Differential Effects of Monetary Policy on Capital Misallocation

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Abstract

This research investigates the supply-side effects of monetary policy interventions on capital misallocation, an area that has received less attention compared to demand-side impacts. We first derive various measures of capital misallocation and efficiency using the methodological framework of Hsieh & Klenow (2009). Utilizing the Compustat database and high-frequency financial market data, we identify monetary policy shocks through a local projections–instrumental variables (LP-IV) approach. Our results confirm that contractionary monetary policy increases capital misallocation and reduces sectoral efficiency, aligning with prior research. However, our observed patterns related to the mechanism challenge traditional financial friction and endogenous markup theories, suggesting that uncertainty—amplified by contractionary policy—induces random dispersion in revenue productivity.

Keywords: Monetary Policy, Misallocation, Productivity, Local Projections, Instrumental Variable

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1 Introduction

This study investigates the supply-side effects of monetary policy interventions on capital misallocation, an area that has received less attention compared to the demand-side impacts. Capital misallocation, defined as the allocation of capital to firms with lower rather than higher returns, has significant adverse effects on aggregate productivity. Understanding the role of monetary shocks in this misallocation, especially through the supply-side, is of paramount importance for designing effective monetary policies. In this paper, we first derive various measures of capital misallocation and efficiency, using the methodological framework of Hsieh and Klenow (2009). We then empirically identify the effects of monetary policy on capital misallocation and efficiency. Additionally, we estimate the differential impacts of monetary policy shocks on firms' revenue total factor productivity (TFPR), employing varying firm characteristics as proxies for financial frictions. This nuanced approach allows us to capture the heterogeneous effects of monetary policy across firms, providing deeper insights into the mechanisms through which monetary policy influences capital allocation and overall economic productivity.

Our primary data source is Compustat, which reports firm-level balance sheet information derived from publicly-listed U.S. firms. Since we do not observe quarterly employment data in the Compustat database, we make two assumptions to derive different measures of capital misallocation and efficiency within the Hsieh and Klenow (2009) framework. Our first assumption is that labor and capital distortions are present and equal. The second assumption is the absence of distortions in labor. Based on the second assumption, our results indicate that a tighter monetary policy leads to higher resource misallocation, evidenced by a 2% increase in the standard deviation of TFPR with a 100 basis point increase in the two-year Treasury rate. This increased dispersion implies that resources are being allocated less efficiently across firms. Furthermore, economic efficiency declines as a result of this policy change, with efficiency dropping by 1% when there are no labor distortions. Both effects also triple when we consider both capital and labor distortions as present and equal.

We also provide evidence that tighter monetary policy shocks increase capital wedges between small and large firms. To provide this evidence, we use the decomposition method developed by David and Venkateswaran (2019). This method allows us to estimate the correlated distortions related to size—measured by output total factor productivity (TFPQ), assets, and sales—as well as random distortions, and then identify the effects of monetary policy shocks on both types of distortions. We find that a 100 basis point increase in the two-year Treasury rate increases capital wedges by more than 1% between small and large firms in the absence of labor distortions. The increase in random distortions is also notable, with the random component related to sales rising by 2% in the absence of labor distortions. These effects triple when we consider both capital and labor distortions as present and equal.

Our empirical results indicate that contractionary monetary policy leads to a reduction in TFPR for firms with high TFPR and markup, which might improve efficiency by reducing the dispersion of TFPR and thereby aligning marginal products of capital more closely across firms. However, contractionary monetary policy also reduces TFPR for young, small, and low net worth firms, which exacerbates financial frictions. This exacerbation of financial frictions highlights how tighter monetary policy disproportionately impacts these vulnerable firms, leading to increased resource misallocation. Consequently, the overall economic efficiency is diminished as the effects of tighter monetary conditions amplify existing financial constraints and distortions within the economy.

Our identification of monetary policy shocks leverages high-frequency data from financial markets, as highlighted in the growing literature (Gertler and Karadi, 2015; Nakamura and Steinsson, 2018; Jarociński and Karadi, 2020). More specifically, we use monetary policy shocks from Jarociński and Karadi (2020), who employ the first principal component of the current-month fed funds futures, the three-month fed funds futures, and the euro-dollar futures at horizons of two, three, and four quarters, similar to the method used by Nakamura and Steinsson (2018). To construct quarterly measures of high-frequency surprises, we sum up the daily surprises for each quarter. We use these high-frequency surprises as an instrument for the two-year Treasury rate to identify the effect of monetary policy shocks on capital misallocation and efficiency. Our primary identifying assumption is that unexpected variations in the fed funds futures and euro-dollar futures within a 30-minute window surrounding the Federal Open Market Committee (FOMC) announcement are exclusively triggered by news about monetary policy.

To identify the differential effect of monetary policy, we implement an instrumental variable technique and a local projections–instrumental variables (LP-IV) approach, using high-frequency interest rate surprises as instrumental variables. The impulse response in the LP-IV method can be characterized as the local average treatment effect (LATE) that satisfies monotonicity, relevance, and exogeneity assumptions. This approach effectively investigates the time-dependent effects of monetary policy shocks on TFPR, precisely capturing the dynamic response of TFPR to monetary policy fluctuations. The findings reveal that smaller, younger, low-TFPR firms, low-markup firms, low net worth, and those with R&D investments are more adversely affected by contractionary monetary policies. Specifically, our results highlight the differential adverse impacts of tighter monetary policy on the TFPR of various firm categories. Small and young firms face increasing challenges over time, while low-markup firms experience delayed negative effects. Firms with R&D investments are significantly and consistently affected from the onset, underscoring their vulnerability to monetary policy shocks.

Our paper enhances the existing literature connecting firm characteristics to monetary policy shocks. Gertler and Gilchrist (1994) establish that firms with fewer assets, typically smaller ones, are more impacted during tight credit periods. Meanwhile, Crouzet and Mehrotra (2020) indicate a weak correlation between asset-based financial constraints and responses to monetary shocks using pre-financial crisis data. Kudlyak and Sanchez (2017) demonstrate that larger firms' sales and short-term debt are more responsive to aggregate shocks. Other studies, including Cloyne et al. (2018), Ottonello and Winberry (2020), and Jeenas (2018), explore the impacts of firm age and leverage on responsiveness to monetary policy shocks. Jordà et al. (2023) provide compelling evidence that monetary policy can have long-lasting real effects, including on TFP, persisting for over a decade. Our paper contributes to this body of work by examining the differential effects of monetary policy shocks on firm-level TFPR and capital misallocation, focusing on the impacts across various firm characteristics such as size, age, markup, and R&D investments.

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. Due to data constraints, following Hsieh and Klenow (2009), we derive different measures of capital misallocation and efficiency to contribute to this literature.

The effects of monetary policy on productivity and capital allocation have been widely documented. Baqaee et al. (2024) investigate how monetary tightening could adversely impact aggregate productivity and TFP if resources are reallocated to less efficient, low-markup firms. Gu and Singh (2024) find that a contractionary monetary policy shock increases markup dispersion by discouraging entrant innovation relative to incumbent innovation. This increased markup dispersion leads to misallocation, reducing allocative efficiency and potentially slowing down TFP growth. In contrast, Albrizio et al. (2023) find that an expansionary monetary policy shock reduces capital misallocation by decreasing within-industry dispersion of firms' MRPK, with high-MRPK firms increasing investment and debt financing more than low-MRPK firms, and slightly increasing firm entry and decreasing exit without significantly changing the composition of entrants and exiters. González et al. (2024) suggest that contractionary monetary policy exacerbates capital misallocation by tightening borrowing constraints on high-productivity, low net worth firms, preventing them from investing optimally.

Countercyclical dispersion in firm-level revenue product is another critical theme in the literature. Kehrig (2011) documents countercyclical dispersion in firm-level revenue product, indicating that economic downturns exacerbate inefficiencies in the allocation of capital. Alam (2020) establishes that capital misallocation, as measured by the dispersion of returns to capital, is higher during recessions and lower during booms. This implies that economic downturns exacerbate inefficiencies in the allocation of capital, which can have significant implications for overall economic productivity and growth. The study of countercyclical dispersion highlights the importance of considering the business cycle when analyzing capital allocation and its effects on productivity.

The remainder of this paper is organized as follows. Section 2 describes our data, the framework used to interpret the data, and how we identify monetary policy. Section 3 documents our estimated impact of monetary policy on aggregate outcomes, while Section 4 explores mechanisms. The last section concludes.

2 Data and Methods

2.1 Data

Our primary data source is Compustat, which reports firm-level balance sheet information derived from publicly-listed U.S. firms.[1] This dataset covers a substantial time period – almost three decades from the first quarter of 1990 to the second quarter of 2019. This is a robust and comprehensive database renowned for its routine quarterly updates and its detailed balance sheet data. Compustat's unique characteristics make it particularly suitable for our monetary policy analysis, given the necessity of quarterly frequency data. Moreover, its comprehensive balance sheet information allows for the construction of necessary variables relevant to our study. Following the literature, we exclude firms operating in the following sectors: Utilities (with standard industry classifications, SIC, ranging from 4900 to 4999); Finance, Insurance, and Real Estate (6000 to 6799); and Public Administration (9100 to 9729). Additionally, we eliminate any duplicate firm-quarter observations and treat strictly negative observations as missing.

From the Compustat data we use quarterly firm-level measures of sales, capital, capital

[1] We use the Compustat database from the Wharton Research Data Services (WRDS): `https://wrds-www.wharton.upenn.edu/`.

depreciation, cost of goods sold, expenses, total assets, industry indicators, and the date of each company's initial public offering (IPO). We also make use of annual firm-level employment data. For firm-level observations with data gaps of up to three quarters, we use linear interpolation to maintain data continuity. We also use the yearly industry-level deflator shipments from the NBER-CES database to deflate sales, average industry wages from the Quarterly Census of Employment and Wages (QCES) database to construct labor costs, along with the quarterly implicit price deflator from the Federal Reserve Bank of St. Louis (FRED). Appendix A details how each variable we use is constructed from the data.

For macroeconomic controls in our analyses, we use quarterly GDP from FRED and a quarterly measure of the excess bond premium from Bauer and Swanson (2023). And for our measures of monetary policy, we use two-year treasury rates from FRED and quarterly high-frequency interest rate surprises from Jarociński and Karadi (2020).

2.2 Measuring Misallocation and Allocative Efficiency

To measure misallocation and allocative efficiency, we follow Hsieh and Klenow (2009). There is a representative perfectly competitive final good firm which demands output Y_s from each sector $s \in S$, taking all prices as given, to maximize total aggregate output (the numéraire) net of input costs, using the following aggregate production function:

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s}, \qquad \sum_{s=1}^{S} \theta_s = 1, \tag{1}$$

where S also denotes the number of sectors, and θ_s is the share of final output from sector s.

