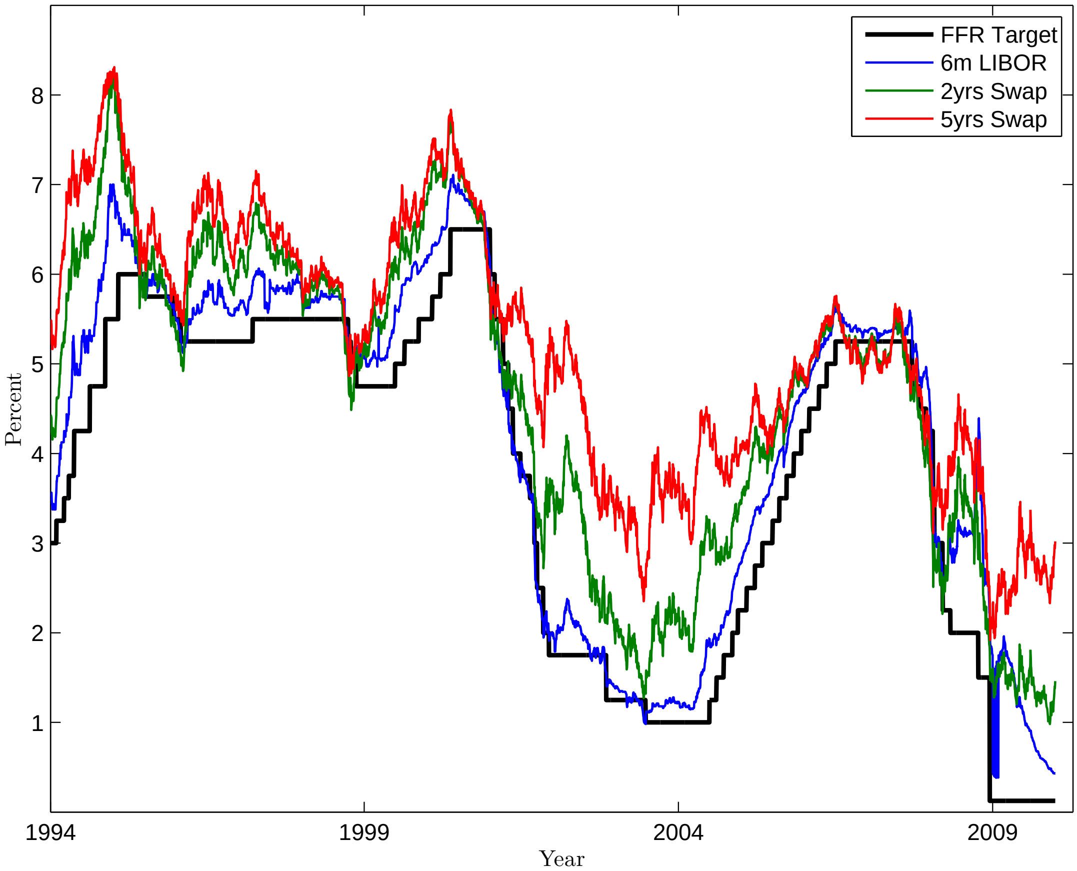
This figure is a scatterplot of the federal funds futures-based measure of monetary policy shocks calculated according to equation (6) for the wide (60-minute) event window versus the tight (30-minute) event window. The full sample ranges from February 1994 through December 2009, excluding the release of September 17, 2001, for a total of 137 observations.

Figure 4: **Return of the CRSP value-weighted index versus Monetary Policy Sh**



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 (6) for the tight (30-minute) event window. The full sample ranges from February 1994 through December 2008, excluding the release of September 17, 2001, for a total of 129 observations. We distinguish between regular FOMC meetings, turning points in monetary policy and intermeeting press releases.

Figure 5: **Time Series of Interest Rates**



This figure plots the time-series of the federal funds target rate, the six months Libor as well as the two- and five-year swap rates from 1994 to 2009.

