Monetary Policy Shocks and Allocative Efficiency across U.S. Firms*

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June 15, 2024

Abstract

This study examines the supply-side effects of monetary policy interventions with a focus on allocative efficiency, an area notably less investigated in comparison to the demand-side effects. Our findings show that contractionary monetary policy shocks reduce allocative efficiency, with the magnitude of this impact varying across firms based on characteristics such as markup, size, and age. To identify the effect of monetary shocks, we use the Structural Vector Autoregressive (SVAR) model alongside local projections using instrumental variables (LP-IV), both of which leverage high-frequency financial market data to construct instruments that induce random variation in monetary policy measures. Furthermore, through the application of a Bayesian SVAR approach, we find that the Federal Reserve's insights into the current economic landscape significantly affect allocative efficiency, highlighting the nuanced relationship between monetary policy and economic distribution mechanisms.

Keywords: Monetary Policy, Allocative Efficiency, Proxy and Bayesian SVAR, LP-IV

JEL Codes: O11, E32, E37, E44, E24

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*We are grateful to Peter J. Klenow and Cian Ruane for their valuable comments and sharing the code to calculate allocative efficiency. We are also grateful to Peter Karadi for sharing the high-frequency surprises database and to German Gutierrez for sharing the industry-level capital risk premium. We thank the seminar participants at the Northeast Ohio Workshop Program held at the Federal Reserve Bank of Cleveland, the Canadian Economics Association meeting in Ottawa, Western Michigan University, the Southern Economic Association conference in Fort Lauderdale, and the Midwest Economic Association conference in Cleveland for their helpful comments.

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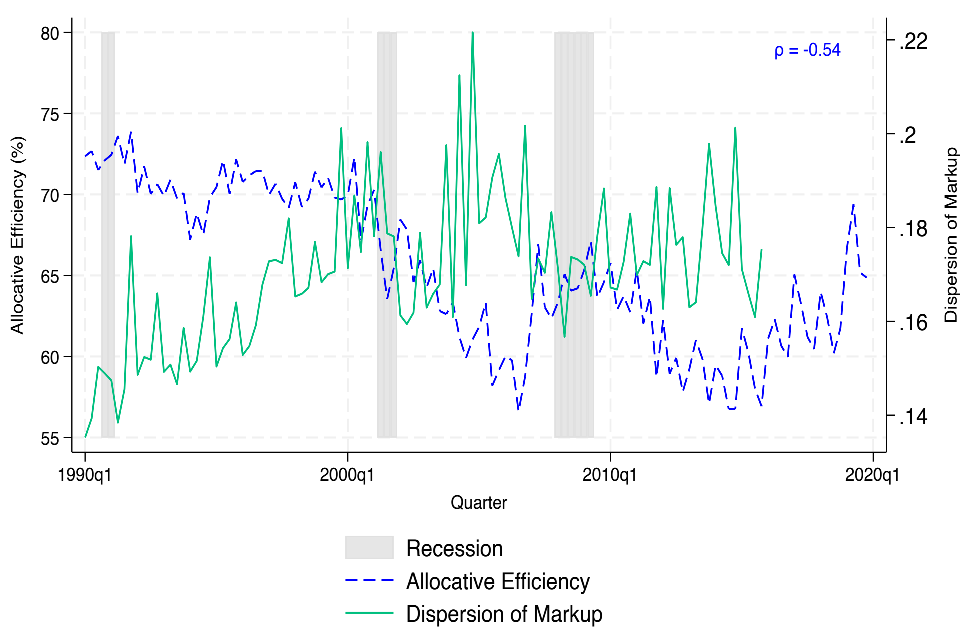
1 Introduction

This research project investigates the supply-side effects of monetary policy interventions, focusing on allocative efficiency— an area less explored compared to demand-side impacts. It highlights the uncertainty surrounding allocative efficiency's sensitivity to monetary policy shocks, a crucial aspect depicted in Figure 1, which illustrates allocative efficiency alongside the dispersion of markups across the United States. Our analysis contributes to the understanding of this area by presenting evidence that contractionary monetary shocks detrimentally affect allocative efficiency. The impact of such shocks varies according to firm-specific attributes including markups, size, and age. Specifically, contractionary monetary policies result in lower nominal factor prices, thereby reducing nominal marginal costs for firms universally. However, firms with higher markups, exhibiting lower pass-through rates, tend to reduce their prices less significantly than those with lower markups (Baqaee et al., 2023; Amiti et al., 2019). This differential pricing response leads to a reallocation of factors from high-markup to low-markup firms, potentially undermining allocative efficiency and consequently, might impair aggregate productivity.

Figure 1: Allocative efficiency and the dispersion of markups in the United States



Note: We use the Compustat database for this graph. Following Bils et al. (2021), we calculate allocative efficiency. Using the user cost approach, we follow Baqaee et al. (2023) to calculate markups. These two series are negatively correlated ($\rho = -0.52$).

We use the Structural Vector Autoregressive (SVAR) model and the local projections using instrumental variables (LP-IV) approach to identify monetary policy shocks. Both estimation techniques emphasize high-frequency data from financial markets in constructing instruments that provide random variation in policy indicators. At the aggregate level, following Gertler and Karadi (2015), we use a proxy SVAR model that combines high-frequency interest rate surprises and a VAR approach. This proxy SVAR model is developed by Stock and Watson (2012). For high-frequency surprises, as Nakamura and Steinsson (2018), we use the first principal component of the surprises in fed funds futures and euro-dollar futures with one year or less to expiration. In this method, calculating daily high-frequency surprises uses five indicators: the current-month fed funds future, the 3-month fed funds futures, and the euro-dollar futures at the horizons of two, three, and four quarters. To construct quarterly measures of high-frequency surprises, we simply sum up the daily surprises for each quarter. Our key identifying assumption is that unexpected changes in the fed funds futures and euro-dollar futures within a 30-minute window starting 10 minutes before and ending 20 minutes after the FOMC announcement arise from news about monetary policy, nothing else occurs within this window. Our VAR model includes allocative efficiency, the consumer price index, the two-year treasury rate, and the excess bond premium. We use the two-year treasury rate as the relevant monetary policy indicator, rather than the federal funds rate because of the zero lower bound. Using publicly listed firms from Compustat and applying the method from Bils et al. (2021) to measure allocative efficiency, we find that a one-standard-deviation surprise monetary tightening induces a roughly 30 basis point increase in the two-year treasury rate and reduces allocative efficiency by one percent.

The FOMC announcement, which is the basis for creating instruments for the proxy SVAR model, reveals information not just about monetary policy but also about the Fed's assessment of the contemporaneous economic outlook. To isolate the effect of monetary policy shocks on allocative efficiency from central bank information shocks, following Jarociński and Karadi (2020), we use a Bayesian SVAR model that combines high-frequency information and sign restrictions. This method analyzes the high-frequency co-movement of interest rates and stock prices in a 30-minute window around the FOMC announcement. In addition, this method uses two assumptions on the announcement surprises; it imposes no restrictions on any macroeconomic and financial variables. The first assumption related to high-frequency information is that announcement surprises are affected only by negative and positive co-movement shocks and not by other stocks. The second assumption related to sign restrictions is that a negative co-movement shock is associated with an interest rate increase and a drop-in stock prices whereas a positive co-movement shock is associated with an increase in both interest rates and stock prices. In our VAR model, we include seven variables: two high-frequency surprise variables and five low-frequency macroeconomic and financial variables; high-frequency surprise variables consist of the surprises in the three-month fed funds futures and the S&P 500 stock market index; low-frequency variables include two-year treasury rate, a stock price index, allocative efficiency, consumer price index, and excess bond premium. We use similar variables of the proxy SVAR estimation. Applying this Bayesian SVAR model, we find that the Fed's information about the contemporaneous economic outlook strongly impacts allocative efficiency.

At the microeconomic level, to identify the average effect of monetary policy on factor misallocation as measured by revenue total factor productivity relative to its industry average, following Jordà et al. (2020), we use the LP-IV approach. In this method, the impulse response can be expressed as the local average treatment effect (LATE) that satisfies monotonicity, relevance, and exogeneity assumptions. We find that adverse monetary shocks lead to an increase in factor misallocation. To identify the heterogeneous effect of monetary policy on factor misallocation, we also use the LP-IV method. We find that low markup firms are more responsive in terms of changes to allocative efficiency to adverse monetary shocks compared to high markup firms. In addition, constrained firms, measured by size and age of firms, are more responsive in terms of changes to allocative efficiency following a tighter monetary shock.

In terms of our contribution to the literature, this is the first empirical paper that connects misallocation literature with monetary policy. Baqaee et al. (2023) identify this supply-side effect of monetary policy. Countercyclical dispersion in firm-level revenue product is documented by Kehrig (2011) and Baqaee et al. (2023). Alam (2020) establishes that capital misallocation, as measured by the dispersion of returns to capital, is higher during recessions and lower during booms, that is, countercyclical. On measures of financial constraints, the influential work of Gertler and Gilchrist (1994) find that firms with fewer assets (typically small firms) are affected more during tight credit periods compared to firms with large assets, given that small firms exhibit greater bank dependence, are unable to issue debt publicly and face greater idiosyncratic risk. However, using data before the financial crisis, Crouzet and Mehrotra (2020) find that differential response to monetary shocks does not provide strong support for asset-based financial constraints. Kudlyak and Sanchez (2017) find that sales and short-term debt of large firms are more responsive to aggregate shocks. Cloyne et al. (2018) argue that, in US data, the response of young firms makes up two-thirds of the total firm investment response of publicly traded firms to monetary shocks. Ottonello and Winberry (2020) show that highly leveraged firms are less responsive to monetary policy shocks, because of higher default risk, while Jeenas (2018) finds that highly leveraged firms are more responsive. Dinlersoz et al. (2018) argue that private, leveraged firms contribute substantially to the decline in sales during the Great Recession.

In describing changes in allocative efficiency due to monetary policy shocks, we also relate to a vast literature on cross-sectional misallocation. Following the seminal work of Hsieh and Klenow (2009) and Restuccia and Rogerson (2008), attention has shifted to identifying the potential sources of resource misallocation. Important contributions to this literature include the study of Asker et al. (2014) on adjustment costs; those of Midrigan and Xu (2014), Moll (2014), and Gopinath et al. (2017) on financial frictions; that of David et al. (2016) on uncertainty; and that of Peters (2018) on markup dispersion. Several recent studies analyze multiple factors at once. For instance, Kehrig and Vincent (2017) combine financial and adjustment frictions to investigate misallocation within rather than between firms. Gopinath et al. (2017) investigate the interaction between capital adjustment costs and size-dependent financial frictions in determining the dynamics of capital allocation, and Song and Wu (2015) study a model with adjustment costs, permanent distortions, and heterogeneity in markups and technologies. David and Venkateswaran (2017) find that a substantial fraction of factor misallocation comes from firm-specific distortions, while adjustment costs and uncertainty make up a modest share of the observed dispersion in the marginal product of capital. In the United States, output per worker between 1960 and 2010 was higher by 0.3 percentage points per year because of declining misallocation associated with declines in discrimination against women and Black Americans (Hsieh et al., 2019). Recently Bils et al. (2021) find rising misallocation and worsening allocative efficiency in the United States and they attribute much, but not all, of this deterioration due to measurement error in firm-level data. However, we find that the measurement error identified in the Census data by Bils et al. (2021) isn't too large for Compustat firms, which is consistent with David and Venkateswaran (2017). We also find that corrected allocative efficiency is highly correlated with uncorrected allocative efficiency.