Sectoral output Y_s, in turn, is similarly produced by a representative firm which demands output from a number M_s of producers in sector s, taking the price of sectoral output P_s and the prices of each sector-s firm P_{si} as given, to maximize sectoral revenue net of input costs, using the following sectoral production function:

$$Y_s = \left(\sum_{i=1}^{M_s} Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{2}$$

where $\sigma \geq 1$ is the elasticity of substitution between goods within a sector, which is assumed common across sectors, and Y_{si} is the output of producer i in sector s.

Within each sector s, firms differ in their productivity A_{si}, and in each period choose labor L_{si} and capital K_{si} to maximize profit, taking input prices as given;

$$\Pi_{si} = P_{si}Y_{si} - (1+\tau_{si}^{L})wL_{si} - (1+\tau_{si}^{K})RK_{si}, \tag{3}$$

subject to the firm's downward-sloping demand curve (derived from the sectoral output firm's problem) and the production function:

$$P_{si} = P_s\left(\frac{Y_s}{Y_{si}}\right)^{\frac{1}{\sigma}}, \tag{4}$$

$$Y_{si} = A_{si}K_{si}^{\alpha_s}L_{si}^{1-\alpha_s}, \quad , \quad 0 < \alpha_s < 1. \tag{5}$$

The output elasticity α_s is sector-specific, but time-invariant and common across firms within a sector. Firms also take as given idiosyncratic labor distortions τ_{si}^{L} and capital distortions τ_{si}^{K}. Factor prices – assumed constant across firms – are w for labor and R for capital.

From the first-order conditions of the firm problem, the following expressions must hold. First, within a sector, the marginal revenue product of labor for firm-si is proportional to the average revenue product of labor, which is proportional to the firm's labor distortion $1+\tau_{si}^{L}$:

$$MRPL_{si} = (1-\alpha_s)\left(\frac{\sigma-1}{\sigma}\right)\frac{P_{si}Y_{si}}{L_{si}} \propto \frac{P_{si}Y_{si}}{L_{si}} \propto (1+\tau_{si}^{L}). \tag{6}$$

This implies that within a sector, firm-specific labor distortions (relative to other firms within a sector) can be obtained from data on the average revenue product of labor for each firm.

Second, we can derive a similar expression for the marginal revenue product of capital:

$$MRPK_{si} = \alpha_s\left(\frac{\sigma-1}{\sigma}\right)\frac{P_{si}Y_{si}}{K_{si}} \propto \frac{P_{si}Y_{si}}{K_{si}} \propto (1+\tau_{si}^{K}). \tag{7}$$

Again, this implies firm-specific relative capital distortions can be obtained from data on the average revenue product of capital for each firm.

Here it is important to note that we do not have quarterly data on firm-level employment. We therefore proceed by assuming $\tau_{si}^{L} = 0$ for all firms. In Appendix C, we discuss how our results change if we instead assume $\tau^L_{si} = \tau^K_{si}$. If $\tau^L_{si} = 0$, equations (6) and (7) imply the following relationship between labor and capital:

$$L_{si} \propto K_{si}(1 + \tau^K_{si}). \tag{8}$$

We can infer a value for firm-level total factor productivity $TFPQ_{si}$ using firm-level data on revenue and capital by combining the production function with first-order conditions in the following way:

$$TFPQ_{si} = A_{si} = \frac{Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \propto \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}(1+\tau^K_{si})^{1-\alpha_s}} \propto \frac{(P_{si}Y_{si})^{\frac{\sigma}{\sigma-1}}}{K_{si}(MRPK_{si})^{1-\alpha_s}}. \tag{9}$$

Under our assumption $\tau^L_{si} = 0$, and following Hsieh and Klenow (2009), a firm's total factor revenue productivity is simply proportional to a function of its $MRPK$:

$$TFPR_{si} = \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s} L_{si}^{1-\alpha_s}} \propto \left(\frac{P_{si}Y_{si}}{K_{si}}\right)^{\alpha_s} \propto (1+\tau^K_{si})^{\alpha_s} \propto MRPK_{si}^{\alpha_s}. \tag{10}$$

We denote efficient sector total factor productivity by $TFP_{s,e}$, defined as sectoral TFP if $TFPR$ were constant across firms. TFP_s denotes actual sector TFP, taking into account differences in $TFPR$ across firms within a sector.

As in Hsieh and Klenow (2009), sectoral productivity and efficiency can be expressed in terms of observed and efficient productivity levels. The observed sectoral total factor productivity (TFP_s) incorporates the effects of resource misallocation across firms, while the efficient sectoral productivity ($TFP_{s,e}$) represents the counterfactual scenario where resources are allocated uniformly across firms within the sector. These are formally defined as:

$$TFP_s = \left[\sum_{i=1}^{M_s} \left(A_{si} \cdot \frac{\overline{TFPR}_s}{TFPR_{si}}\right)^{\sigma-1}\right]^{\frac{1}{\sigma-1}},$$

$$TFP_{s,e} = \left(\sum_{i=1}^{M_s} A_{si}^{\sigma-1}\right)^{\frac{1}{\sigma-1}},$$

where $TFPQ_{si}$ is our measure of A_{si}, and $\overline{TFPR}_s$ is the average $TFPR_{si}$ across all firms in sector s, weighted by their revenue shares. The efficiency of resource allocation within the sector is measured by the ratio:

$$\text{efficiency}_s = \frac{TFP_s}{TFP_{s,e}}. \tag{11}$$

This efficiency ratio measures the extent to which actual sectoral productivity approaches the efficient benchmark. A value of $\text{efficiency}_s = 1$ indicates perfect allocation, where resources are optimally distributed across firms, while values less than one reflect the extent of productivity losses due to misallocation.

The literature distinguishes between two primary sources of distortions affecting firm-level revenue productivity ($TFPR_{si}$): random distortions and correlated distortions. Random distortions arise from idiosyncratic factors that are independent of a firm's productivity ($TFPQ_{si}$), such as firm-specific shocks or operational inefficiencies. These distortions introduce variability in $TFPR_{si}$, leading to inefficiencies in resource allocation that are unpredictable and firm-specific. Correlated distortions, on the other hand, are systematically related to firm-level productivity and tend to have a more significant impact on efficiency. These distortions are parameterized by γ_s, which measures the elasticity of $TFPR_{si}$ with respect to $TFPQ_{si}$. A higher γ_s implies that more productive firms face relatively greater distortions, which systematically misalign resource allocation and disproportionately reduce sectoral efficiency. To better understand the impact of monetary policy on efficiency, we follow David and Venkateswaran (2019) in assuming the following relationship between $TFPR_{si}$ and $TFPQ_{si}$:

$$TFPR_{si} \propto MRPK_{si} \propto (1 + \tau_{si}^K) = TFPQ_{si}^{\gamma_s} \cdot \epsilon_{si},$$

or equivalently in logarithmic form:

$$\ln(TFPR_{si}) = \text{constant}_s + \gamma_s \cdot \ln(TFPQ_{si}) + \ln(\epsilon_{si}), \tag{12}$$

where $\ln(\epsilon_{si})$ captures random distortions with a mean of zero and variability represented by its standard deviation within sector s. The parameter γ_s quantifies the strength of correlated distortions, which systematically link distortions to firm productivity. The constant term, constant_s, accounts for sector-specific factors that are uniform across all firms.

The impact of misallocation on sectoral efficiency depends on three key factors. First, random dispersion in $TFPR_{si}$, captured by $\ln(\epsilon_{si})$, introduces random inefficiencies in resource allocation. These distortions are firm-specific and unrelated to productivity. For firms with a given productivity, a higher $TFPR_{si}$ encourages too few inputs while a lower $TFPR_{si}$ encourages too many, leading to inefficiencies. Second, the strength of correlated distortions (γ_s) amplifies efficiency losses by systematically driving resources away from high-productivity firms and towards low-productivity firms. A higher γ_s magnifies this inefficiency. Finally, the underlying distribution of firm productivity ($TFPQ_{si}$) determines the potential inefficiency from correlated distortions. Sectors with greater dispersion in productivity are more impacted from a given strength of correlated distortions γ_s, as a greater difference in productivity implies a bigger systematic difference in $TFPR_{si}$ from a given (γ_s).

Within this framework, the dispersion in $TFPR_{si}$, influenced by $\ln(\epsilon_{si})$ and $\gamma_s \cdot \ln(TFPQ_{si})$, determines the gap between actual sectoral productivity (TFP_s) and the counterfactual efficient productivity ($TFP_{s,e}$). This gap is reflected in the efficiency ratio, $\text{efficiency}_s = \frac{TFP_s}{TFP_{s,e}}$, which quantifies the extent of misallocation. Addressing these distortions—by reducing random heterogeneity ($\ln(\epsilon_{si})$) or weakening the strength of correlated distortions (γ_s)—can improve TFP_s and move it closer to $TFP_{s,e}$, enhancing sectoral efficiency.

This framework offers a robust approach to analyzing how monetary policy impacts efficiency by influencing misallocation. Policy-induced variations in γ_s or $\ln(\epsilon_{si})$ affect the dispersion of $TFPR_{si}$, thereby shaping sectoral productivity (TFP_s). Understanding these dynamics is essential for crafting targeted interventions that enhance resource allocation, stimulate economic growth, and optimize sectoral efficiency. By differentiating between random and correlated distortions, the framework also allows us to evaluate the consistency of different proposed theories of how monetary policy may impact misallocation.

2.3 Identifying the Dynamic Effects of Monetary Policy Shocks

In this section, we employ the local projections–instrumental variables (LP-IV) approach, a methodology developed by Jordà et al. (2023), to estimate the dynamic responses of several variables to monetary policy shocks. This method, which leverages high-frequency interest rate surprises as instruments, allows us to trace the effects of policy shocks across different forecast horizons, capturing the full temporal dimension of monetary policy's impact. We use the following estimation equations:

$$Y^j_{s,t+h} = \alpha_{s,h} + \alpha_{t,h} + \beta^j_h \Delta r_t + \sum_{k=1}^{4} \gamma^h_k \cdot \boldsymbol{x}_{t-k} + u_{s,t+h} \tag{13}$$

$$\Delta r_t = \kappa_s + \alpha_t + \varepsilon^m_t \lambda + \sum_{k=1}^{4} \zeta^h_k \cdot \boldsymbol{x}_{t-k} + v_{s,t} \tag{14}$$

$Y^j_{s,t+h}$ represents one of the following outcomes (indexed by j) within sector s at time $t+h$: sector efficiency ($TFP_s/TFP_{s,e}$); standard deviation of $\ln(TFPR)$; standard deviation of $\ln(TFPQ)$; the strength of correlated distortions (γ_s); and the standard deviation of random distortions, $\ln(\epsilon_{si})$ from Section 2.2. Ultimately, we are interested in the impact of monetary policy on aggregate efficiency through misallocation. For any given impact on efficiency, information about how monetary policy affects other outcomes helps us to decompose the efficiency impact into that coming from changes in the productivity distribution across firms, the relationship between productivity and $TFPR$, and across-firm random heterogeneity in $TFPR$.