Table 1: **Descriptive Statistics For High-Frequency Data**

This table reports descriptive statistics for monetary policy shocks (bps) in Panel A and for the returns of the CRSP value-weighted index in Panel B, separately for all 129 event days between 1994 and 2008, turning points in monetary policy, and intermeeting policy decisions. The policy shock is calculated as the scaled change in the current month federal funds futures in a 30-minute window bracketing the FOMC press releases around the release times. The return of the CRSP value-weighted index is calculated as the weighted average of the constituents' returns in the respective event windows, where the market capitalizations at the end of the previous trading days are used to calculate the weights.

Panel A. Monetary Policy Shocks			
	All Event Days	Turning Points	Intermeeting Releases
Mean	-1.67	-9.29	-12.23
Median	0.00	-3.00	-5.73
Std	9.21	15.90	23.84
Min	-46.67	-39.30	-46.67
Max	16.30	5.00	15.00
Nobs	129	7	8
Panel B. CRSP value-weighted Returns			
	All Event Days	Turning Points	Intermeeting Releases
Mean	-0.03%	0.99%	0.62%
Median	-0.12%	0.38%	1.53%
Std	0.81%	1.87%	1.92%
Min	-2.86%	-0.76%	-2.86%
Max	4.72%	4.72%	2.48%
Nobs	129	7	8

Table 2: **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 3: **Response of the 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 lag of the industry returns (columns (2)–(4)) (see equation (7)). 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 codes		
		equally weighted	previous month Mcap	previous day Mcap
	(1)	(2)	(3)	(4)
		Panel A. Point Estimates		
β	−3.96∗∗∗	−0.63∗∗∗	−0.58∗∗∗	−0.58∗∗∗
	(0.11)	(0.19)	(0.18)	(0.18)
ρ		0.82∗∗∗	0.87∗∗∗	0.87∗∗∗
		(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	14.38%	7.20%	14.41%	14.20%
Observations	7,890	7,890	7,890	7,890
Log-L		-7,375	-4,747	-4,728
		Panel B. Decomposition		
Direct Effect		−0.79∗∗∗	−0.76∗∗∗	−0.76∗∗∗
		(0.13)	(0.09)	(0.09)
Indirect Effect		−2.78∗∗∗	−3.62∗∗∗	−3.59∗∗∗
		(0.44)	(0.44)	(0.43)
Total Effect		−3.57∗∗∗	−4.38∗∗∗	−4.35∗∗∗
		(0.56)	(0.52)	(0.52)

Standard errors in parentheses

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

Table 4: **Response of the 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 lag of the industry returns (see equation (7)). 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 codes (1)	SAR: 2002 codes (2)	SAR: time-varying (3)
	Panel A. Point Estimates		
β	-1.70***	-1.16***	-1.41***
	(0.35)	(0.28)	(0.36)
ρ	0.59***	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	10.74%	7.05%	12.37%
Observations	9,153	9,130	8,781
Log-L	-9,378	-10,214	-8,054
	Panel B. Decomposition		
Direct Effect	-1.79***	-1.24***	-1.54***
	(0.11)	(0.12)	(0.10)
Indirect Effect	-2.35***	-2.30***	-2.70***
	(0.15)	(0.23)	(0.18)
Total Effect	-4.14***	-3.54***	-4.24***
	(0.26)	(0.35)	(0.28)

Standard errors in parentheses

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

Table 5: **Response of the 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 lag of the industry returns (see equation (7)) 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		
β	$-1.56{*}{*}{*}$	0.09	$-0.61{*}$	-0.22	$-0.83{*}{*}{*}$
	(0.38)	(0.61)	(0.33)	(0.21)	(0.27)
ρ	$0.77{*}{*}{*}$	$0.91{*}{*}{*}$	$0.86{*}{*}{*}$	$0.92{*}{*}{*}$	$0.84{*}{*}{*}$
	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)
Constant	0.03	0.08	0.00	-0.01	$-0.03{*}$
	(0.03)	(0.09)	(0.02)	(0.02)	(0.02)
adj R^2	55.32%	-1.80%	28.16%	1.19%	20.49%
Observations	676	682	2,233	2,998	3,611
Log-L	-565	-759	-1,627	-1,610	-2,353
			Panel B. Decomposition		
Direct Effect	$-1.84{*}{*}{*}$	0.13	$-0.80{*}{*}{*}$	-0.32	$-1.04{*}{*}{*}$
	(0.26)	(0.23)	(0.12)	(0.30)	(0.14)
Indirect Effect	$-5.07{*}{*}{*}$	0.90	$-3.58{*}{*}{*}$	-2.39	$-4.21{*}{*}{*}$
	(0.60)	(1.67)	(0.52)	(2.24)	(0.54)
Total Effect	$-6.90{*}{*}{*}$	1.04	$-4.38{*}{*}{*}$	-2.71	$-5.26{*}{*}{*}$
	(0.76)	(1.90)	(0.62)	(2.53)	(0.66)