The remainder of this paper is organized as follows. Section 2 provides methods including the Bils et al. (2021) framework of misallocation, estimation methods, data sources, and firm characteristics. Section 3 explains the macro-level evidence of monetary policy on allocative efficiency. Section 4 presents the micro-level responses of monetary policy. Section 5 concludes.

2 Method

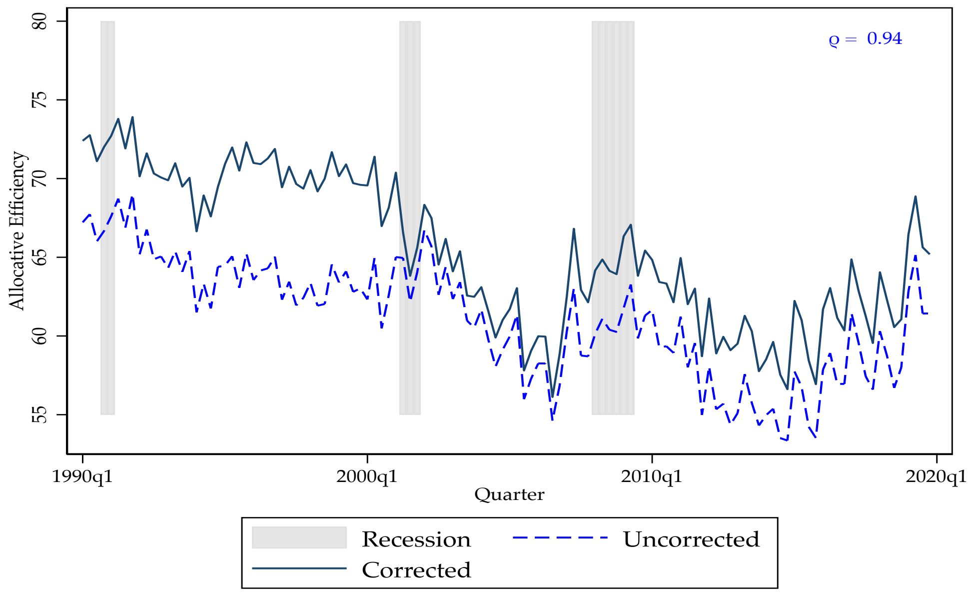
2.1 Measuring Allocative Efficiency

To measure allocative efficiency, we will follow Bils et al. (2021) and assume that in each period there are three types of firms: perfectly competitive final good producers, who combine goods from sectors using a Cobb-Douglas production function; perfectly competitive sectoral good producers, who combine intermediate goods using a CES production function; and monopolistically competitive intermediate good producers in each sector, who produce intermediate goods using a Cobb-Douglas production function. We measure the aggregate allocative efficiency as:

$$\hat{AE}_t = \prod_{s=1}^{S} \hat{AE}_{st} \frac{\theta_{st}}{\sum_{s=1}^{S} \gamma_s \theta_{st}} \tag{1}$$

where, $\hat{AE}_s = \left[\sum_i^{N_s} \left(\frac{TFPQ_{si}}{TFPQ_s}\right)^{\epsilon-1} \left(\frac{TFPR_{si}}{TFPR_s}\right)^{1-\epsilon}\right]^{\frac{1}{\epsilon-1}}$, $TFPR_{si} = \frac{\hat{R}_{si}}{(\hat{K}_{si}^{\alpha_s} \hat{L}_{si}^{1-\alpha_s})^{\gamma_s} \hat{X}_{si}^{1-\gamma_s}}$, $TFPQ_{si} = \frac{(\hat{R}_{si})^{\frac{\epsilon}{\epsilon-1}}}{(\hat{K}_{si}^{\alpha_s} \hat{L}_{si}^{1-\alpha_s})^{\gamma_s} \hat{X}_{si}^{1-\gamma_s}}$, $TFPQ_s = \left[\sum_{i=1}^{N_s} TFPQ_{si}^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}$ and $TFPR_s = (\frac{\epsilon}{\epsilon-1})[\frac{MRPL_s}{(1-\alpha_s)\gamma_s}]^{(1-\alpha_s)\gamma_s}[\frac{MRPK_s}{\alpha_s\gamma_s}]^{\alpha_s\gamma_s}[\frac{MRPX_s}{1-\gamma_s}]$ $MRPL_s$, $MRPK_s$, and $MRPX_s$ are the revenue-weighted harmonic mean values of the marginal products of labor, capital, and intermediates, respectively. In the absence of measurement error, TFPR would be proportional to the distortion and TFPQ would be proportional to productivity.

Figure 2: Allocative Efficiency



Note: We use the Compustat database for this graph. Following Bils et al. (2021), we calculate allocative efficiency.

Without measurement error, Equation (1) is equal to true allocative efficiency. To address measurement error, we use the method developed by Bils et al. (2021). Figure 2 shows the corrected and uncorrected allocative efficiency, which are highly correlated. This graph also shows that additive measurement error isn't too large for Compustat firms, which is consistent with David and Venkateswaran (2017). Our calculated allocative efficiency is consistent with the recent literature (Bils et al., 2021). Figure 2 shows that the average allocative efficiency in the United States for public limited firms is 66.52% and the allocative efficiency declines over time. This means that resource misallocation increases over time in the United States.

2.2 Proxy SVAR

To identify the dynamic effects of a monetary policy shock on aggregate allocative efficiency, we use the proxy SVAR. Following Gertler and Karadi (2015), we combine high-frequency interest rate surprises as external instruments for the monetary policy variable and a VAR approach. This proxy SVAR is developed by Stock and Watson (2012) and Mertens and Ravn (2013). In this paper, for external instruments, we use high-frequency interest rate surprises as well as pure monetary policy shocks from Jarociński and Karadi (2020) that do not have information shocks.

Let our general structural form of the VAR is given by:

$$AY_t = \sum_{j=1}^{p} C_j Y_{t-j} + \epsilon_t$$

where, Y_t is a vector variables, A and C_j $\forall$ $j \geq 1$ are conformable coefficient matrices, and ϵ_t is a vector of structural white noise shocks. To get the reduced form representation, we multiply both sides by A^{-1}. Then,

$$Y_t = \sum_{j=1}^{p} B_j Y_{t-j} + u_t$$

where u_t is the reduced form shock expressed as a function of the structural shocks:

$$u_t = S\epsilon_t$$

with B_j=A^{-1} C_j and $S = A^{-1}$. Suppose, the variance-covariance matrix of the reduced form model equals $\sum$. We have $\sum = E[U_t U_t^{'}] = E[SS']$.

We assume $i_t^p \in Y_t$ to be the policy indicator that in our case will be the two-year treasury rate. The exogenous variation of the policy indicator stems from the policy shock ϵ_t^p. Suppose, s denotes the column in S corresponding to the impact of the policy shock ϵ_t^p on each element of the vector of reduced form residuals u_t. To compute the impulse responses to a monetary shock, we need to estimate:

$$Y_t = \sum_{j=1}^{p} B_j Y_{t-j} + s\epsilon_t^p \tag{2}$$

Let Z_t be a vector of instrumental variables and let ϵ_t^q be a structural shock other than the policy shock. In order for the instrumental variables to be a valid instrument for the policy shock ϵ_t^p, we need $E[Z_t\epsilon_t^{p'} = \phi]$ and $E[Z_t\epsilon_t^{q'} = 0]$. This means that Z_t is correlated with the monetary policy shock and uncorrelated with all other structural shocks in the system.

We next explain exactly how we use interest rate futures as external instruments to identify exogenous monetary policy shocks. In the VAR model, we include allocative efficiency, the log consumer price index, the two-year treasury rate as the policy indicator, and the excess bond premium. As mentioned before, we use the two-year treasury rate as the relevant monetary policy indicator, rather than the federal funds rate because of the zero lower bounds.

2.3 Jorda LP-IV

To identify the causal effect of monetary policy shocks on misallocation, we estimate the following set of Jorda (2020)-style LP-IV model:

$$ln(Y_{i,t+h}) - ln(Y_{i,t}) \quad = \quad \alpha_{i,h} + \alpha_{sy,h} + \Delta\hat{r}_t\beta_h + \boldsymbol{x}_{i,t-1}\boldsymbol{\gamma}_h + u_{i,t+h}, \tag{3}$$

where $Y_{i,t+h}$ and $Y_{i,t}$ are a measure of firm-level misallocation, $h \geq 1$ indexes the forecast horizon, and i indexes a firm. $\alpha_{i,h}$ is a firm fixed effect, $\alpha_{sy,h}$ is a sector-by-year fixed effect, and $\boldsymbol{x}_{i,t-1}$ is a set of macroeconomic and firm-level controls. The estimates of $\Delta\hat{r}_t$ come from the first stage regression using an instrument z_t. The coefficient β_h measures how the cumulative response of misallocation in quarter $t+h$ to a monetary policy shock in quarter t depends on firm characteristics in quarter $t-1$.

The impulse response can be expressed like the *local average treatment effect* (LATE):

$$\mathcal{R}_{LATE} = E(\boldsymbol{y}_1 - \boldsymbol{y}_0 \mid \Delta r, \boldsymbol{x}, z) = \boldsymbol{\beta} = (\beta_1, ..., \beta_h)',$$

which can be estimated from the sequence of equations in expression (5). $\boldsymbol{y}_1$ and $\boldsymbol{y}_0$ are potential outcomes when $\Delta r = 1$ and $\Delta r = 0$ respectively. Three assumptions are required to estimate the causal effects:

1. Monotonicity: $\frac{\delta E(\Delta r|\boldsymbol{x})}{\delta z} \geq 0$. We assume that adverse monetary policy shocks measured by high-frequency surprises raise two-year treasury rates.

2. **Relevance:** $L(\Delta r \mid \boldsymbol{x}, z) \neq L(\Delta r \mid \boldsymbol{x})$, where, for example, $L(\Delta r \mid \boldsymbol{x}, z)$ refers to the linear projection of Δr on $\boldsymbol{x}$ and z.

3. **Exogeneity:** $L(\boldsymbol{y}_j \mid \boldsymbol{x}, \Delta r, z) = L(\boldsymbol{y}_j \mid \boldsymbol{x}, \Delta r)$ for $j = 0, 1$

2.4 High-Frequency Instruments

To identify shocks to monetary policy, we use high-frequency data from futures markets around within a 30-minute window starting 10 minutes before and ending 20 minutes after the FOMC announcement, nothing else occurs within this window. Table A1 shows major unconventional monetary policy announcements by the Fed from 2009 - 2015. We use the high-frequency interest surprises from Jarociński and Karadi (2020) that developed based on Gürkaynak et al. (2005) and Nakamura and Steinsson (2018). Specifically, this is the first principal component of the surprises in fed funds futures and euro-dollar futures with one year or less to expiration[1]. They use five indicators to estimate the surprises: the current-month fed funds future, the 3-month fed funds future, and the euro-dollar futures at the horizons of two, three, and four quarters. Figure 3 shows the time series of high-frequency surprises. However, this standard high-frequency futures markets surprises reveal information not just about monetary policy but also about the central bank's assessment of the economic outlook.