The $h \geq 1$ term in the above equations indexes the forecast horizon. The term $\alpha_{s,h}$ represents an industry fixed effect, controlling for time-invariant unobserved characteristics unique to each industry. $\alpha_{t,h}$ is a time fixed effect accounting for time-varying influences on economic performance indicators, such as technological changes. In both equations we include $\boldsymbol{x}_{t-k}$, a vector representing GDP growth and the excess bond premium, both with a four-quarter lag, to control for their potential influence on outcomes independent of monetary policy shocks. The variable Δr_t is the quarterly change in the two-year treasury rate. ε^m_t is an unweighted measure of quarterly high-frequency interest rate surprises from Jarociński and Karadi (2020), which we use as an instrument for Δr_t. The coefficient β^j_h measures the dynamic effect of a monetary policy shock in quarter t on outcomes in $t + h$, conditional on macroeconomic controls observed in the preceding quarter $t - 1$. Following Jordà et al. (2020), the model interprets the impulse response as the local average treatment effect (LATE), subject to assumptions of monotonicity, relevance, and exogeneity, enabling precise conclusions about the causal impact of monetary policy shocks on economic outcomes. Finally, given differences in the relative size of industries, we weight each industry-quarter observation by that industry's average (over all quarters) aggregate sales share in the data.

2.4 Identifying Heterogenous Effects of Monetary Policy Shocks

The preceding section describes how we evaluate the impact of monetary policy on overall economic efficiency. To better understand the mechanisms through which monetary policy affects misallocation and efficiency, we also investigate the relative impact of monetary policy shocks across firms conditional on firm characteristics. Different theories of how monetary policy might impact efficiency generate testable implications for how firm characteristics should matter for relative outcomes. This section introduces a model that extends our analysis of dynamic effects to consider relative firm-level outcomes conditional on characteristics that are heterogeneous across firms. In particular, we consider pre-monetary shock measures of $TFPR$, size, age, and assets (relative to sales). We again employ an instrumental variables approach that leverages high-frequency interest rate surprises to identify causal effects of monetary shocks on relative firm-level outcomes.

We use the following estimation model:

$$\begin{aligned} \ln(TFPR_{i,t+h}) - \ln(TFPR_{i,t}) = \alpha_{i,h} + \alpha_{sy,h} + \Delta r_t \gamma_h + (Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\eta^j_h \\ + (Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\Delta r_t \beta^j_h + \sum_{k=1}^{4} \gamma^h_k \cdot \boldsymbol{x}_{t-k} + u_{i,t+h} \end{aligned} \tag{15}$$

$$\Delta r_t = \kappa_s + \alpha_t + \varepsilon^m_t \lambda + (Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\tau^j_h + \sum_{k=1}^{4} \zeta^h_k \cdot \boldsymbol{x}_{t-k} + v_{s,t} \tag{16}$$

$$\begin{aligned} (Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\Delta r_t = \kappa_i + \alpha_{sy} + \Delta r_t \gamma + (Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\eta \\ + (Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\varepsilon^m_t \lambda + \sum_{k=1}^{4} \zeta^h_k \cdot \boldsymbol{x}_{t-k} + v_{i,t} \end{aligned} \tag{17}$$

Here $TFPR_{i,t}$ represents $TFPR$ for firm i at time t relative to 'average' $\overline{TFPR_s}$ across all firms in industry s at time t. The term $\alpha_{i,h}$ represents a firm fixed effect, controlling for any time-invariant unobserved firm-level characteristics. $\alpha_{sy,h}$ is an industry-by-year fixed effect accounting for time-varying, sector-specific influences on $TFPR$, such as technological changes or industry-specific regulations. $Z^j_{i,t-1}$ represents our observed firm-level characteristics, one of initial $TFPR$, size, age, and assets (relative to sales), demeaned for each firm following Ottonello and Winberry (2020) as $(Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])$. As in Section 2.3 we include $\boldsymbol{x}_{i,t-k}$ to control for GDP growth and the excess bond premium. The variable Δr_t represents the quarterly change in the two-year treasury rate, and ε^m_t is the unweighted measure of quarterly high-frequency interest rate surprises, derived from Jarociński and Karadi (2020). We use $(Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\varepsilon^m_t$ as an instrument for $(Z^j_{i,t-1} - \mathbb{E}[Z^j_{i,t}])\Delta r_t$ and ε^m_t as an instrument for Δr_t. The coefficient β^j_h measures the cumulative effect of a monetary policy shock in quarter t on $TFPR$ in quarter $t+h$, conditional on firm characteristics.

From Section 2.2 we note that the absolute value of $TFPR_i$ includes variables that are common across firms within an industry-quarter and unrelated to distortions. We therefore focus on the relative impact of monetary shocks for firms with heterogeneous characteristics. β^j_h captures this effect, representing the marginal impact of a monetary policy shock for a firm with characteristic Z that is 1% higher. Finally, we again weight each firm-industry-quarter observation by its industry's average aggregate sales share.

Using Spanish data, Albrizio et al. (2023) find an expansionary monetary shock lowers across-firm dispersion in MRPK (the measure of TFPR in our benchmark analysis) by lowering MRPK for firms with initially high MRPK more than for firms with initially low MRPK. They argue that if MRPK is interpreted as a proxy for how binding are financial frictions, then high MRPK firms are those with more binding constraints, with capital use further from its optimal (unconstrained) level. They propose that an expansionary shock alleviates constraints for all firms, but has a greater impact on the most constrained firms. We can test the implications of their theory by first looking at the impact of monetary policy on dispersion of MRPK; second, duplicating their analysis of how initial MRPK predicts the relative impact of monetary policy across firms; and third, testing whether more direct proxies for financial constraints (like assets/revenue) predict relative impacts in a similar way. For example, if the first two analyses replicate Albrizio et al.'s results, but the analysis of asset ratios does not, then we may need to consider other mechanisms.

Meier and Reinelt (2024) and Baqaee et al. (2024) both note that if firms are heterogeneous with respect to the price-setting frictions they face, then an expansionary monetary policy shock can lower dispersion in price/cost markups. High (low) initial markups imply low (high) pass-through from changes in costs to changes in prices. As a result, expansionary monetary policy which raises costs would result in lower markup increases for firms with initially high markups, relative to low-markup firms, thereby decreasing dispersion in markups. We note that our measure of TFPR is equivalent to that of average markups (revenue/factor costs). If we find that expansionary policy decreases TFPR dispersion by lowering TFPR for high-TFPR firms (relative to low-TFPR firms), then this is consistent with their story. And if we further find that our analysis of asset ratios is not consistent with Albrizio et al. (2023), then this pass-through mechanism is potentially more consistent. However we do note that the pass-through mechanism, as stated, relies on random dispersion in price-setting frictions. This is unsatisfying in the sense that the mechanism essentially relies on random unexplained heterogeneity across firms. An alternative story incorporates the endogenous relationship between markups and pass-through, on the one hand, and firm-level productivity or demand on the other. Peters (2020), for example, shows that in an oligopolistic setting firms with higher productivity or higher demand for their product endogenously choose higher markups and exhibit lower pass-through. The implications of this alternative mechanism include those from Meier and Reinelt and Baqaee et al. But this alternative mechanism also predicts that TFPR should be positively correlated with firm productivity in general. We can therefore consider the importance of this implication by also looking at our estimate of γ_s (the elasticity of TFPR with respect to firm productivity) across industries. The endogenous markup mechanism requires that γ_s is widely positive across industries.

Finally, because we decompose changes in the dispersion of TFPR due to monetary policy into changes in γ_s and changes in the dispersion of the random component of TFPR (ϵ), we can gather more evidence about whether any of the above theories are important drivers of the data. If γ_s barely changes due to a monetary shock (even if it does move in a consistent direction), while most of the impact on TFPR dispersion is due to the impact on random dispersion, then we must conclude that much of the total impact is still unexplained by current theory.

3 Impact of Monetary Policy

In this section we report descriptive statistics of the outcomes we are interested in, followed by the results of our analysis of the impact of monetary policy shocks on these outcomes, and finally the results of our analysis of the heterogeneous effect of monetary policy across firms.

3.1 Characteristics of Economic Performance Indicators

As previously mentioned, we derived our economic performance indicators based on two assumptions regarding labor and capital distortions. The first assumption posits that labor and capital distortions are equal, while the second assumes the absence of distortions in labor. This section presents the descriptive statistics of various economic performance indicators under the second assumption. The analysis in Table 1 provides an overview of these indicators, including the standard deviations of MRPK, TFPR, TFPQ, efficiency, and both correlated and random distortions measured through TFPQ, assets, and sales coefficients. Our results related to the first assumption are presented in Appendix C.

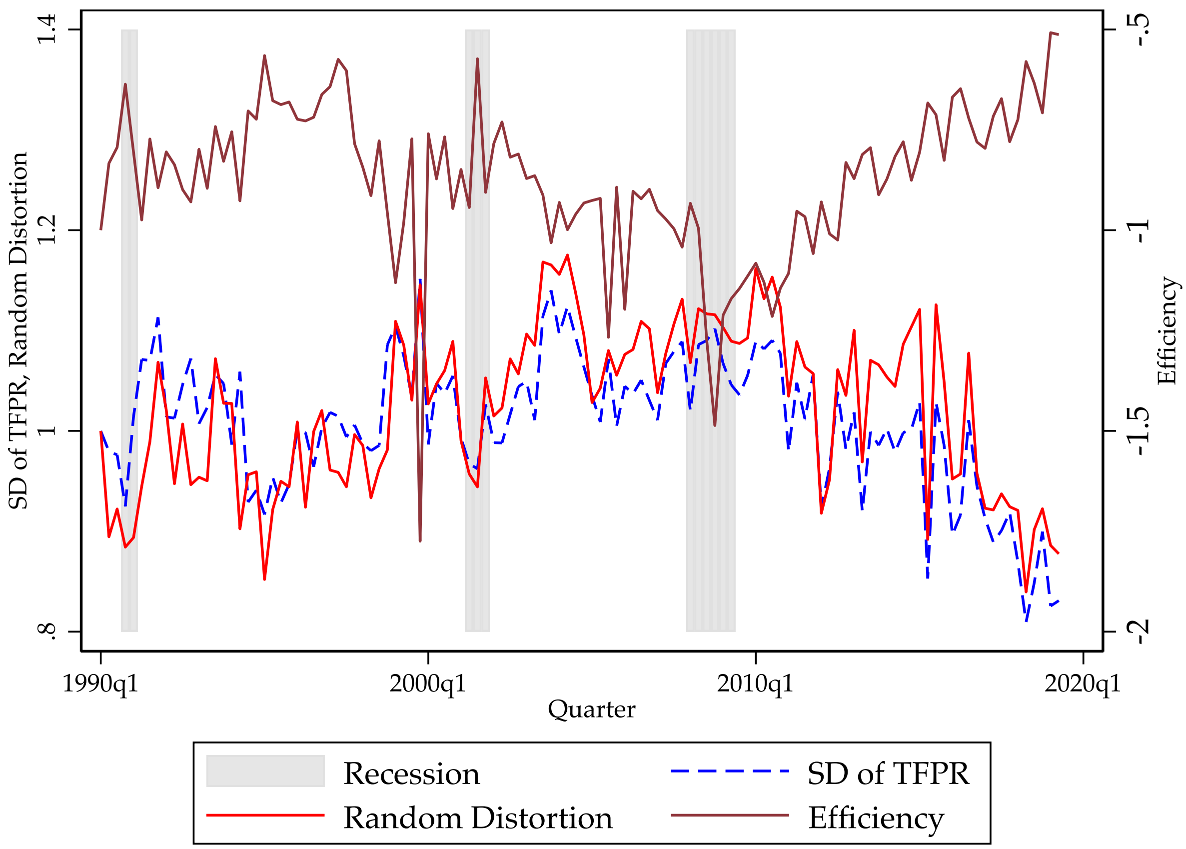
Table 1: Descriptive statistics of economic performance indicators