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

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

This table reports the results of regressing industry returns in a 30-minute event window bracketing the FOMC press releases on the federal funds futures based measure of monetary policy shock, v_t, and an input-output network-weighted lag of the industry returns (see equation (7)). 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	industry-demeaned	pseudo W	1994 – 2008
	(1)	(2)	(3)	(4)
	Panel A. Point Estimates			
β	-1.92***	-0.59*	-3.24***	-0.35
	(0.47)	(0.33)	(1.23)	(0.29)
ρ	0.51***	0.86***	0.19***	0.87***
	(0.06)	(0.04)	(0.05)	(0.02)
Constant	-0.03*		-0.06	-0.01
	(0.02)		(0.07)	(0.01)
adj R^2	14.38%	14.12%	14.38%	5.39%
Observations	7,890	7,890	7,890	10,857
Log-L	-6,918	-4,672	-7,225	-5,205
	Panel B. Decomposition			
Direct Effect	-1.94***	-0.77***	-3.23***	-0.46***
	(0.10)	(0.09)	(0.10)	(0.06)
Indirect Effect	-2.00***	-3.46***	-0.74***	-2.19***
	(0.11)	(0.41)	(0.02)	(0.30)
Total Effect	-3.94***	-4.23***	-3.97***	-2.66***
	(0.21)	(0.49)	(0.13)	(0.37)

Standard errors in parentheses

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

Table 7: **Response of the 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 lag of the industry returns (see equation (7)) 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.*

	Baseline Estimates	Close to Endconsumer		Far from Endconsumer	
		Re-estimated	Implied	Re-estimated	Implied
	(1)	(2)	(3)	(4)	(5)
Direct Effect	−1.21	−2.37	−2.03	−1.08	−1.10
Indirect Effect	−3.02	−2.77	−2.20	−3.05	−3.12
Total Effect	−4.23	−5.14	−4.23	−4.12	−4.23
Direct Effect [%]	28.65%	46.09%	47.91%	26.11%	26.11%
Indirect Effect [%]	71.35%	53.91%	52.09%	73.89%	73.89%

Table 8: **Response of the 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 lag 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

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

Online Appendix: Production Networks and the Stock Market Response to Monetary Policy Shocks

Ali Ozdagli and Michael Weber

Not for Publication

I Extended Model: Labor and Wage Stickiness

One potentially undesirable property of the benchmark model is that M has no effect on the real variables. This is easy to solve by introducing the traditional wage stickiness, that is, wages are set in advance but the household should provide any labor demanded at the agreed-upon wage in the second stage.[1] In this case, the utility function should have a leisure component that only kicks in in the first stage and wages are determined by the first stage labor market clearing condition. When we take wages from the first stage as given, the explicit modelling of this first stage is not relevant for our purpose; hence, we focus on the second stage where agents make decisions given the wage level. We will see that although wage stickiness addresses the issue of monetary neutrality, the role of production network in the reaction of firms' net income will be exactly the same as in the benchmark model.