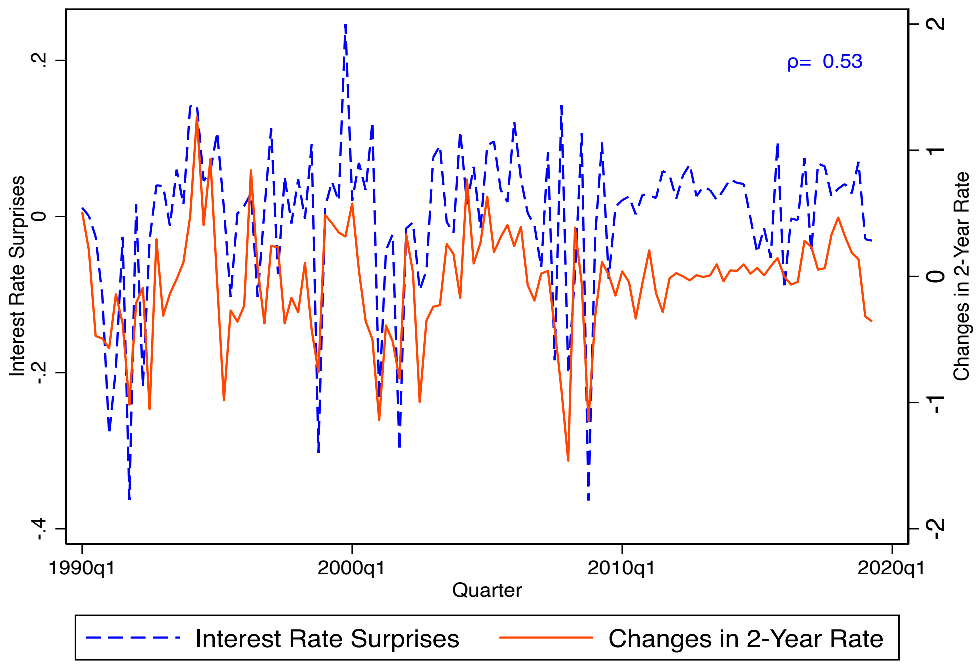
Jarociński and Karadi (2020) propose separating monetary policy shocks from contemporaneous information shocks by analyzing the high-frequency co-movement of high-frequency interest rate surprises and stock prices in a 30-minute window around the policy announcement[2]. They decompose the high-frequency surprises into monetary policy shock and central bank contemporaneous information shock. For the monetary policy shock, they calculate two measures: Poor Man monetary policy shocks and Median rotation monetary policy shocks. Figure A2 shows the two-time series of monetary policy shocks. To construct quarterly mea-

[1] Federal funds futures are traded on the Chicago Board of Trade. The surprises are based on a tick-by-tick dataset of actual futures trades obtained from Genesis Financial Technologies.

[2] Following Miranda-Agrippino and Ricco (2021), we address this concern in robustness analysis by allowing GDP growth and inflation forecasts from the *'Green Book'* of the Federal Reserve Board of Governors to predict differences in firm behavior alongside the measures of monetary policy shocks.

sures of monetary policy shocks from the high-frequency series, we simply sum up the daily shocks for each quarter.

Figure 3: High-frequency interest rate surprises



Note: This graph shows the time series of high-frequency interest rate surprises from Jarocinski & Karadi (2020), who use high-frequency data from futures markets around within a 30-minute window starting 10 minutes before and ending 20 minutes after the FOMC announcement. Following Nakamura and Steinsson (2018), we use the first principal component of the surprises in fed funds futures and euro-dollar futures with one year or less to expiration. Calculating the surprises uses five indicators: the current-month fed funds future, the 3-month fed funds future, and the euro-dollar futures at the horizons of two, three, and four quarters.

2.5 Markups

We construct firm-level estimates of markups using the user-cost of approach. The other alternative would be the ratio estimator of markups developed by De Loecker et al. (2020) based on the production function estimation approach. We don't use this approach because of the challenges in identifying output elasticities from revenue data, as recently emphasized by Bond et al. (2021).

Following Baqaee et al. (2023), we assume that the operating surplus of each firm consists of payments of capital and rents:

$$OS_{it} - r_{it}K_{it} = \left(1 - \frac{1}{\mu_{it}}\right) Q_{it}$$

where OS_{it} is operating income after depreciation and minus income taxes, r_{it} is the user-cost of capital, K_{it} is the quantity of capital, μ_{it} is the markups, and Q_{it} is the net sales. Following Gutiérrez and Philippon (2017), we calculate the user cost of capital:

$$r_{it} = r_t^f + RP_{st} - (1 - \delta_{st})\, \mathbb{E}[\Pi_{st+1}]$$

where r_t^f is the risk-free rate, RP_{st} is the industry-level capital risk premium, δ is the industry-level BEA depreciation rate, and $\mathbb{E}[\Pi_{st+1}]$ is the expected growth in the relative price of capital. We assume expected capital gains are equal to realized capital gains, measured as the growth in the relative price of capital compared to the PCE deflator. Due to limitations on the industry-level risk premium,[3] we calculate markups from 1990 to 2015 using the user-cost approach.

2.6 Data

We use quarterly firm-level balance sheet data of publicly listed US firms for the period 1990:I to 2019:II from Compustat. The main advantage of Compustat is that it has quarterly data, a frequency that is appropriate to study monetary policy, and it has rich balance-sheet information which allows the construction of key variables of interest. The main disadvantage is that it excludes privately held firms.[4] We exclude firms in utilities (sic $\in$ [4900; 4999]), finance, insurance, real estate (sic $\in$ [6000, 6799]), and public administration. We drop duplicate firm-quarter observations. We discard observations of sales (*saleq*), costs of goods sold (*cogsq*) and net property, plant, and equipment (*ppentq*) and total assets (*atq*) that are weakly negative. We fill three-quarter gaps in the firm-specific series of these variables by linear interpolation. We fill in missing values of depreciation and amortization(*dpq*), selling,

[3]Thanks to German Gutierrez for sharing the industry-level risk premium.

[4]An alternative is Quarterly Financial Reports (QFR) which is comprehensive and includes private and smaller firms, but the database is not openly available; an example using QFR is Crouzet and Mehrotra (2020).

general and administrative expenses ($xsgaq$), debt in current liabilities ($dlcq$), long-term debt ($dlttq$) and cash and short-term investments ($cheq$) by zero. We discard observations of these same variables if they are strictly negative.

To construct a measure of allocative efficiency following Bils et al. (2021), we use sales ($saleq$) and capital stock ($ppentq$) from the Compustat quarterly sample. We calculate the quarterly employment variable based on the yearly employment variable (emp). To calculate the labor costs, we use industry-level wages from the Quarterly Census of Employment and Wages (QCEW) program database. Since Compustat does not have the material costs, we impute the material costs as the cost of goods sold ($cogsq$) from Compustat plus administrative and selling expenses ($xsgaq$) from Compustat less depreciation (dpq) from Compustat and labor costs. We trim the .5% tails of $\frac{TFPR_{si}}{TFPR_s}$ and $\frac{TFPQ_{si}}{TFPQ_s}$ in each quarter, pooling all industries. After trimming the sample, we recalculate the sector shares, TFPR, and TFPQ. We use the company's initial public offering date ($ipodate$) to calculate the age of a firm. We use the quarterly implicit price deflator from the FRED database for the nonfarm business sector.

Table 1: Firm characteristics

Variables	Overall	Relative Firm Characteristics High Markup	Large Firms	Old Firms
Assets ($ billion)	2.54	1.49	35.21	3.61
Employees (thousand)	8.65	1.77	17.16	4.04
Sales ($ billion)	0.58	1.75	25.52	4.10
Age of Firms	16.47	1.18	1.59	3.78
Markup	0.98	1.37	1.08	1.06
log(Labor productivity)	10.76	1.02	1.44	1.17
log(TFP)	0.32	1.29	0.93	1.01
log(TFPRsi)	0.38	1.61	0.75	0.94
log(TFPQsi)	3.13	1.60	2.06	1.47
Relative obs		1.18	0.46	0.99
Observations'000	399	194	126	199

Note: This table shows firm characteristics relative to counter groups. For example, high markup is compared to low markup firms. Assets and sales are averages from 1990:I to 1919:II within the group expressed in real US$2012; values are deflated by the quarterly implicit price deflator for the nonfarm business sector from the FRED database. We calculate TFP by estimating the production function using Olley and Pakes (1996) applying the Ackerberg et al. (2015) correction.

Table 2 provides firm characteristics of Compustat firms. We use three measures of firm characteristics: markup, size, and age of firms. We use the size and age of firms to capture firm-level financial frictions. To measure markups, we use the use-cost approach as mentioned before. We measure firm size based on total assets and firm age based on the initial public offering date. The table shows that high markup firms have higher assets, more employees, larger sales, and higher productivity.

Table 3 shows the standard correlation (lower triangular matrix) among firm characteristics and contemporaneous correlation of those using the regression-based filter of Hamilton (2018) (upper triangular matrix). Both correlations are positive for markups with assets, sales, and age of firms.

Table 2: Correlation among firm characteristics

Variables	**Markups**	**ln(Real Assets)**	**ln(Real Sales)**	**ln(Firm Age)**
Markups	1.00	0.11	0.39	0.01
ln(Real Assets)	0.25	1.00	0.64	0.00
ln(Real Sales)	0.36	0.94	1.00	0.01
ln(Firm Age)	0.14	0.33	0.35	1.00

Note: This table shows the standard correlation (lower triangular matrix) among firm characteristics and contemporaneous correlation of those using the regression-based filter of Hamilton (2018) (upper triangular matrix).

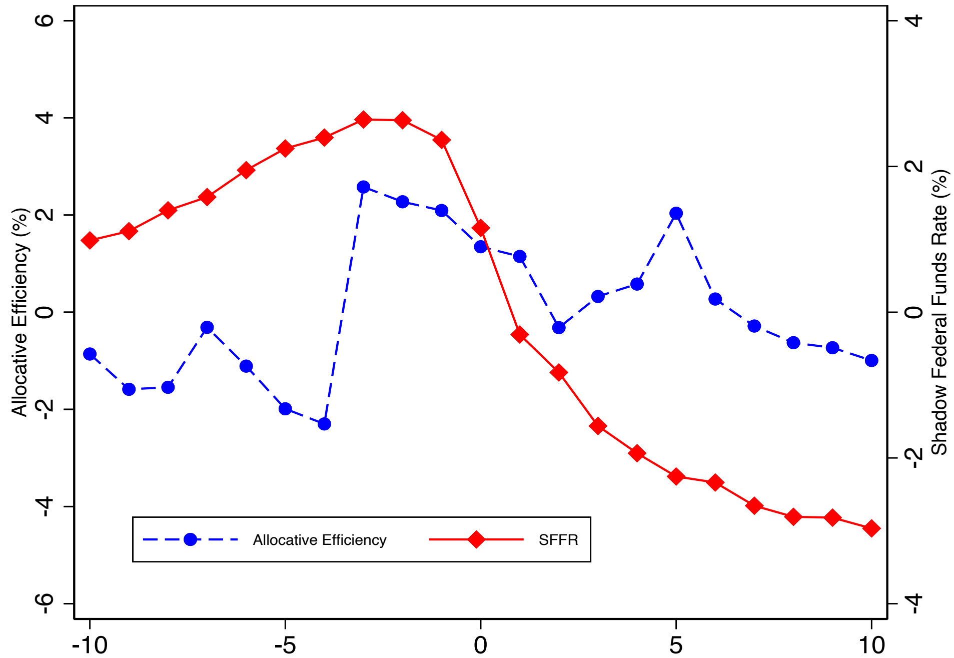
3 Macro-level evidence

In this section, we explain the causal effects of monetary policy shocks on allocative efficiency. First, we explain aggregate allocative efficiency using the Burns-Mitchell event study Diagram. Then, we discuss the causal effects of monetary policy shocks on aggregate allocative efficiency and firm-level misallocation.