	Obs	Mean	SD	Min	Max
Standard deviation of TFPR	6709	0.29	0.09	0.07	0.80
Efficiency	6709	-0.02	0.02	-0.36	-0.00
Correlated Distortion (Sales Coefficients)	6709	-0.01	0.04	-0.22	0.41
Random Distortion (Sales Coefficients)	6709	0.28	0.09	0.06	0.78
Correlated Distortion (Age Coefficients)	6709	-0.02	0.08	-1.18	0.66
Random Distortion (Age Coefficients)	6709	0.28	0.09	0.06	0.71
Correlated Distortion (Net Worth Coefficients)	6709	-0.16	0.12	-1.12	0.68
Random Distortion (Net Worth Coefficients)	6709	0.26	0.08	0.05	0.66
Correlated Distortion (Assets Coefficients)	6709	-0.03	0.03	-0.24	0.35
Random Distortion (Assets Coefficients)	6709	0.28	0.09	0.07	0.79

Note: This table provides the descriptive statistics of various economic performance indicators for the second assumption regarding labor and capital distortions. The second assumption considers an absence of distortions in labor.

Table 1 shows that the **correlated distortions** and **random distortions** are highlighted to illustrate their impact on economic performance. For instance, the mean correlated distortion in sales coefficients is relatively low at 0.02, with a standard deviation of 0.07, suggesting modest but notable deviations from the norm. In contrast, the random distortion in sales coefficients exhibits a higher mean value of 0.31 and a standard deviation of 0.10, reflecting a broader range of deviations. Similarly, for age coefficients, the mean correlated distortion is approximately zero, but with a considerable standard deviation of 0.13, indicating significant variability. The random distortion in age coefficients also maintains a mean of 0.31, with a similar standard deviation. Furthermore, the net worth coefficients demonstrate a mean correlated distortion of -0.06 and a standard deviation of 0.08, whereas the random distortion shows a mean of 0.29 and a standard deviation of 0.09. These findings underscore the importance of accounting for both **correlated** and **random distortions** when analyzing economic performance indicators, as they reveal critical insights into the underlying variability and potential inefficiencies in the data.

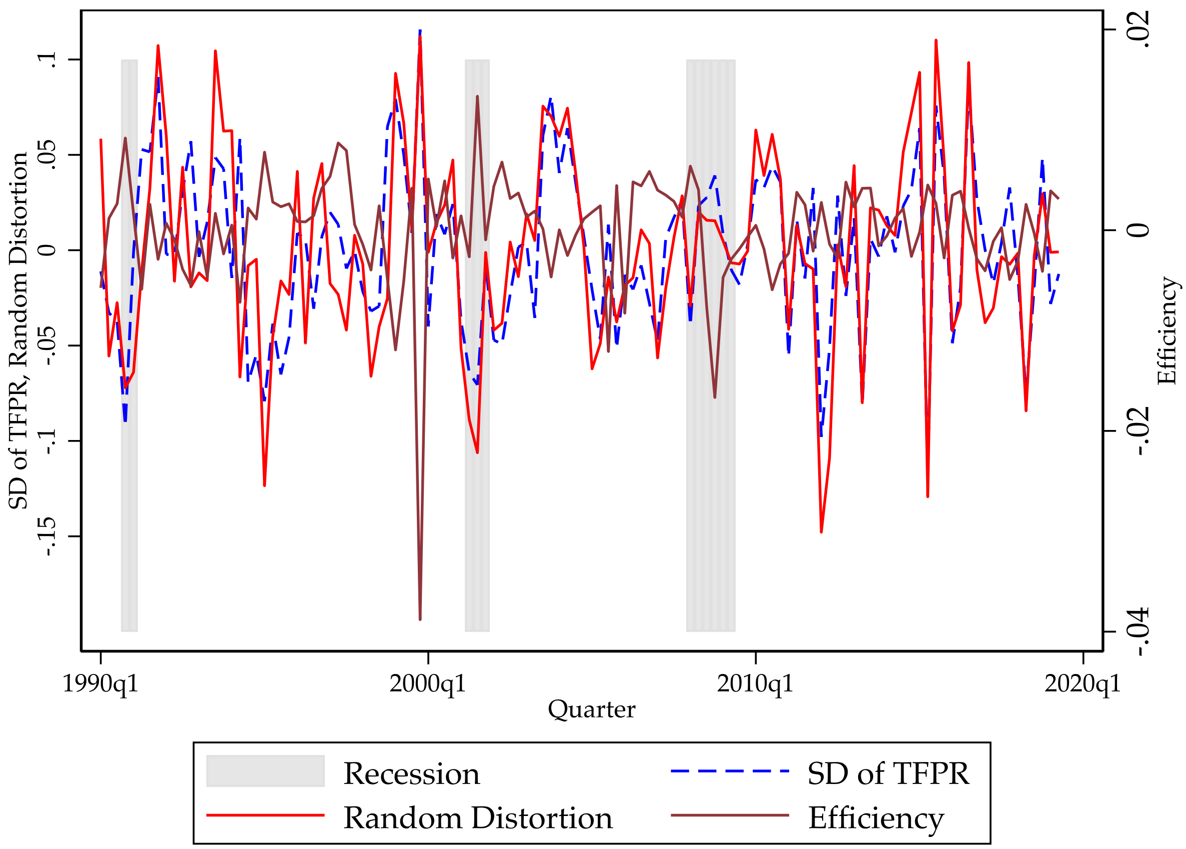
Figure 1: Economic performance indicators over time



Note:

To observe the pattern of these economic performance indicators over time, we plot the standard deviations of MRPK and TFPR, efficiency, and random distortions measured by sales. In Figure 1, the solid brown line represents the measured efficiency, the dashed blue line represents the standard deviations of MRPK and TFPR, and the solid red line represents random distortion. These lines highlight that economic recessions are associated with increased distortions and inefficiencies, as evidenced by the spikes in the standard deviation of MRPK/TFPR and the random distortion during shaded recession periods.

Figure 2: Cyclical components of economic performance indicators



Note: This figure provides the cyclical components of various economic performance indicators for the second assumption regarding labor and capital distortions. The second assumption considers an absence of distortions in labor.

In Figure 2, we plot the cyclical components of economic performance indicators. A key observation is that the standard deviation of TFPR, random distortion, and efficiency exhibit distinct cyclical patterns, with substantial increases in variability during recession periods. Additionally, the efficiency measure often moves inversely to the standard deviation of TFPR and random distortion during certain periods. The accompanying note explains that the figure provides cyclical components of various economic performance indicators based on assumptions regarding labor and capital distortions, with the second assumption considering the absence of labor distortions.

3.2 Contemporaneous Effects of Monetary Policy Shocks

In this section, we present the causal effect of monetary policy, specifically a two-year rate change, on various economic performance indicators. Table 2 examines the effect of monetary policy on misallocation (measured by the standard deviation of MRPK or the standard deviation of TFPR), distribution of productivity, and efficiency, whereas Table 3 identifies the effect of monetary policy on the sources of misallocation.

- **SD of TFPR:** The coefficient for the two-year rate change is 0.016 and statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate increases the standard deviation of TFPR by approximately 2% (Table 2). This suggests that monetary policy changes lead to greater dispersion in TFPR, implying increased resource misallocation when there are no distortions in labor.

- **SD of TFPQ:** The coefficient for the two-year rate change is -0.017 and is not statistically significant. This implies that a 100 basis points increase in the two-year Treasury rate does not have a significant impact on the standard deviation of TFPQ, suggesting that monetary policy changes do not substantially affect productivity distribution when there are no labor distortions.

- **Efficiency:** The coefficient for the two-year rate change is -0.011 and statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate decreases efficiency by around 1% (Table 2). This suggests that monetary policy changes may lead to a decline in overall economic efficiency under the assumption of no labor distortions.

Table 2: Causal effect of monetary policy on economic performance indicators

	SD of TFPR	SD of TFPQ	Efficiency
Two-Year Rate Change	0.016***	-0.017	-0.011***
	(0.005)	(0.013)	(0.002)
N	6709	6709	6709

Note: In all specifications, we include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. We also include macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters. All specifications use sales weights to capture industry heterogeneity. Statistical significance is indicated by ***, **, and *, representing the 1%, 5%, and 10% levels, respectively.

- **Sales Coefficients (Correlated):** The coefficient for the two-year rate change is -0.014 and statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate decreases correlated distortions measured using the sales coefficients by approximately 1.4% (Table 3). This suggests that monetary policy changes reduce correlated distortions related to sales in the absence of labor distortions.

- **Sales Coefficients (Random):** The coefficient for the two-year rate change is 0.020 and statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate increases random distortions measured using the sales coefficients by around 2% (Table 3). This suggests that monetary policy changes enhance distortions related to sales when there are no labor distortions.

- **Age Coefficients (Correlated):** The coefficient for the two-year rate change is -0.009 and not statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate does not have a significant impact on correlated distortions measured using the age coefficients (Table 3). This suggests that monetary policy changes do not significantly affect correlated distortions related to age in the absence of labor distortions.