The firm's problem is modified to include labor, l, and wage, w,

$$\pi_i = \max p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - w l_i - f_i \text{ with } y_i = z_i l_i^{\beta} \left(\prod_{j=1}^{N} x_{ij}^{\omega_{ij}} \right)^{\alpha}, \tag{A.1}$$

where the FOCs are

$$\begin{aligned} \alpha \omega_{ij} p_i y_i &= p_j x_{ij}, \\ \beta p_i y_i &= w l_i, \end{aligned}$$

and therefore,

$$\pi_i = (1 - \alpha - \beta) R_i - f_i. \tag{A.2}$$

The consumer passively supplies labor and collects income from wages, profits, and fixed costs. Hence, the FOC associated with her utility maximization problem is the same as before:

$$c_i = \frac{w \sum_{i=1}^{N} l_i + \sum_{i=1}^{N} (\pi_i + f_i)}{N p_i} = \frac{(1 - \alpha) \sum_{i=1}^{N} R_i}{N p_i}, \tag{A.3}$$

[1] An alternative would be price stickiness, but this requires significant changes in the model by introducing monopolistic competition. Moreover, under monopolistic competition, tractable analytical solutions require strong assumptions so that the demand elasticity of the firms and consumers for a particular good is the same, e.g., Basu (1995), whereas heterogenous demand elasticities are actually at the heart of the input-output structure in our model.

which, together with the market clearing condition and FOC of the firm, gives

$$y_i = c_i + \sum_{j=1}^{N} x_{ji} = (1-\alpha)\frac{\sum_{i=1}^{N} R_i}{N p_i} + \alpha \frac{\sum_{j=1}^{N} \omega_{ji} p_j y_j}{p_i}, \tag{A.4}$$

or with cash-in-advance constraint,

$$R_i = (M/N) + \alpha \sum_{j=1}^{N} \omega_{ji} R_j, \tag{A.5}$$

which is the exact same equation as in the benchmark model. Therefore, we will get the same results for revenues as in the benchmark model ($\hat{R} = \hat{M}$) and equation (23) for net income. This result is due to the Cobb-Douglas assumption, which we will relax in the next section.

However, real variables will now be affected by money supply. When we plug the first-order conditions of the firm i into the production function, we get

$$y_i = z_i l_i^{\beta} \left(\prod_{j=1}^{N} \left(\frac{\alpha \omega_{ij} p_i y_i}{p_j} \right)^{\omega_{ij}} \right)^{\alpha}. \tag{A.6}$$

We can express this last equation, the FOC of the firm with respect to labor, and $p_i y_i = R_i$ in logarithmic form,

$$\begin{aligned} (1-\alpha)\,\hat{y}_i &= \beta \hat{l}_i + \alpha \hat{p}_i - \alpha \sum_{j=1}^{N} \omega_{ij} \hat{p}_j, \\ \hat{p}_i + \hat{y}_i &= \hat{R}_i = \hat{M}, \\ \hat{l}_i &= \hat{R}_i = \hat{M}, \end{aligned}$$

where $\hat{x} = \log(x)$ and we omit terms, such as z_i, that do not respond to changes in money supply. This gives us $3N$ equations for $3N$ unknowns, $\hat{p}_i$, $\hat{y}_i$, and $\hat{l}_i$.

In particular, plugging the last two equations into the first one of these three equations, we get

$$\begin{aligned} (1-\alpha)\left(\hat{M} - \hat{p}_i\right) &= \beta \hat{M} + \alpha \hat{p}_i - \alpha \sum_{j=1}^{N} \omega_{ij} \hat{p}_j, \\ (1-\alpha-\beta)\,\hat{M} &= \hat{p}_i - \alpha \sum_{j=1}^{N} \omega_{ij} \hat{p}_j, \end{aligned}$$

or equivalently, letting $\hat{p} \equiv (\hat{p}_1, ..., \hat{p}_N)'$ be the log-price vector,

$$(1-\alpha-\beta)\,\hat{M} = (I - \alpha W)\hat{p}, \tag{A.7}$$

which reveals that prices do not move one-to-one with money supply, i.e., $\hat{p} \neq \hat{M}$, as expected. It is also straightforward to derive the output from this last equation and $\hat{p}_i + \hat{y}_i = \hat{R}_i = \hat{M}$:

$$\hat{y} = \hat{M} - \hat{p} = \left[I - (1-\alpha-\beta)(I - \alpha W)^{-1}\right]\hat{M}. \tag{A.8}$$