3.1 Aggregate Allocative Efficiency and Burns-Mitchell Diagram

Figure 4 shows the average pattern of allocative efficiency around cyclical peaks, as measured by the start quarter of recessions (2001q1 and 2007q4) in the United States since 1990. An average cycle is obtained as follows. First, the peak of the cycle is isolated. Then the surrounding observations are normalized by the value of the variable at the peak. This procedure is repeated for each peak in the data span and the average across all cycles is computed. Specifically, we calculate the number of these graphs: $x_t = \frac{1}{N}\sum_{i=1}^{N}\left(y_{it} - \frac{1}{21}\sum_{t=-10}^{10} y_{it}\right)$, where y_{i0} is the quarter of business cycle peak. We use Shadow Federal Fund Rate from Wu and Xia (2016).

Figure 4: Burns-Mitchell Diagram



Note: This figure shows the average pattern of allocative efficiency around cyclical peaks. We use Shadow Federal Fund Rate from Wu and Xia (2016). Both allocative efficiency and Shadow Federal Fund Rate are in percent.

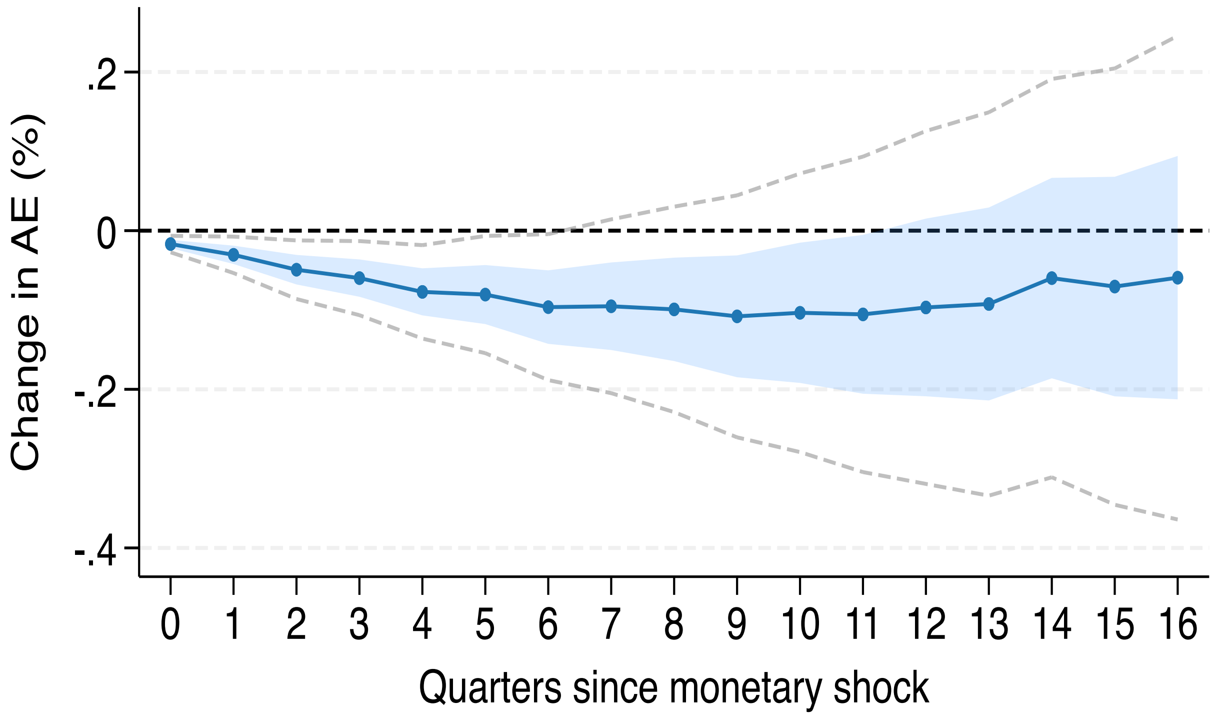
3.2 Local Projection of Contractionary Shocks

To assess the dynamic response of allocative efficiency to monetary policy shocks, we use a local projection method as outlined by Jordà (2005). This approach allows us to directly estimate the impact of these shocks on allocative efficiency over different horizons. The empirical specification employed for this purpose is detailed as follows:

$$\begin{aligned}\Delta \log \mathrm{AE}_{t\to t+h} = a^h &+ \sum_{k=0}^{4} b_k^h \cdot \mathrm{Shock}_{t-k} \\ &+ \sum_{k=1}^{4} c_k^h \cdot \Delta \log \mathrm{AE}_{t-k\to t} + \epsilon_t^h\end{aligned}$$

In this specification, $\Delta \log \mathrm{AE}_{t\to t+h}$ represents the logarithmic change in allocative efficiency from period t to $t+h$, capturing the evolution of allocative efficiency over the horizon of interest. The term a^h is a constant term specific to each horizon h, capturing fixed effects that might influence the efficiency change over time. The coefficients b_k^h quantify the response of allocative efficiency to monetary shocks (Shock_{t-k}) lagged by k periods, with each term capturing the effect of these shocks at different lags. A negative value of b_k^h ($b_k^h < 0$) is indicative of a contractionary monetary policy shock adversely affecting allocative efficiency, suggesting that such shocks lead to a deterioration in the efficient allocation of resources within the economy. Moreover, the coefficients c_k^h measure the impact of past changes in allocative efficiency on its future trajectory, thereby allowing for an assessment of the dynamic properties of allocative efficiency itself. The inclusion of these lagged changes in allocative efficiency serves to control for the autoregressive nature of allocative efficiency, ensuring that the estimated effects of monetary shocks are not confounded by the inherent dynamics of allocative efficiency. The term ϵ_t^h denotes the error term, capturing unobserved factors that may affect the change in allocative efficiency at horizon h. We use the identification of monetary policy shocks as outlined by Jarociński and Karadi (2020), utilizing their methodology to isolate exogenous movements in monetary policy that are devoid of the contemporaneous reaction of the economy to other, non-policy related shocks. This identification strategy allows for a clear interpretation of the estimated coefficients as the causal impact of monetary policy shocks on allocative efficiency.

Figure 5: Local projection of a contractionary shock on allocative efficiency

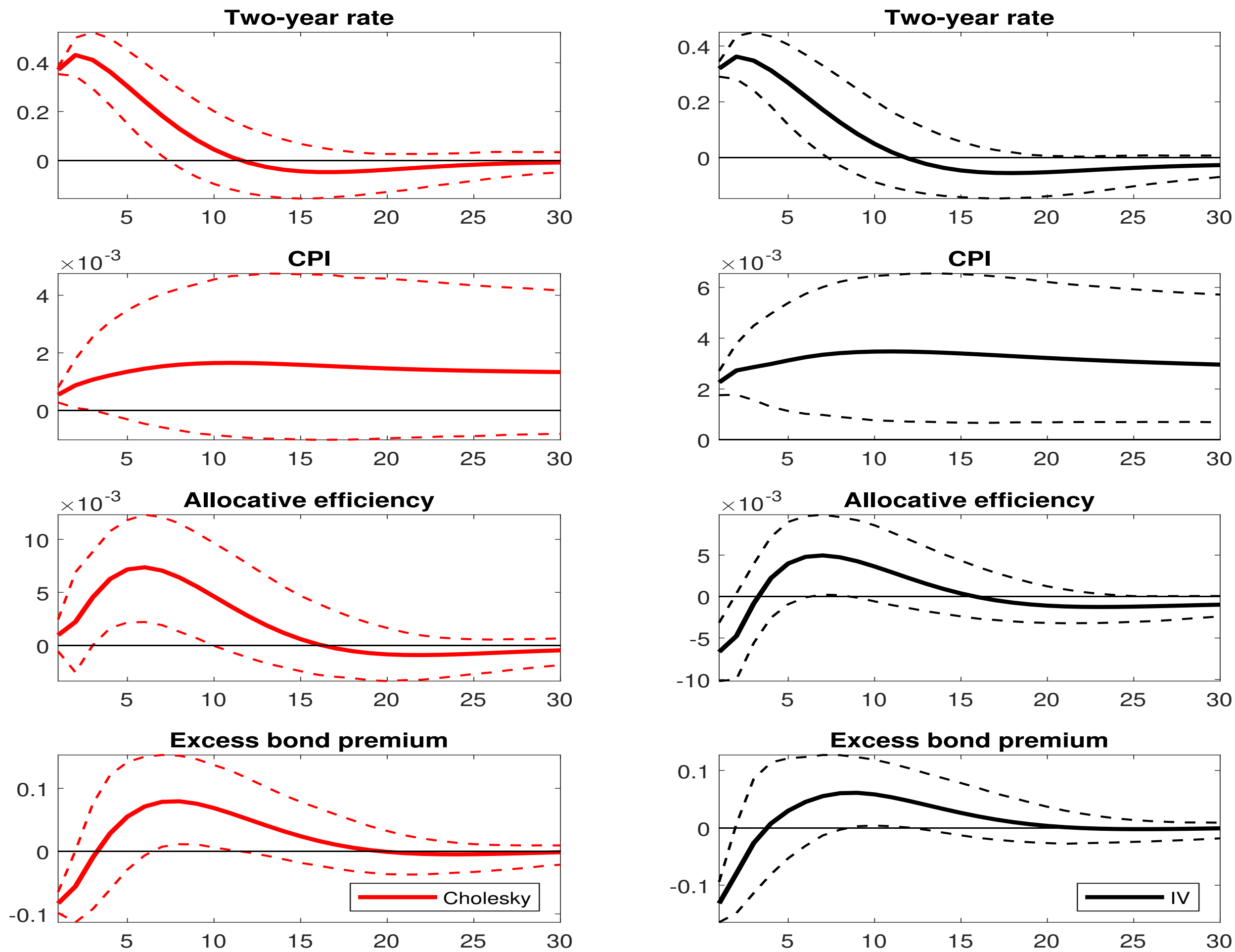


Note: The shaded region indicates Newey-West standard errors. Dashed lines are 95% confidence intervals.