- **Age Coefficients (Random):** The coefficient for the two-year rate change is 0.013

and statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate increases random distortions measured using the age coefficients by around 1.3% (Table 3). This suggests that monetary policy changes enhance distortions related to age when there are no labor distortions.

- **Net Worth Coefficients (Correlated):** The coefficient for the two-year rate change is 0.005 and not statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate does not have a significant impact on correlated distortions measured using the net worth coefficients (Table 3). This suggests that monetary policy changes do not significantly affect correlated distortions related to net worth in the absence of labor distortions.

- **Net Worth Coefficients (Random):** The coefficient for the two-year rate change is 0.014 and statistically significant, indicating that a 100 basis points increase in the two-year Treasury rate increases random distortions measured using the net worth coefficients by around 1.4% (Table 3). This suggests that monetary policy changes enhance distortions related to net worth when there are no labor distortions.

Table 3: Causal effect of monetary policy on sources of capital misallocation

	Sales Coefficient		**Age Coefficient**		**Net Worth Coefficient**	
	Correlated	Random	Correlated	Random	Correlated	Random
Two-Year Rate Change	-0.014***	0.020***	-0.009	0.013**	0.005	0.014***
	(0.004)	(0.005)	(0.009)	(0.005)	(0.006)	(0.005)
N	6709	6709	6709	6709	6709	6709

Note: In all specifications, we include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. We also include macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters. All specifications use sales weights to capture industry heterogeneity. Statistical significance is indicated by ***, **, and *, representing the 1%, 5%, and 10% levels, respectively.

In summary, the results indicate that a 100 basis points increase in the two-year Treasury rate significantly increases the standard deviation of TFPR by approximately 2%, suggesting greater resource misallocation. The same rate increase does not significantly affect the standard deviation of TFPQ but decreases overall economic efficiency by around 1%. Additionally, the rate change significantly impacts correlated and random distortions in sales and net worth, while it does not significantly affect correlated distortions related to age. These findings suggest that a tighter monetary policy exacerbates inefficiencies in the economy by amplifying random distortions, thereby hindering optimal resource allocation and reducing overall economic productivity.

3.3 Effects of Monetary Policy Shocks

Economic Performance Indicator

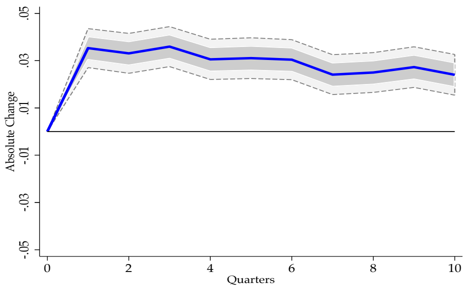
Figure 3 presents the dynamic effects of contractionary policy shocks on various economic performance indicators. The figure is divided into three panels, each illustrating the response of different measures to the policy shock over a 10-quarter horizon.

Panel (a) of Figure 3 shows the standard deviation of TFPR. The blue line represents the estimated coefficient β_h^{TFPR}, with the shaded areas indicating the 68% and 90% error bands. The results suggest that contractionary policy shocks lead to a significant increase in the standard deviation of TFPR. This increase in dispersion among firms' TFPR is notable and indicates a varied response across firms to the tightening of monetary policy. The increase is most pronounced in the first few quarters following the shock, suggesting an initial diverging effect. However, as time progresses, the effect stabilizes and begins to revert to the baseline level, indicating that firms gradually adjust to the new monetary conditions.

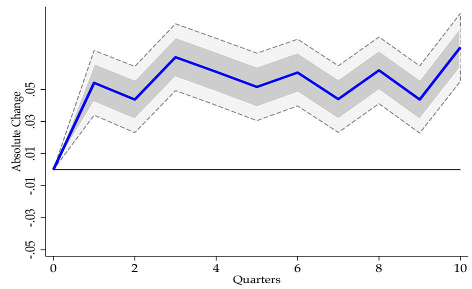
Panel (b) of Figure 3 depicts the standard deviation of TFPQ. Unlike the response of TFPR, the standard deviation of TFPQ does not exhibit a significant effect. The estimated coefficient β_h^{TFPQ}, shown by the blue line, does not significantly differ from zero. This indicates that contractionary policy shocks do not have a notable impact on the variability of TFPQ among firms. The absence of a significant effect suggests that the productivity quantity response to monetary policy shocks is more heterogeneous and does not follow a clear pattern.

Figure 3: Dynamic effects of contractionary policy shocks on economic performance indicator

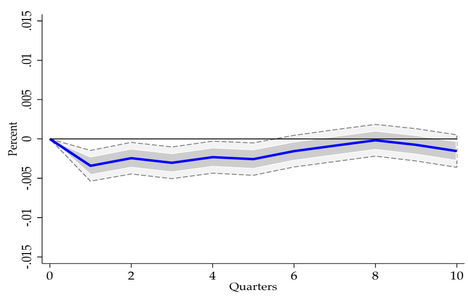
(a) SD of TFPR



(b) SD of TFPQ



(c) Efficiency



Note: The figures display the effects of contractionary policy shocks on economic performance indicators. We estimate the coefficient β_h^J over quarters h for economic performance indicators, using Model 1 (refer to Model 1 for details). Panel (a) shows the standard deviation of TFPR, while panel (b) shows the standard deviation of TFPQ. Panel (c) depicts the efficiency measure. The shaded areas in each panel represent the 68% and 90% error bands. The analysis includes industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included.

The third panel, panel (c) of Figure 3, illustrates the response of an efficiency measure to contractionary policy shocks. The estimated coefficient is again represented by the blue line, with the shaded areas showing the error bands. The efficiency measure shows a significant initial decrease, followed by a gradual recovery towards the baseline level. This indicates that contractionary policy shocks initially reduce firms' efficiency, but firms gradually adjust their practices to regain their previous efficiency levels.

In summary, Figure 3 demonstrates that contractionary policy shocks have distinct and varied impacts on different economic performance indicators. The standard deviation of TFPR shows a significant increase, indicating a short-term diverging effect of the shocks on firms' productivity revenue. The standard deviation of TFPQ, on the other hand, exhibits no significant effect, suggesting that the variability in firms' productivity quantities does not follow a consistent pattern in response to monetary policy shocks. Finally, the efficiency measure shows a significant initial reduction, followed by a recovery, suggesting resilience in firms' operational efficiency in the face of contractionary policy shocks. These findings underscore the importance of a multifaceted approach when assessing the effects of monetary policy on economic performance.

Sources of Capital Misallocation

Figure 4 presents the dynamic effects of contractionary policy shocks on various sources of capital misallocation. The figure is divided into six panels, each illustrating the response of different measures of capital misallocation to the policy shock over a 10-quarter horizon.

Panel (a) of Figure 4 shows the correlated distortion based on sales. The blue line represents the estimated coefficient $\beta_h^{\text{Correlated Sales}}$, with the shaded areas indicating the 68% and 90% error bands. The results suggest that there is no clear pattern in the response of correlated distortions based on sales to contractionary policy shocks. This implies that the misallocation of capital correlated with sales does not exhibit a consistent response to monetary policy changes.

Panel (b) of Figure 4 depicts random distortion based on sales. The blue line representing the estimated coefficient $\beta_h^{\text{Random Sales}}$ shows that random distortions in capital allocation based on sales significantly increase due to contractionary policy shocks. This highlights the pronounced impact of monetary policy on the randomness in sales-based capital allocation.

Panel (c) of Figure 4 illustrates the correlated distortion based on firm age. The estimated coefficient $\beta_h^{\text{Correlated Age}}$ shows no clear pattern, indicating that the response of correlated distortions based on age to monetary policy shocks is not consistent. This suggests that age-related capital misallocations do not exhibit a uniform response to monetary tightening.

Panel (d) of Figure 4 shows random distortion based on firm age. The estimated coefficients $\beta_h^{\text{Random Age}}$ and the associated error bands indicate a significant increase in random distortions. This implies that random age-based distortions in capital allocation are significantly impacted by contractionary policy shocks, reflecting changes in the randomness of age-related capital misallocations over time.

Panel (e) of Figure 4 depicts correlated distortion based on net worth. Similar to sales and age, the response does not exhibit a clear pattern. The blue line and shaded error bands suggest that correlated distortions based on net worth do not have a consistent response to contractionary monetary policy.

Panel (f) of Figure 4 illustrates random distortion based on net worth. The estimated coefficients $\beta_h^{\text{Random Net Worth}}$ show significant increases, with the blue line and error bands indicating notable effects. This suggests that random misallocations of capital based on net worth are significantly influenced by contractionary policy shocks, highlighting the sensitivity of net worth-related capital allocation mechanisms to monetary policy changes.

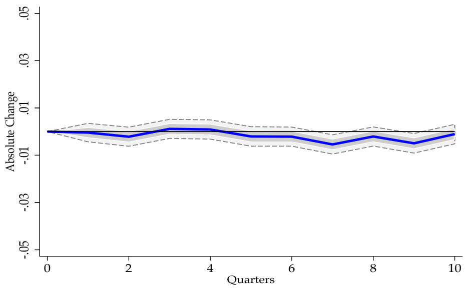
Panel (g) of Figure 4 shows the correlated distortion based on TFPQ. The blue line represents the estimated coefficient $\beta_h^{\text{Correlated TFPQ}}$, with the shaded areas indicating the 68% and 90% error bands. The results suggest that there is a moderate response in correlated distortions based on TFPQ to contractionary policy shocks, though the effects vary across time.

Panel (h) of Figure 4 depicts random distortion based on TFPQ. The estimated coefficient $\beta_h^{\text{Random TFPQ}}$ shows a noticeable increase in random distortions after a contractionary policy shock. The results indicate that random misallocations of capital based on TFPQ are significantly influenced by monetary policy, with larger and more persistent effects compared to correlated distortions.

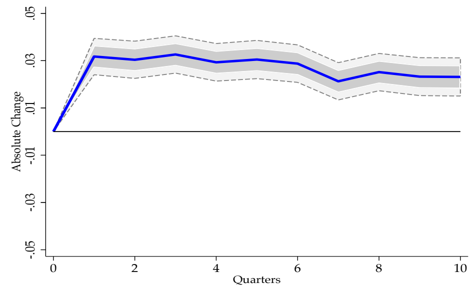
In summary, Figure 4 demonstrates that contractionary policy shocks have varied effects on different sources of capital misallocation. There is no clear pattern in correlated distortions based on sales, age, and net worth. However, random distortions in all three cases significantly increase due to contractionary monetary policy. These findings highlight the complexity and heterogeneity of capital misallocation responses to monetary policy, emphasizing the need for nuanced analysis when evaluating such effects.