II Extension: CES Production with Labor and Wage Stickiness

This section introduces a CES production function in order to show how network structure can play a role in the response of aggregate stock market to monetary policy. We are directly focusing on the case of wage stickiness because in the absence of nominal frictions, the results of the benchmark model hold for any homogenous production function. To see this, note that we have $\hat{R}_i = \hat{M}$ in the absence of nominal frictions because monetary neutrality holds. Moreover, when production function is homogenous, the operating profits are a constant fraction of revenue. Therefore, the formula for net income is the same as in the benchmark model, $\pi_i = \kappa R_i - f_i$ where κ is a constant number. Therefore, we will get the same stock price reaction as before. Therefore, to avoid repetition, we focus on the case of wage stickiness below.

The main difference from the last model is the CES production function of the form

$$\begin{aligned} y_i &= z_i[\theta X_i^r + (1-\theta) l_i^r]^{\alpha/r}, && \text{(A.9)} \\ X_i &= \prod_{j=1}^{N} x_{ij}^{\omega_{ij}}, && \text{(A.10)} \end{aligned}$$

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

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

and the FOC w.r.t. this input is

$$\begin{aligned} p_i \frac{\partial y_i}{\partial x_{ij}} &= p_j \Rightarrow \omega_{ij} \alpha \frac{\theta X_i^r}{\theta X_i^r + (1-\theta) l_i^r} p_i y_i = p_j x_{ij} && \text{(A.11)} \\ &\Rightarrow \omega_{ij} \alpha \theta_i p_i y_i = p_j x_{ij}, && \text{(A.12)} \end{aligned}$$

where

$$\theta_i \equiv \frac{\theta X_i^r}{\theta X_i^r + (1-\theta) l_i^r} \tag{A.13}$$

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

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

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

$$\pi_i = p_i y_i - \sum_{j=1}^{N} p_j x_{ij} - w l_i - f_i = (1-\alpha) p_i y_i - f_i, \tag{A.14}$$

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

$$c_i = \frac{\sum_{i=1}^{N} (\pi_i + w l_i + f_i)}{N p_i} = \frac{\sum_{i=1}^{N} (1-\alpha\theta_i) R_i}{N p_i}. \tag{A.15}$$

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 good, gives the following equation:

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

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):

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

We can rewrite the first equation in matrix form as before:

$$(I - \alpha W' D(\theta))R = \begin{pmatrix} M/N \\ \vdots \\ M/N \end{pmatrix}_{N\times 1} = m, \tag{A.16}$$

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

Note that this model differs from the previous models in an important way. In the previous models, 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 κ is a constant and $\sum_{i=1}^{N} R_i$ is proportional to money supply due to cash-in-advance constraints. Therefore, in the previous models, network structure does not play a direct role for the reaction of the 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 θ_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 aggregate stock market to monetary policy through θ_i.

III 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 $(n+1)\times(n+1)$ and takes the form,

$$D = \begin{bmatrix} 0 & \mu \\ 0 & \gamma \end{bmatrix}, \tag{A.17}$$

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

$$\mu = (MAKE * P) * \frac{1}{\sum_{i=1}^{C} C_i}. \tag{A.18}$$

We define Γ as an $n \times n$ matrix of intermediate input purchases that industry j makes from industry i. Γ corresponds to the REVSHARE matrix in Section IV (see equation 26).

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

$$C^{c.n} = C * diag(C * 1)^{-1} = \begin{bmatrix} 0 & \hat{\mu}^\top \\ 0 & \hat{\Gamma} \end{bmatrix} \tag{A.19}$$

We then define steps to end consumer, S, as the following,

$$\begin{aligned} S &= (1 - \hat{\Gamma}^\top)^{-1} \\ &= .... + (\hat{\Gamma}^\top)^2\hat{\mu} + \hat{\Gamma}^\top\hat{\mu} + \hat{\mu} \\ &= 1 \end{aligned} \tag{A.20}$$

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 2 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**

		Unexpected Change (bps)		Expected Change (bps)		
Release Date	Release Time	Tight Window	Wide Window	Tight Window	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