3.3 Aggregate Allocative Efficiency

We estimate the effects of a monetary policy shock on aggregate allocative efficiency using a proxy SVAR model that contains both economic and financial variables. We use the 4-variable proxy SVAR specification used by Gertler and Karadi (2015), applying it to quarterly data. We use the two-year treasury rate, consumer price index (CPI), allocative efficiency, and excess bond premium. Figures 6 and 7 show the impulse responses of these variables for the interest rate surprises and Poor Man's monetary shocks. The right panels show the case where monetary policy shocks are identified using external instruments.

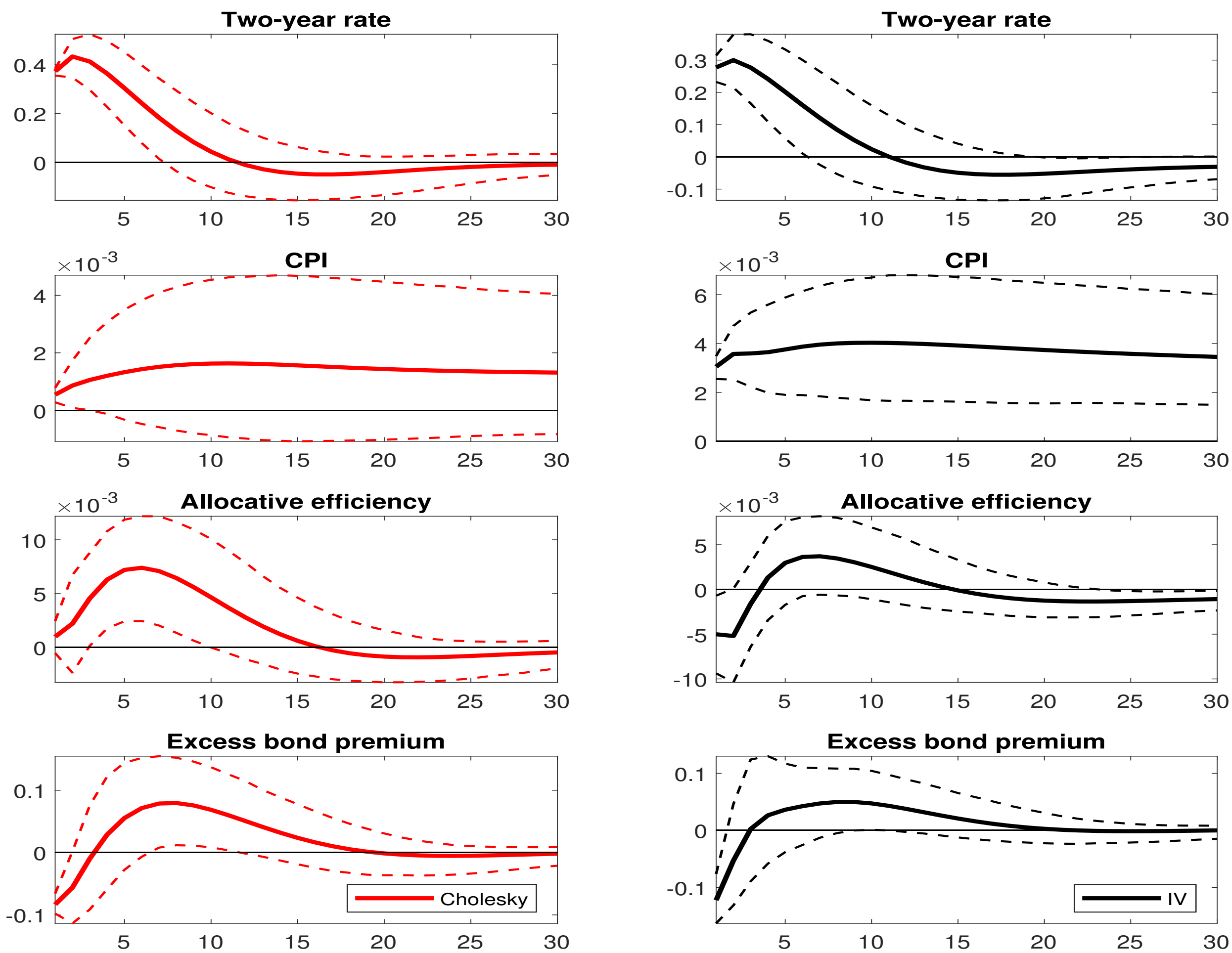
Figure 6: Dynamic effects of a one standard deviation shock (First Principal shocks)



Note: These graphs use a structural VAR developed by Gertler and Karadi (2015) and show impulse responses to one standard deviation monetary policy shock from a 4-variable proxy SVAR. All variables are in percentages. 90% confidence intervals from wild bootstrap.

For comparison, the left panels show the case using a standard Cholesky identification. In each case, the panels report the estimated impulse responses along with 90 percent confidence bands, computed using bootstrapping methods. As the top right panel shows, a one standard deviation surprise monetary tightening induces a roughly 30 basis point increase in the two-year treasury rate. Consistent with the theoretical prediction, there is a significant decline in aggregate allocative efficiency. The effect on allocative efficiency disappeared after four quarters. Consistent with the price puzzle, there is an increase in the consumer price index, which is statistically significant. These impulse responses show that a one-standard-deviation surprise monetary tightening induces a roughly 30 basis point increase in the two-year treasury rate and reduces allocative efficiency by one percent. Thus, these results are consistent with our previous results that adverse monetary policy shocks lead to decrease allocative efficiency and increase resource misallocation.

Figure 7: Dynamic effects of a one standard deviation shock (Poor Man's shocks)



Note: These graphs use a structural VAR developed by Gertler and Karadi (2015) and show impulse responses to one standard deviation monetary policy shock from a 4-variable proxy SVAR. All variables are in percentages. 90% confidence intervals from wild bootstrap.

3.4 Bayesian SVAR

Following Jarocinski & Karadi (2020), we use a Bayesian SVAR that enables us to combine HFI and sign restrictions in order to identify the monetary policy shocks on allocative efficiency. Let m_t be a vector of surprises in financial variables in quarter t and y_t be a vector of macroeconomic and financial variables. We use a VAR model with m_t and y_t and a restriction that m_t does not depend on the lags of either m_t or y_t and has a zero mean,

$$\begin{pmatrix} m_t \\ y_t \end{pmatrix} = \sum_{p=1}^{P} \begin{pmatrix} 0 & 0 \\ B_{YM}^p & B_{YY}^p \end{pmatrix} \begin{pmatrix} m_{t-p} \\ y_{t-p} \end{pmatrix} + \begin{pmatrix} 0 \\ C_y \end{pmatrix} + \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix}, \begin{pmatrix} u_t^m \\ u_t^y \end{pmatrix} \sim N(0, \sum)$$

where N denotes the normal distribution.

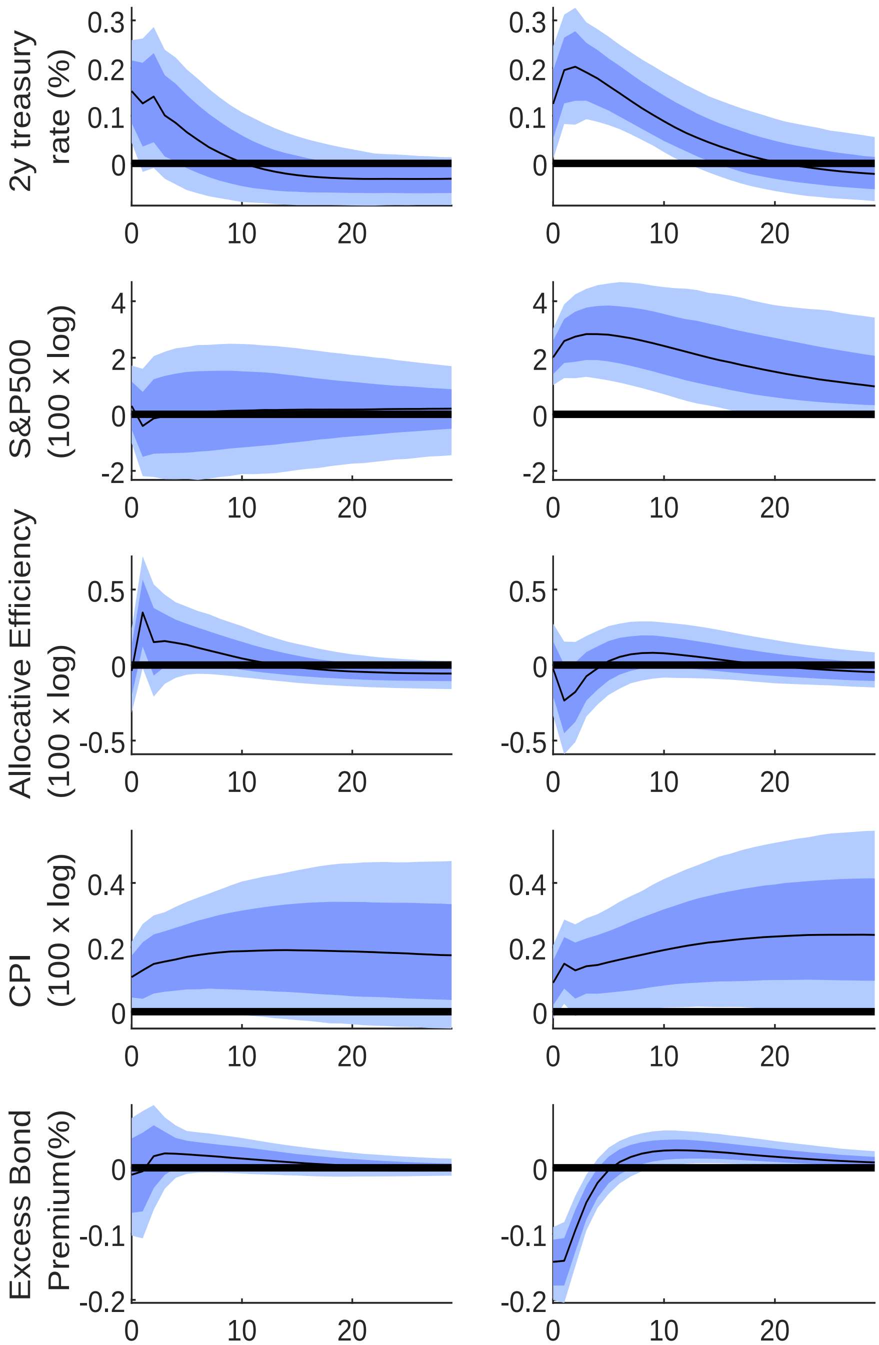
We identify two structural shocks transmitted through the central bank announcements: Monetary policy (negative co-movement shock) and Central bank information (positive co-movement). Figure A3 shows the negative and positive co-movement. We use two assumptions on the announcement surprises to isolate these shocks; we impose no restrictions on any macroeconomic and financial variables. Our assumption related to HFI is that the announcement surprises m_t are affected by the two announcement shocks (the negative co-movement shock and positive co-movement) and not by other shocks. Our assumption related to sign restrictions is that a negative co-movement shock is associated with an interest rate increase and a drop in stock price. A positive co-movement shock is a complementary shock that is associated with an increase in both interest rates and stock prices. Table 4 shows our set of identification restrictions.