Figure 4: Dynamic effects of contractionary policy shocks on sources of capital misallocation

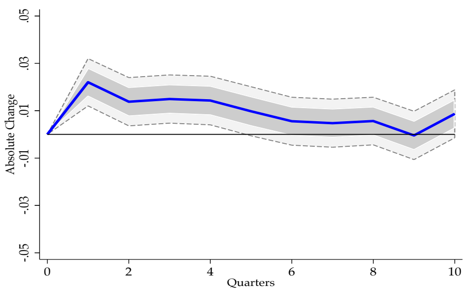
(a) Correlated Distortion (Sales)



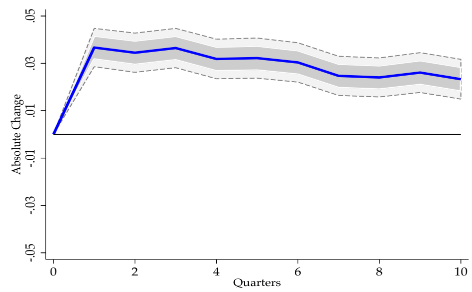
(b) Random Distortion (Sales)



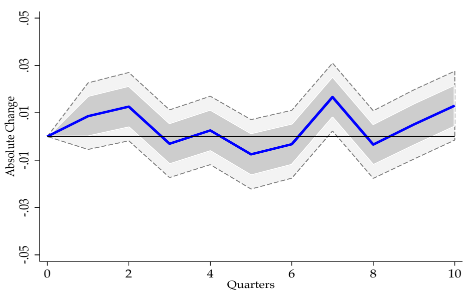
(c) Correlated Distortion (Age)



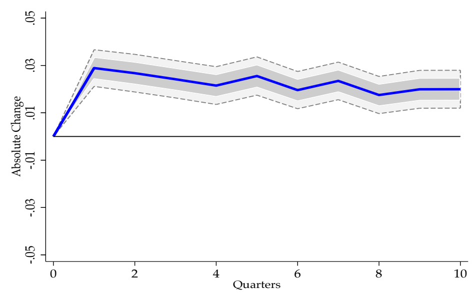
(d) Random Distortion (Age)



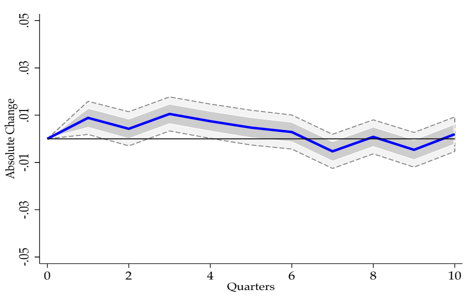
(e) Correlated Distortion (Net Worth)



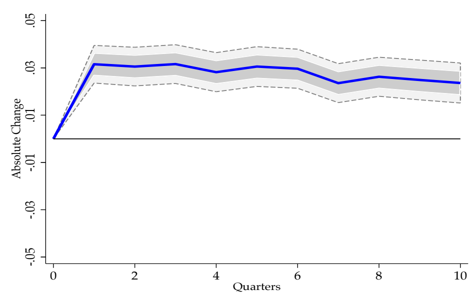
(f) Random Distortion (Net Worth)



(g) Correlated Distortion (TFPQ)



(h) Random Distortion (TFPQ)



Note: The figures illustrate the impact of contractionary policy shocks on capital misallocation across different sources. Panel (a) shows correlated distortion by sales, and panel (b) shows random distortion by sales. Panel (c) and (d) present correlated and random distortions by age, respectively. Panel (e) shows correlated distortion by net worth, and panel (f) shows random distortion by net worth. Panel (g) shows correlated distortion based on total factor productivity (TFPQ), while panel (h) presents random distortion based on TFPQ. The shaded areas represent 68% and 90% error bands. Industry and quarter fixed effects, along with lagged macroeconomic controls (GDP growth and excess bond premium), are included.

4 Mechanisms: Differential Effects of Monetary Policy

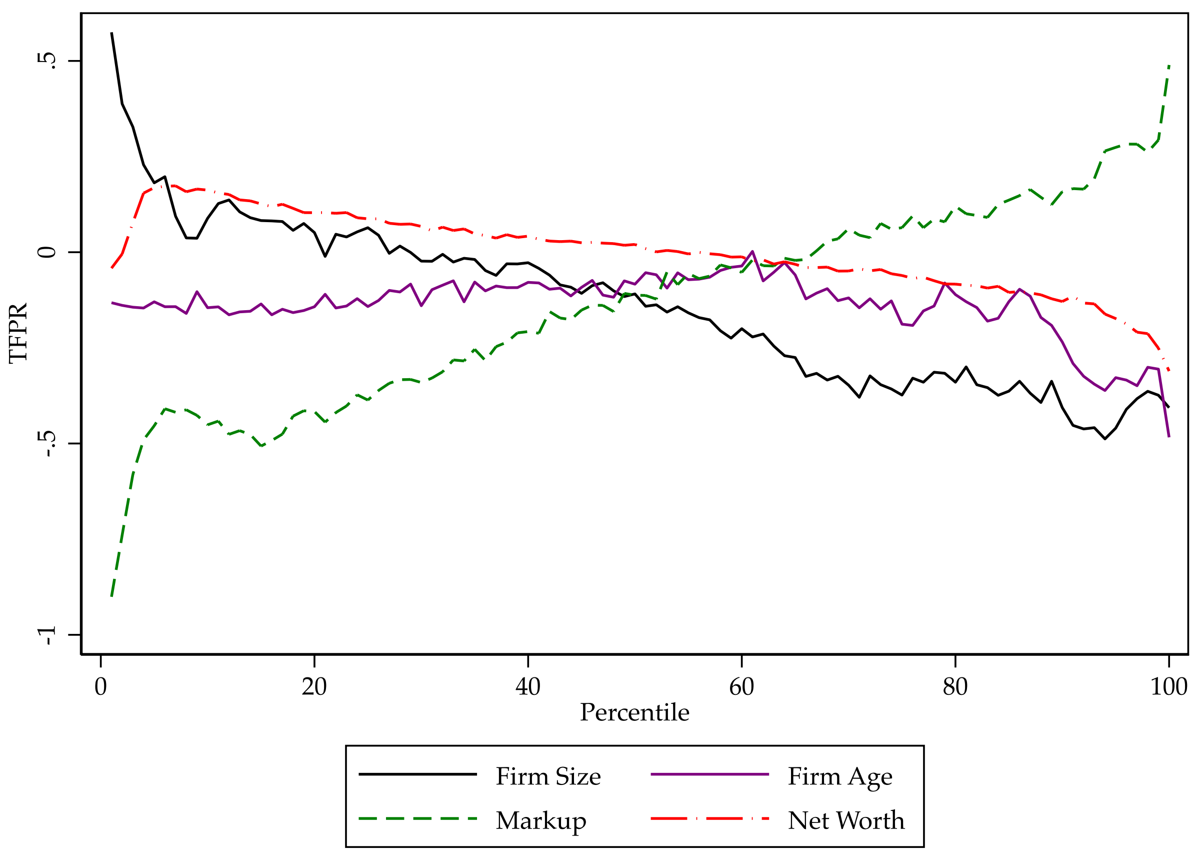
The existing literature has demonstrated that the transmission of monetary policy varies based on specific firm characteristics that proxy for financial constraints. Cloyne et al. (2018) observed that younger firms that do not distribute dividends tend to increase their investment more following an expansionary monetary policy shock. This implies that younger firms may face fewer financial constraints, allowing them to capitalize on favorable borrowing conditions. Similarly, Jeenas (2018) found that firms with high leverage or low liquidity are more responsive to monetary policy changes. These firms, often constrained by their financial positions, react strongly to changes in interest rates as their borrowing costs are significantly affected. Additionally, Albrizio et al. (2023) argue that high-MRPK firms exhibit a stronger reduction in investment and debt financing in response to contractionary monetary policy shocks compared to low-MRPK firms. This indicates that MRPK (Marginal Revenue Product of Capital) more accurately reflects the financial constraints affecting a firm's ability to respond to monetary policy changes. High-MRPK firms, likely constrained in their investment opportunities, cut back more sharply when monetary conditions tighten.

This section examines various firm-specific factors, such as TFPR, markup, age, size, and net worth, to understand the differential impacts of monetary policy. By analyzing these characteristics, we can identify how different types of firms adjust their behavior in response to monetary policy shocks, providing a nuanced view of the transmission mechanism.

Before delving into the differential effects of monetary policy, we first provide some descriptive statistics and patterns from the Compustat database. Figure 5 illustrates the relationship between TFPR and various firm characteristics, including firm size, firm age, and net worth. The vertical axis represents the logarithm of the ratio of firm-specific TFPR ($TFPR_{si}$) to the sector average TFPR ($\overline{TFPR}_s$). The horizontal axis shows the percentile distribution of firm size, firm age, markup, and net worth relative to their industry average.

In Figure 5, we observe a noticeable positive association between markup and TFPR, indicating that firms with higher markups tend to exhibit higher TFPR values. This suggests that firms capable of charging higher prices relative to their costs are also more productive, potentially due to better management or more efficient production processes. Conversely, there is a negative association between firm size and TFPR, suggesting that larger firms tend to have lower TFPR values. This might indicate that smaller firms are more efficient in utilizing their resources, possibly due to less bureaucratic inertia or more innovative practices. The association between firm age and TFPR is relatively stable, showing less variability across percentiles, which suggests a weaker association compared to the other characteristics. This stability implies that age alone does not significantly influence productivity once other factors are controlled for.

Figure 5: TFPR and firm characteristics



Note: The vertical axis shows the log ratio of $TFPR_{si}$ to $\overline{TFPR}_s$, while the horizontal axis represents the percentile of firm size, age, markups, and net worth relative to their industry average.

TFPR Heterogeneity and Monetary Policy

In this study, we aim to investigate the impact of contractionary monetary policy shocks on TFPR heterogeneity among firms. Specifically, we test whether such shocks lead to a more pronounced increase in TFPR for firms that initially have higher TFPR compared to those with lower TFPR. The underlying hypothesis, drawn from Albrizio et al. (2023), posits that high MRPK firms respond more significantly to contractionary monetary policy by reducing investment and debt financing. This reaction results in a relative decrease in capital allocation for these firms, thereby increasing their MRPK and exacerbating MRPK dispersion. The broader implication is that such dispersion in MRPK translates into inefficient resource allocation within the economy, underscoring MRPK as a more accurate indicator of financial constraints influencing firms' responses to monetary policy changes.

The results of this analysis have significant implications for understanding the mechanisms through which monetary policy affects economic efficiency. If contractionary monetary policy indeed exacerbates TFPR heterogeneity, it suggests that monetary policy could amplify inefficiencies in resource allocation. This would mean that policy measures need to account for these differential impacts to mitigate adverse effects on economic efficiency.