Table 3: Identification restrictions

Variable	Shock		
	Monetary policy (negative co-movement)	**CB information** (positive co-movement)	**Other**
m_t, high frequency			
Interest rate surprise	+	+	0
Stock price surprise	−	+	0
y_t, low frequency			
Interest rate	+	+	0
Stock price index	−	+	0
Other	•	•	•

Note: Restrictions on the contemporaneous responses of variables to shocks. +, −, 0, and • denote the respective sign restrictions, zero restrictions, and unrestricted responses.

Figure 8: Impulse responses to a one standard deviation shock



Note: These graphs use a Bayesian SVAR developed by Jarocinski & Karadi (2020) and show impulse responses to a one standard deviation shock. Median (line), percentiles 16–84 (darker band), percentiles 5–95 (lighter band). The left panel is for monetary policy (negative co-movement) and the right panel is for central bank information (positive co-movement).

In our VAR model, we include seven variables: two high-frequency surprise variables in m_t and five low-frequency macroeconomic and financial variables in y_t; m_t consists of the surprises in the three-month fed funds futures and the S&P 500 stock market index; y_t includes a two-year treasury rate, a stock price index, allocative efficiency, CPI, and excess bond premium. We use similar variables of the proxy VAR estimation. Figure 8 shows impulse responses to a one standard deviation shock using the Bayesian VAR developed by Jarocinski & Karadi (2020). This figure shows that the Fed's information about the contemporaneous economic outlook strongly impacts allocative efficiency.

4 Micro-level evidence

4.1 Firm-Level Misallocation by Firm Characteristics

To identify the static heterogeneous effect of monetary policy shocks on firm-level misallocation, we use instrumental variables:

$$ln(Y_{i,t}) \;=\; \alpha_i + \alpha_{sy} + \phi^j \ \mathbb{1}_{\{i \in \mathcal{I}^j_{t-1}\}} + \Delta\hat{r}_t\beta + \Delta\hat{r}_t \ \mathbb{1}_{\{i \in \mathcal{I}^j_{t-1}\}}\beta^j + \boldsymbol{x}_{i,t-1}\boldsymbol{\gamma} + u_{i,t}, \tag{4}$$

where $Y_{i,t}$ is a measure of firm-level misallocation and i indexes a firm, α_i is a firm fixed effect, α_{sy} is a sector-by-year fixed effect, $\mathbb{1}_{\{i \in \mathcal{I}^j_{t-1}\}}$ is an indicator variable of firm characteristics, $\boldsymbol{x}_{i,t-1}$ is a set of macroeconomic and firm-level controls, and the estimates of $\Delta\hat{r}_t$ come from the first stage regression using an instrument z_t. The coefficient β^j measures the static heterogeneous response of firm-level misallocation to a monetary policy shock in quarter t depending on firm characteristics in quarter $t-1$.

Table 4: Effects of monetary policy on misallocation

Variables	**Firm-Level Misallocation**		
	(1)	(2)	(3)
2-Year Rate Change	-0.0321	-0.0421	-0.0485
	(0.03)	(0.03)	(0.03)
High Markups × 2-Year Rate Change	-0.0225		
	(0.02)		
High Markups × Large Firms × 2-Year Rate Change		-0.0317	
		(0.03)	
High Markups × Old Firms × 2-Year Rate Change			0.0025
			(0.02)
Firm Controls	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes
N	338368	338368	338368

Note: An observation is a firm and quarter combination. Our firm controls include markup, size, and age of firms with a lag, and macro controls include CPI, excess bond premium, and GDP growth with two lags. Standard errors are clustered at the firm level and cluster standard errors are in parentheses. ***, **, and * indicate statistically significant coefficients at the 1%, 5%, and 10% percent levels.

Table 5 shows the cross-section evidence of the effects of monetary policy on firm-level misallocation by firm characteristics. This table provides evidence that adverse monetary policy shocks lead to an increase in firm-level misallocation, however, this effect is lower for high markup firms and further lower for large firms with high markups. The coefficient for old firms with high markups is not significant at the 10% level. This could be due to the measure that we use to calculate the age of a firm, which is calculated since incorporation instead of since foundation as pointed out by Cloyne et al. (2018).

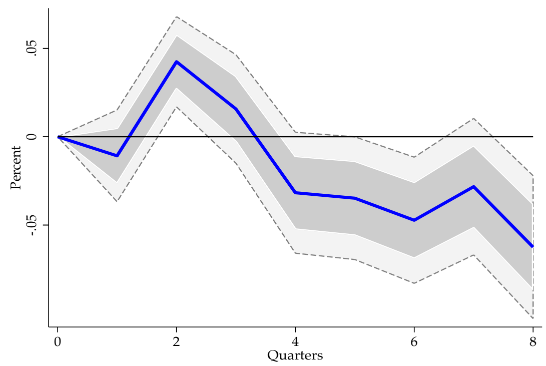
In order to estimate the dynamics of differential responses to a policy shock across firms, we estimate the following set of Jorda (2020)-style LP-IV model:

$$ln(Y_{i,t+h}) - ln(Y_{i,t}) = \alpha_{i,h} + \alpha_{sy,h} + \phi_h^j \ \mathbb{1}_{\{i \in \mathcal{I}_{t-1}^j\}} + \Delta\hat{r}_t \beta_h + \Delta\hat{r}_t \ \mathbb{1}_{\{i \in \mathcal{I}_{t-1}^j\}} \beta_h^j + \boldsymbol{x}_{i,t-1} \boldsymbol{\gamma}_h + u_{i,t+h}, \quad (5)$$

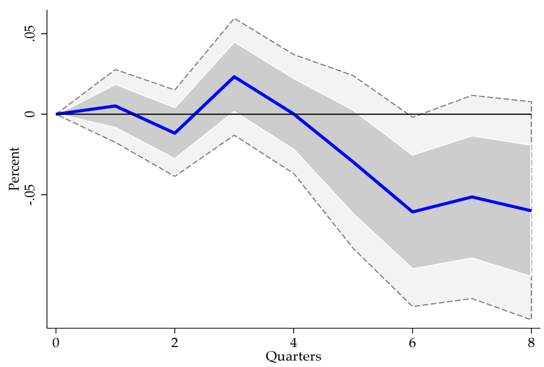
where $Y_{i,t+h}$ and $Y_{i,t}$ are a measure of firm-level misallocation, $h \geq 1$ indexes the forecast horizon, and i indexes a firm. $\alpha_{i,h}$ is a firm fixed effect, , $\alpha_{sy,h}$ is a sector-by-year fixed effect, $\mathbb{1}_{\{i \in \mathcal{I}_{t-1}^j\}}$ is an indicator variable of firm characteristics, and $\boldsymbol{x}_{i,t-1}$ is a set of macroeconomic and firm-level controls. The estimates of $\Delta\hat{r}_t$ come from the first stage regression using an instrument z_t. The coefficient β_h^j measures how the cumulative heterogeneous response of allocative efficiency in quarter $t+h$ to a monetary policy shock in quarter t depends on firm characteristics in quarter $t-1$.

Figure 10 shows the dynamic heterogeneous effects of monetary policy shocks on firm-level misallocation by firm characteristics. Figure 9a shows the dynamic differential effects of high relative to low markup firms and the effect is highest in quarter 6. We get similar results if we interact with large and old firms (see Figures 9b and 9c).

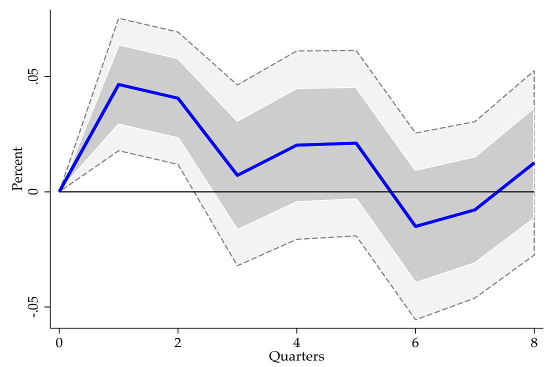
Figure 9: Heterogeneous effects of shocks on misallocation by firm characteristics



(a) Difference of Coefficients (High - Low)



(b) High markups and Large Firms



(c) High markups and Old Firms

Note: Dynamics of the interaction coefficient of the change in treasury rates instrumented by monetary policy shocks and a firm characteristic for firm-level misallocation over time. Our firm controls include markup, size, and age of firms with a lag, and macro controls include CPI, excess bond premium, and GDP growth with two lags. Shaded areas report 90% and 68% error bands.

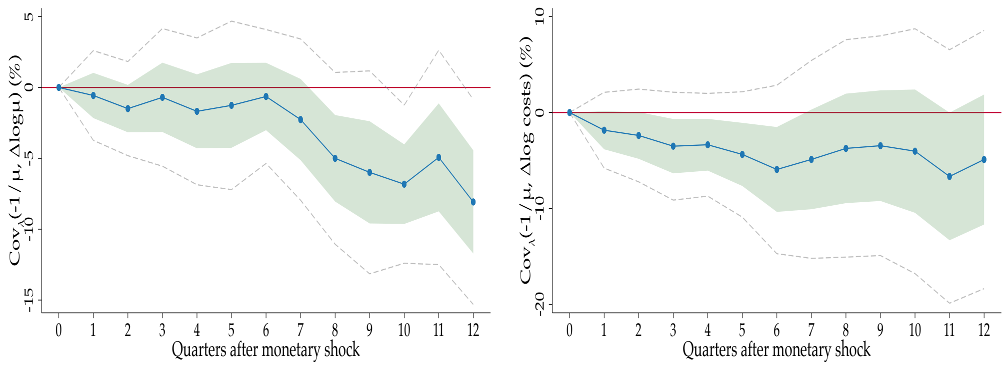
4.2 Local Projection of a Contractionary Shock on allocative efficiency

Following Baqaee et al. (2023), we estimate the local projections using the equation $\Delta \log TFPR = \Delta \log \mu_0 + \Delta \log w$, where μ and w represent markup and wage, respectively. The covariance formulas are presented as follows:

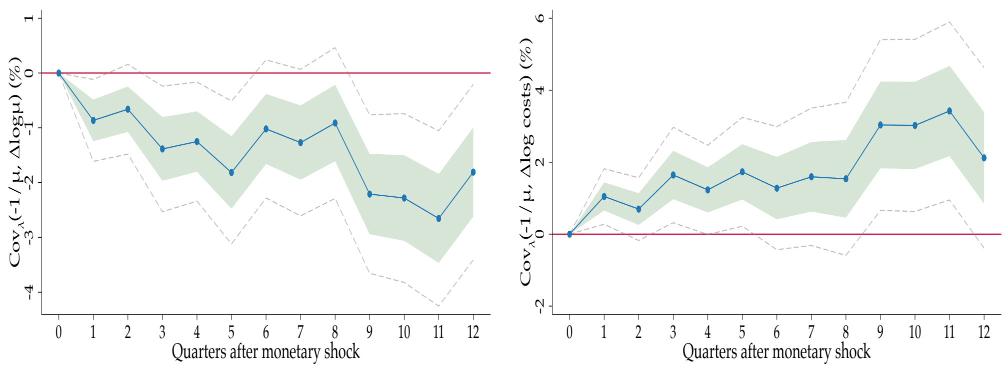
$$
\begin{aligned}
Cov_\lambda\left(-\frac{1}{\text{TFPR}}, \Delta \log \text{TFPR}_{t\to t+h}\right) &= a^h + \sum_{k=0}^{4} b_k^h \cdot \text{Shock}_{t-k} \\
&+ \sum_{k=1}^{4} c_k^h \cdot Cov_\lambda\left(-\frac{1}{\text{TFPR}}, \Delta \log \text{TFPR}_{t-k\to t}\right) + \epsilon_t^h, \\
Cov_\lambda\left(-\frac{1}{\text{TFPR}}, \Delta \log \text{Costs}_{t\to t+h}\right) &= \tilde{a}^h + \sum_{k=0}^{4} \tilde{b}_k^h \cdot \text{Shock}_{t-k} \\
&+ \sum_{k=1}^{4} \tilde{c}_k^h \cdot Cov_\lambda\left(-\frac{1}{\text{TFPR}}, \Delta \log \text{Costs}_{t-k\to t}\right) + \epsilon_t^h.
\end{aligned}
$$

In these equations, $Cov_\lambda\left(-\frac{1}{\text{TFPR}}, \Delta \log \text{TFPR}_{t\to t+h}\right)$ is the sale-weighted covariance between the inverse TFPR at time t and the change in TFPR from time t to time $t+h$. Here, $b_k^h > 0$ suggests that a contractionary shock causes high-TFPR firms to increase their TFPR more than low-TFPR firms. Similarly, $Cov_\lambda\left(-\frac{1}{\text{TFPR}}, \Delta \log \text{Costs}_{t\to t+h}\right)$ is the sale-weighted covariance between the inverse TFPR at time t and the change in total costs from time t to time $t+h$, where $\tilde{b}_k^h < 0$ indicates that a contractionary shock reallocates resources away from high-TFPR firms towards low-TFPR firms. Lastly, Shock_t represents the Jarocinski & Karadi (2020) shock in quarter t.

Figure 10: Local projection of a contractionary shock on AE



(a) $Cov_{\lambda}(-1/TFPR, \Delta logTFPR)$ **(b)** $Cov_{\lambda}(-1/TFPR, \Delta logCosts)$



(c) $Cov_{\lambda}(-1/TFPR, \Delta logTFPR)$ within NAICS-3 **(d)** $Cov_{\lambda}(-1/TFPR, \Delta logCosts)$ within NAICS-3

Note: The shaded region indicates Newey-West standard errors in panels (a)-(b) and Driscoll-Kraay standard errors in panels (c)-(d). Dashed lines are 95% confidence intervals.

5 Conclusion and Policy Implications

We ask the following questions: What is the causal effect of monetary policy shocks on allocative efficiency? Does the effect differ by firm characteristics such as markup, size, and age of firms? We provide evidence that tighter monetary shocks reduce allocative efficiency, however, the effect of these shocks differs by firm characteristics such as markup, size, and age of firms.

This paper uses Compustat firm-level data from 1990:I to 2019:II and monetary policy shocks measured by high-frequency surprises from Jarocinski & Karadi (2020). In addition, we use the proxy SVAR and the LP-IV proposed by Jorda (2020). We find that tighter monetary shocks reduce allocative efficiency, however, the effect of these shocks differs by firm characteristics. For example, low markup firms are more responsive to these shocks compared to high markup firms. In addition, constrained firms, measured by size and age of firms, are responsive in terms of changes to allocative efficiency following a tighter monetary shock.

The main contribution of this paper is that monetary policy shocks affect allocative efficiency. Specifically, it is seen that rate cuts increase efficiency, involving a movement of factors from low-markup to high-markup firms, which are more productive. The opposite happens with rate hikes, as resources transfer in favor of low-markup firms. Therefore, countercyclical monetary shocks meant to prop up the economy in a recession, work their way by influencing the markup differential between high- and low-markup firms. In the Great Recession, for example, as rate cuts took hold in the midst of the recession, this markup difference rose along with an economic rebound in GDP and continued for some years. Prior to the recession, rates were peaking around 2005-2006, when the markup difference was falling and GDP growth had peaked. Additionally, financial frictions, proxied by firms' asset size and age, impinge on allocative efficiency as financing constraints bind following rate increases. Firms with larger assets and more experienced (older) tend to fare better in tightening conditions. An interesting insight of the paper is that monetary tightening reduces GDP growth, but it is also associated with a loss of allocative efficiency. By symmetry, favorable policy shocks have the opposite effects on GDP growth and efficiency. That the effect on GDP growth is accompanied by changes in efficiency suggests something more robust about the nature of monetary policy effects.

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Appendix A: Variable Definitions, Sources, and Data Construction

Gross Output, Q_{si}**:** Quarterly net sales (*saleq*) from Compustat; deflated by an industry-level price index, the yearly deflator for shipments (*piship*) from the NBER-CES database. We use log-linear interpolation for the missing observations.

Labor, L_{si}**:** We construct quarterly employment based on the yearly employment data (*emp*) by merging annual and quarterly Compustat series using the firm identifier (*gvkey*) and time (*datadate*). We use log-linear interpolation for the missing observations.

Labor Cost, wL_{si}**:** We construct quarterly labor cost by multiplying quarterly employment (L_{si}) constructed as explained before with the average industry wages from the Quarterly Census of Employment and Wages (QCEW) program database. The industry wage is calculated using the ratio of the total quarterly wages to the average employment for three months of a quarter from the QCEW database. We use the quarterly implicit price deflator from the FRED database for the nonfarm business sector.

Capital, K_{si}**:** Value of property, plant, and equipment, net of depreciation, from Compustat. We use log-linear interpolation for the missing observations. We use the quarterly implicit price deflator from the FRED database for the nonfarm business sector.

Intermediates, X_{si}**:** To construct intermediates, we consider only material costs. We measure material costs as the cost of goods sold (*cogsq*) from Compustat plus administrative and selling expenses (*xsgaq*) from Compustat less depreciation (*dpq*) from Compustat and labor cost constructed (wL_{si}) as explained before. We use log-linear interpolation for the missing observations. We use the quarterly implicit price deflator from the FRED database for the nonfarm business sector.

Appendix B: Allocative Efficiency

To measure allocative efficiency, we will follow Bils et al. (2021) and assume that in each period there are three types of firms: perfectly competitive final good producers, who combine goods from sectors using a Cobb-Douglas production function; perfectly competitive sectoral good producers, who combine intermediate goods using a CES production function; and monopolistically competitive intermediate good producers in each sector, who produce intermediate goods using a Cobb-Douglas production function.

The final good producer's production function is

$$Q = \prod_{s=1}^{S} Q_s^{\theta_s}, \quad where \quad \sum_{s=1}^{S} \theta_s = 1$$

where S denotes the number of sectors and θ_s is the share of final output from sector s. The price of the final good normalizes, P, to 1.

The sectoral good producer's production function is

$$Q_s = \left(\sum_{i=1}^{N_s} Q_{si}^{1-\frac{1}{\epsilon}} \right)^{\frac{1}{1-\frac{1}{\epsilon}}}$$

where $\epsilon \geq 1$ is the elasticity of substitution between intermediate goods within a sector, Q_{si} is the output of intermediate good producer i, N_s is the total number of intermediate good producers in the sector, and P_s is the price index of output from sector s.

Firms in a sector differ in their productivity levels, A_{si} and face a Dixit-Stiglitz-type constant elasticity demand system, and they each choose a quantity (equivalently, price) to maximize the profit function:

$$\Pi_{si} \quad = \quad R_{si} - (1+\tau_{si}^{L})wL_{si} - (1+\tau_{si}^{K})rK_{si} - (1+\tau_{si}^{X})PX_{si},$$

subject to the firm's downward-sloping demand curve and the production function:

$$\begin{aligned} Q_{si} &= Q_s \left(\frac{P_{si}}{P_s} \right)^{-\epsilon} \\ Y_{si} &= A_{si}(K_{si}^{\alpha_s} L_{si}^{1-\alpha_s})^{\gamma_s} X_{si}^{1-\gamma_s}, \quad where, \quad 0 < \alpha_s, \gamma_s < 1 \end{aligned}$$

where L_{si} is the firm's labor, K_{si} is the firm's capital, X_{si} is the firm's intermediate input, and $R_{si}(= P_{si}Q_{si})$ is the firm's revenues. The output elasticities α_s and γ_s are sector-specific, but time-invariant and common across firms within a sector. Firms also face idiosyncratic labor distortions τ^L_{si}, capital distortions τ^K_{si}, and intermediate input distortions τ^X_{si}. The factor prices–assumed constant across firms–are w for labor and r for capital.

We can derive sector-level TFP as a function of firm-level productivity and distortions as well as decompose it into the product of four terms:

$$TFP_s = \underbrace{\left[\frac{1}{N_s}\sum_i^{N_s}\left(\frac{A_{si}}{\tilde{A}_s}\right)^{\epsilon-1}\left(\frac{\tau_{si}}{\tau_s}\right)^{1-\epsilon}\right]^{\frac{1}{\epsilon-1}}}_{AE_s=Allocative\ Efficiency} \times \underbrace{\left[\frac{1}{N_s}\sum_i^{N_s}\left(\frac{A_{si}}{\bar{A}_s}\right)^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}}_{PD_s=Productivity\ Dispersion} \times \underbrace{N_s^{\frac{1}{\epsilon-1}}}_{Variety} \times \underbrace{\bar{A}_s}_{Ave.\ Productivity}$$

where, $\tilde{A}_s$ is the power mean of idiosyncratic productivities, $\left[\frac{1}{N_s}\sum_i^{N_s} A_{si}^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}$, and $\bar{A}_s$ is the geometric mean of idiosyncratic productivities, $\prod_{i=1}^{N_s} A_{si}^{\frac{1}{N_s}}$. Where, $\tau_{si} = [(1+\tau^L_{si})^{1-\alpha_s}(1+\tau^K_{si})^{\alpha_s}]^{\gamma_s}(1+\tau^X_{si})^{1-\gamma_s}$, $\tau_s = [(1+\tau^L_s)^{1-\alpha_s}(1+\tau^K_s)^{\alpha_s}]^{\gamma_s}(1+\tau^X_s)^{1-\gamma_s}$, $(1+\tau^L_s) = [\sum_{i=1}^{N_s}\frac{R_{si}}{R_s}\frac{1}{1+\tau^L_{si}}]^{-1}$, and similarly for $(1+\tau^K_{si})$ and $(1+\tau^X_{si})$. AE_s is maximized and equal to 1 when there is no variation in the distortions across firms ($\tau_{si} = \tau_s\ \forall i$).