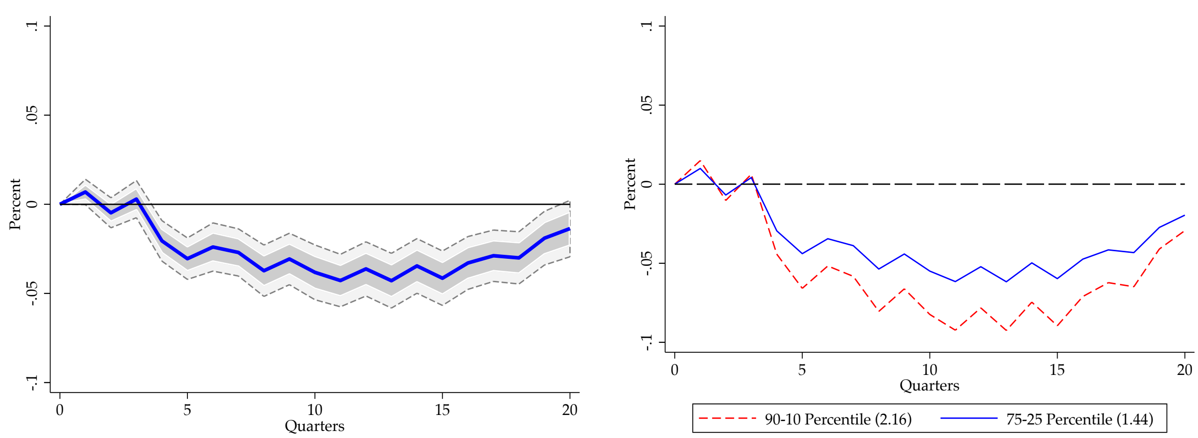
Figure 6 illustrates the dynamic effects of contractionary policy shocks on TFPR over a span of 20 quarters, based on Model 2, which includes industry and quarter fixed effects along with various macroeconomic controls. Contrary to the findings of Albrizio et al. (2023), our results indicate that contractionary monetary policy shocks do not increase TFPR more for high-TFPR firms than for low-TFPR firms.

Panel (a) of Figure 6 presents the estimated coefficient β_h^{TFPR} across different quarters h, with the shaded area representing 68% and 90% error bands, indicating the degree of estimation uncertainty. Initially, the coefficient β_h^{TFPR} is close to zero, suggesting minimal immediate impact of contractionary policy shocks on TFPR. However, over time, the coefficient exhibits a negative trend, indicating a reduction in TFPR due to contractionary policy shocks. This negative effect becomes more pronounced between 10 and 12 quarters and then stabilizes around -0.05 percent. This implies that firms with higher initial TFPR experience a smaller decrease in TFPR compared to firms with lower TFPR following contractionary monetary policy shocks. Specifically, after a 100 basis point increase in the two-year Treasury rate, a firm with a TFPR that is 1% higher than another firm reduces its TFPR by 0.05 percentage points less. This suggests that contractionary monetary policy tends to reduce systematic differences in TFPR between high and low TFPR firms.

Panel (b) of Figure 6 shows the effects of contractionary policy shocks on TFPR, conditional on the initial relative TFPR. The graph includes two lines representing different percentile ratios: the red dashed line represents the 90-10 percentile ratio (relative TFPR of 2.16), and the blue solid line represents the 75-25 percentile ratio (relative TFPR of 1.44). For both percentile ratios, the initial impact of contractionary policy shocks is minimal. Over time, both lines exhibit a downward trend, similar to Panel (a), indicating a reduction in TFPR due to policy shocks. The impact is more significant for the 90-10 percentile ratio compared to the 75-25 percentile ratio, suggesting that firms with higher initial TFPR face larger negative impacts. The trend is consistent across both lines, but the relative reduction in TFPR is more pronounced in the higher percentile ratio. The $\beta_h^{\text{TFPR}} \times$ Initial Relative TFPR at around 12 quarters for the 90-10 percentile ratio is around 0.1, implying that after a 100 basis point increase in the two-year Treasury rate, a firm at the 90th percentile reduces its TFPR by 0.1 percentage points less than a firm at the 10th percentile.

Figure 6: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{TFPR}) (b) $\beta_h^{TFPR}\times$ Initial Relative TFPR



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{TFPR} over quarters h for TFPR, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{TFPR}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{TFPR} \times$ Initial Relative TFPR, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of TFPR, respectively. The relative TFPR of 2.16 is the ratio of a firm's TFPR at the 90th percentile to a firm's TFPR at the 10th percentile. The relative TFPR of 1.44 is the ratio of a firm's TFPR at the 75th percentile to a firm's TFPR at the 25th percentile.

These findings indicate that contractionary monetary policy tends to reduce TFPR heterogeneity, contrary to the hypothesis that such policy would increase TFPR more for high-TFPR firms and less for low-TFPR firms.

Since TFPR is closely linked to markup, firms with higher initial markups are better able to absorb the effects of contractionary monetary policy shocks, leading to a smaller decrease in TFPR. Their stronger pricing power and efficiency allow them to maintain higher prices relative to costs, acting as a buffer against monetary tightening. In contrast, low-markup firms, which face more competitive pressures, experience larger reductions in both markup and TFPR as they adjust prices downward. This aligns with the literature, which suggests that high-markup firms, due to their lower pass-through rates, are less affected by monetary shocks, while low-markup firms face greater declines in prices and productivity. The resulting markup dispersion can lead to inefficient resource allocation, as high-markup firms dominate, reducing overall economic productivity (Baqaee et al., 2024).

Net Worth Heterogeneity and Monetary Policy

In this section, we explore the relationship between net worth heterogeneity among firms and the impact of monetary policy. Specifically, we investigate whether contractionary monetary policy shocks have a more pronounced effect on TFPR of low net worth firms compared to high net worth firms. This line of inquiry is critical for understanding the broader implications of monetary policy on economic efficiency and resource allocation.

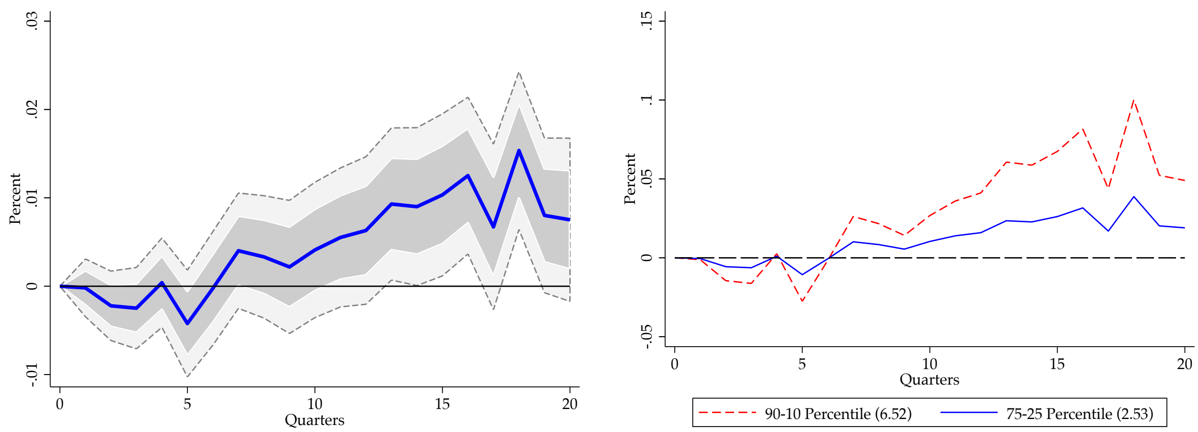
The central hypothesis being tested is whether contractionary monetary policy shocks increase TFPR more for firms with low net worth than for those with high net worth. According to Gonzalez et al. (2024), low net worth firms are more likely to face borrowing constraints when monetary policy tightens. These constraints limit their ability to invest in growth opportunities, leading to a relative decrease in capital and an increase in their TFPR. As a result, the dispersion of TFPR across firms increases, indicating a less efficient allocation of resources within the economy. This inefficiency highlights net worth as a critical measure of financial constraints that affect firms' responses to changes in monetary policy.

The implications of these results are significant for the mechanisms suggested in the literature regarding how monetary policy might affect economic efficiency. If low net worth firms are disproportionately affected by contractionary policy, it suggests that monetary policy can exacerbate existing financial disparities and lead to greater inefficiencies in resource allocation. This finding underscores the importance of considering firm-level financial health when evaluating the broader economic impacts of monetary policy decisions.

Figure A4 illustrates the dynamic effects of contractionary policy shocks on TFPR over 20 quarters, with a focus on net worth. The analysis, based on Model 2, includes industry and quarter fixed effects along with various macroeconomic controls.

Figure 7: Effects of contractionary policy shocks on TFPR

(a) Coefficient ($\beta_h^{NetWorth}$) (b) $\beta_h^{NetWorth} \times$ Initial Relative Net Worth



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient $\beta_h^{NetWorth}$ over quarters h for net worth, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient $\beta_h^{NetWorth}$, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{NetWorth} \times$ Initial Relative Net Worth, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of net worth, respectively. The relative net worth of 6.52 is the ratio of a firm's net worth at the 90th percentile to a firm's net worth at the 10th percentile. The relative net worth of 2.53 is the ratio of a firm's net worth at the 75th percentile to a firm's net worth at the 25th percentile.

Panel (a) of Figure 7 presents the estimated coefficient $\beta_h^{\text{NetWorth}}$ across different quarters h, with shaded areas representing the 68% and 90% error bands to indicate estimation uncertainty. Initially, the coefficient $\beta_h^{\text{NetWorth}}$ is close to zero, suggesting minimal immediate impact of contractionary policy shocks on TFPR. Over time, the coefficient shows an increasing trend, indicating that the impact grows. The coefficient peaks around the 17th to 18th quarters, suggesting a stronger effect during this period before stabilizing slightly.

Notably, after a 100 basis point increase in the two-year Treasury rate, a firm with net worth 1% higher than another firm increases its TFPR by 0.012 percentage points more. This suggests that contractionary monetary policy tends to increase systematic differences in TFPR between low and high net worth firms.

Panel (b) of Figure 7 depicts the interaction term $\beta_h^{\text{NetWorth}} \times$ Initial Relative Net Worth, with two lines representing different percentile ratios: the red dashed line for the 90-10 percentile ratio (relative net worth of 6.52) and the blue solid line for the 75-25 percentile ratio (relative net worth of 2.53). Both ratios show minimal initial impact, similar to Panel (a). Over time, the 90-10 percentile ratio (red dashed line) shows a more pronounced positive trend compared to the 75-25 percentile ratio (blue solid line), indicating that firms with higher initial relative net worth experience a larger impact. This suggests that firms with higher initial net worth are more significantly affected by contractionary policy shocks compared to firms with lower initial net worth.