We can infer sectoral allocative efficiency using the following expression:

$$\hat{AE}_s = \left[\sum_i^{N_s}\left(\frac{TFPQ_{si}}{TFPQ_s}\right)^{\epsilon-1}\left(\frac{TFPR_{si}}{TFPR_s}\right)^{1-\epsilon}\right]^{\frac{1}{\epsilon-1}} \tag{6}$$

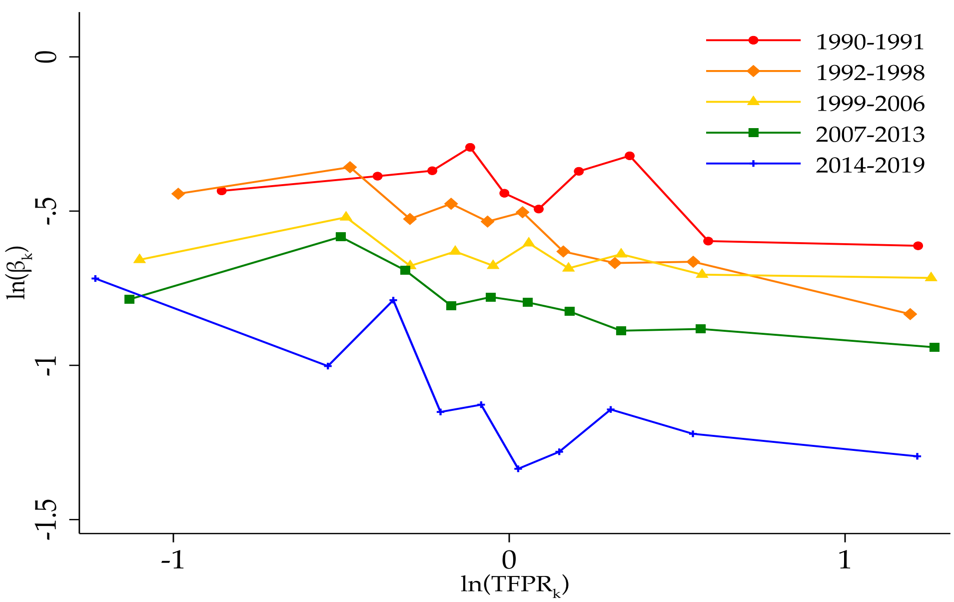
where, $TFPR_{si} = \frac{\hat{R}_{si}}{(\hat{K}_{si}^{\alpha_s}\hat{L}_{si}^{1-\alpha_s})^{\gamma_s}\hat{X}_{si}^{1-\gamma_s}}$, $TFPQ_{si} = \frac{(\hat{R}_{si})^{\frac{\epsilon}{\epsilon-1}}}{(\hat{K}_{si}^{\alpha_s}\hat{L}_{si}^{1-\alpha_s})^{\gamma_s}\hat{X}_{si}^{1-\gamma_s}}$, $TFPQ_s = \left[\sum_{i=1}^{N_s} TFPQ_{si}^{\epsilon-1}\right]^{\frac{1}{\epsilon-1}}$ and $TFPR_s = (\frac{\epsilon}{\epsilon-1})[\frac{MRPL_s}{(1-\alpha_s)\gamma_s}]^{(1-\alpha_s)\gamma_s}[\frac{MRPK_s}{\alpha_s\gamma_s}]^{\alpha_s\gamma_s}[\frac{MRPX_s}{1-\gamma_s}]^{1-\gamma_s}$. $MRPL_s$, $MRPK_s$, and $MRPX_s$ are the revenue-weighted harmonic mean values of the marginal products of labor, capital, and intermediates, respectively. In the absence of measurement error, TFPR would be proportional to the distortion and TFPQ would be proportional to productivity.

Aggregate allocative efficiency is:

$$\hat{AE}_t = \prod_{s=1}^{S}\hat{AE}_{st}\frac{\theta_{st}}{\sum_{s=1}^{S}\gamma_s\theta_{st}} \tag{7}$$

Without measurement error, this is equal to true allocative efficiency. To address measurement error, we use the method developed by Bils et al. (2021). To calculate a corrected measure of misallocation, we first construct a plant-level estimate of $\hat{\tau}$ as $ln(\hat{\tau}) = ln(TFPR) + ln(\hat{\beta}_k) + \epsilon$. We assume ϵ is lognormally distributed with a mean of zero and a variance given by $-Cov[ln(TFPR), ln(\hat{\beta}_k)] - Var(ln(\hat{\beta}_k))$. To estimate the coefficient of input growth, $ln(\hat{\beta}_k)$, we regress output growth on input growth separately for each decile k of TFPR after controlling sector-year fixed effects.[5] Figure A1 shows the $ln(\hat{\beta}_k)$, which are consistent with Bils et al. (2021).

Figure A1: Beta slopes



Note: We use the Compustat database for this graph. Following Bils et al. (2021), we estimate $ln(\hat{\beta}_k)$.

[5]see Bils et al. (2021) for the steps to correct the measurement error.

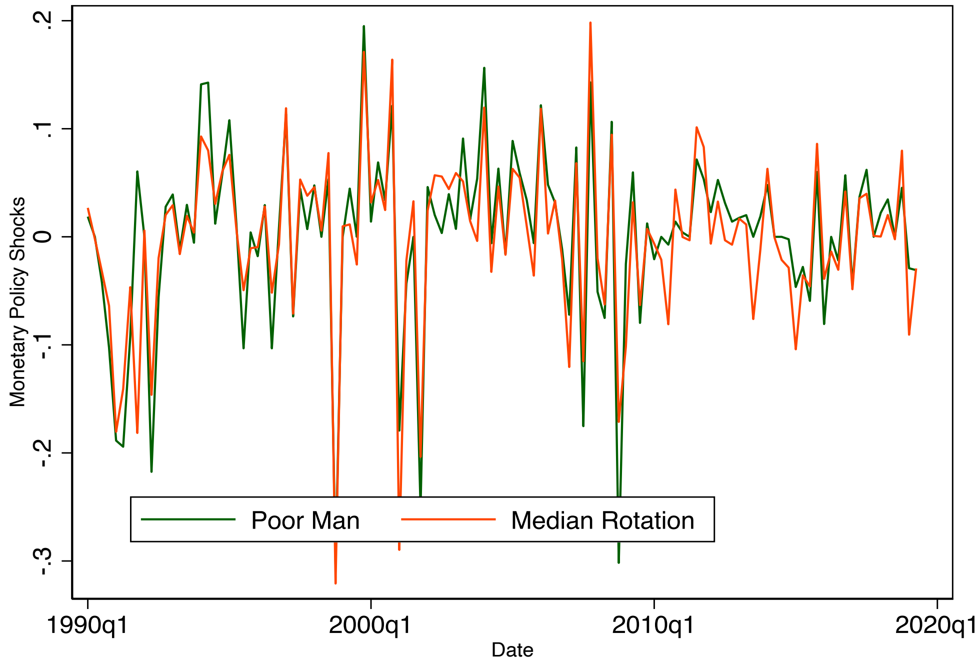
Appendix C: High-Frequency Surprises

Table A1: Major unconventional monetary policy announcements by the Fed, 2009 - 2015

Dates	**FOMC Announces**
March 18, 2009	Expects to keep the federal funds rate between 0 and 25 basis points (bp) for "an extended period", and will purchase \$750B of mortgage-backed securities, \$300B of longer-term Treasuries, and \$100B of agency debt ("QE1")
November 3, 2010	Will purchase an additional \$600B of longer-term Treasuries ("QE2")
August 9, 2010	Expects to keep the federal funds rate between 0 and 25 bp "at least through mid-2013"
September 21, 2011	Will sell \$400B of short-term Treasuries and use the proceeds to buy \$400B of long-term Treasuries ("Operation Twist")
January 25, 2012	Expects to keep the federal funds rate between 0 and 25 bp "at least through late 2014"
September 13, 2012	Expects to keep the federal funds rate between 0 and 25 bp "at least through mid-2015", and that it will purchase \$40B of mortgage-backed securities per month for the indefinite future
December 12, 2012	Will purchase \$45B of longer-term Treasuries per month for the indefinite future, and expects to keep the federal funds rate between 0 and 25 bp at least as long as the unemployment remains above 6.5% and inflation expectations remain subdued
December 18, 2013	Will start to taper its purchases of longer-term Treasuries and mortgage-backed securities to paces of \$40B and \$35B per month, respectively
December 17, 2014	"it can be patient in beginning to normalize the stance of monetary policy"
March 18, 2015	"an increase in the target range for the federal funds rate remains unlikely at the April FOMC meeting"

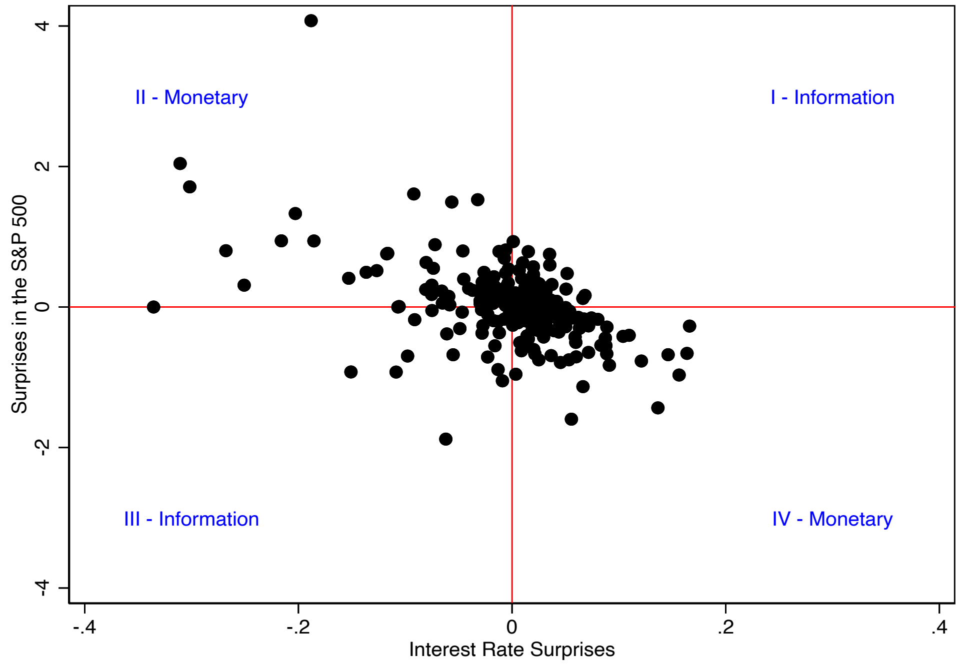
Note: ...

Figure A2: High-frequency interest rate surprises



Note: This figure shows the Poor Man monetary policy shocks and Median rotation monetary policy shocks from Jarocinski & Karadi (2020), who use high-frequency data from futures markets around within a 30-minute window starting 10 minutes before and ending 20 minutes after the FOMC announcement. Following Nakamura and Steinsson (2018), we use the first principal component of the surprises in fed funds futures and euro-dollar futures with one year or less to expiration. Calculating the surprises uses five indicators: the current-month fed funds future, the 3-month fed funds future, and the euro-dollar futures at the horizons of two, three, and four quarters.

Figure A3: Monetary and Fed Information Shocks



Note: This figure shows the scatter plot of the interest rate surprises and the surprises in the S&P 500. Each dot represents one FOMC announcement. Quadrants II and IV show the negative co-movement shocks between interest rates and stock prices whereas quadrants I and III show the positive co-movement of those variables.