These results support the findings of Gonzalez et al. (2024), providing empirical evidence that net worth heterogeneity plays a significant role in determining the impact of monetary policy on firms' productivity.

Size Heterogeneity and Monetary Policy

In this section, we investigate the impact of contractionary monetary policy shocks on TFPR across firms of varying sizes. Specifically, we examine whether smaller firms experience a more significant increase in TFPR compared to larger firms following such shocks. The premise is rooted in the hypothesis that monetary policy does not uniformly affect all firms but rather imposes differential effects based on firm size. This heterogeneity arises from smaller firms' limited access to capital markets and their heavier reliance on external financing, such as bank loans.

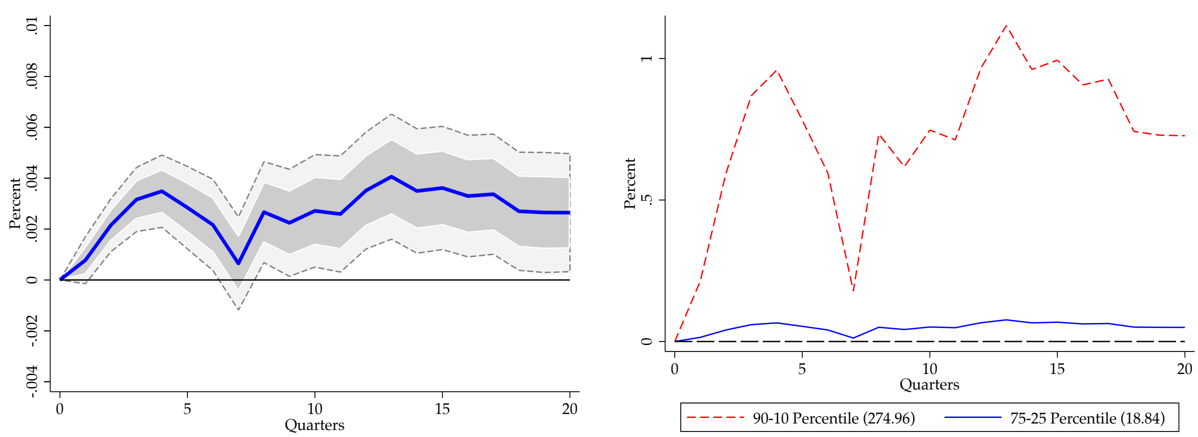
The primary research question we are addressing is whether contractionary monetary policy shocks increase TFPR more for smaller firms than for larger firms. This question is crucial as it touches upon the mechanisms through which monetary policy might influence economic efficiency. If smaller firms are disproportionately impacted, it implies a misallocation of resources, which could hinder overall economic efficiency. Understanding these dynamics helps in assessing the broader implications of monetary policy on economic performance.

The findings of this study have significant implications for the mechanisms proposed in the literature about the impact of monetary policy on efficiency. According to Gertler and Gilchrist (1994), smaller firms face more substantial constraints during periods of monetary tightening. These constraints limit their investment and production capabilities more severely than those of larger firms. As a result, the disparity in TFPR between small and large firms widens, indicating an inefficient allocation of resources across the economy. This increased dispersion in TFPR suggests that monetary policy can exacerbate inefficiencies, particularly through its differential impact on firms based on their size.

Figure 8 illustrates the dynamic effects of contractionary policy shocks on TFPR by firm size over a span of 20 quarters. The analysis is based on Model 2, which incorporates industry and quarter fixed effects along with various macroeconomic controls.

Figure 8: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{Size}) (b) $\beta_h^{Size} \times$ Initial Relative Size



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{Size} over quarters h for size, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{Size}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{Size} \times$ Initial Relative Size, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of size, respectively. The relative size of 274.96 is the ratio of a firm's size at the 90th percentile to a firm's size at the 10th percentile. The relative size of 18.84 is the ratio of a firm's size at the 75th percentile to a firm's size at the 25th percentile.

Panel (a) of Figure 8 displays the estimated coefficient β_h^{Size} across different quarters

h. The shaded area represents the 68% and 90% error bands, which indicate the degree of estimation uncertainty. Initially, the coefficient β_h^{Size} fluctuates around zero, suggesting that contractionary policy shocks have an immediate impact on TFPR. Over time, the coefficient β_h^{Size} begins to show a positive trend, indicating that contractionary policy shocks might lead to an increase in firm size over the long run, with the coefficient fluctuating around 0.004 percent. Specifically, after a 100 basis point increase in the two-year Treasury rate, a firm with a size in terms of assets that is 1% higher than another firm increases its TFPR by 0.004 percentage points more. This suggests that contractionary monetary policy tends to increase systematic differences in TFPR between small and large firms.

Panel (b) of Figure 8 presents the effects of contractionary policy shocks on TFPR by firm size, conditional on the initial relative size. The graph includes two lines representing different percentile ratios: the red dashed line represents the 90-10 percentile ratio, with a relative size of 274.96, and the blue solid line represents the 75-25 percentile ratio, with a relative size of 18.84. For both percentile ratios, the impact of contractionary policy shocks varies over time. The red dashed line shows more pronounced fluctuations, indicating that firms at the higher end of the size distribution experience more significant changes. In contrast, the blue solid line remains relatively stable, suggesting that firms at the middle of the size distribution are less affected by contractionary policy shocks. The larger fluctuations observed in the 90-10 percentile ratio imply that the effects of contractionary policy shocks are more substantial for larger firms compared to smaller firms.

The results of this study support the findings of Gertler and Gilchrist (1994). Specifically, the analysis demonstrates that contractionary monetary policy shocks lead to a more pronounced increase in TFPR for smaller firms compared to larger firms. This outcome aligns with the notion that smaller firms, due to their limited access to capital and higher dependency on external financing, are more adversely affected by monetary policy tightening.

Age Heterogeneity and Monetary Policy

Monetary policy, particularly contractionary shocks, can have heterogeneous effects on firms of different ages. We aim to test whether contractionary monetary policy shocks increase TFPR more for younger firms and less for older firms. This investigation is crucial because it provides insights into the efficiency mechanisms proposed in the literature. Understanding these differential impacts can help explain how monetary policy influences economic dynamics and overall market efficiency.

Monetary policy, especially in its contractionary form, is known to affect firms' access to capital and borrowing costs. Younger firms, which typically have less established credibility and weaker relationships with lenders, are more vulnerable to such policy changes. Cloyne et al. (2018) highlight that younger firms experience significant productivity decreases following monetary tightening due to their heavy reliance on external finance. This reduced borrowing capacity directly impacts their capital, leading to increased TFPR. The increase in TFPR is more pronounced for younger firms not paying dividends, as they face asset value fluctuations more acutely under tighter monetary conditions. Consequently, this capital reduction and the resulting TFPR increase cause greater dispersion in TFPR across firms of different ages.

The implications of these findings are significant for the mechanisms suggested in the literature regarding monetary policy's effect on efficiency. Differential responses to monetary policy can stifle growth and innovation in younger firms, leading to a less dynamic and competitive market structure. This stifling effect could hinder overall economic efficiency and growth, as younger firms are often key drivers of innovation and competition.

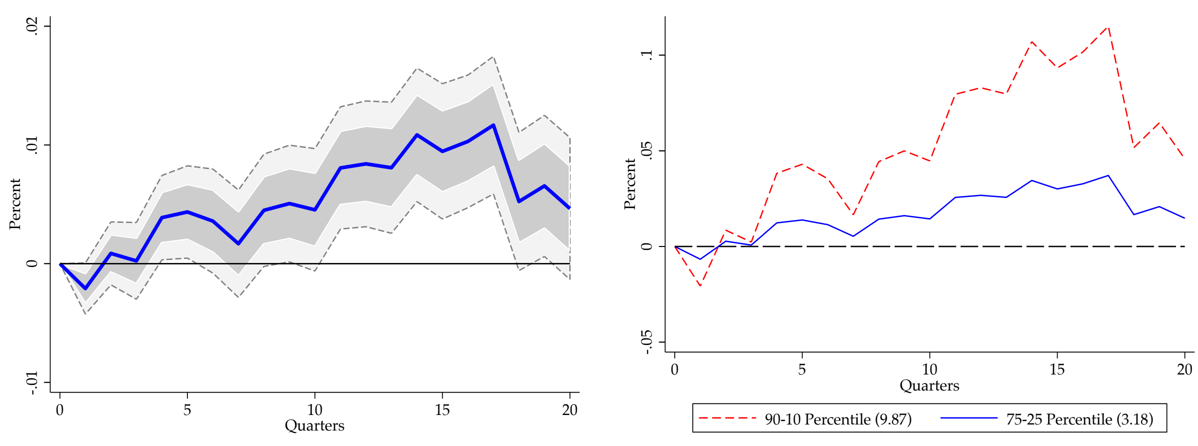
Figure 9 illustrates the dynamic effects of contractionary policy shocks on firm age over a span of 20 quarters. The analysis is based on Model 2, which incorporates industry and quarter fixed effects along with various macroeconomic controls.

Panel (a) of Figure 9 displays the estimated coefficient β_h^{Age} across different quarters h. The shaded area represents the 68% and 90% error bands, indicating the degree of estimation uncertainty. Initially, the coefficient β_h^{Age} fluctuates around zero, suggesting that contractionary policy shocks have a minimal immediate impact on firm age. Over time, the coefficient β_h^{Age} begins to show a slight positive trend, indicating that contractionary policy shocks might lead to a small increase in firm age over the long run. This increase, however, remains relatively minor, with the coefficient fluctuating around 0.01 percent. Specifically, after a 100 basis point increase in the two-year Treasury rate, a firm that is 1% older than another firm increases its TFPR by 0.01 percentage points more. This suggests that contractionary monetary policy tends to increase systematic differences in TFPR between small and large firms.

Panel (b) of Figure 9 presents the effects of contractionary policy shocks on firm age, conditional on the initial relative age. The graph includes two lines representing different percentile ratios: the red dashed line represents the 90-10 percentile ratio, with a relative age of 9.87, and the blue solid line represents the 75-25 percentile ratio, with a relative age of 3.18. For both percentile ratios, the impact of contractionary policy shocks varies over time. The red dashed line shows more pronounced fluctuations, indicating that firms at the higher end of the age distribution experience more significant changes. In contrast, the blue solid line remains relatively stable, suggesting that firms at the middle of the age distribution are less affected by contractionary policy shocks. The larger fluctuations observed in the 90-10 percentile ratio imply that the effects of contractionary policy shocks are more substantial for older firms compared to younger firms.

Figure 9: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{Age}) (b) $\beta_h^{Age}\times$ Initial Relative Age



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{Age} over quarters h for age, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{Age}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the β_h^{Age} $\times$ Initial Relative Age, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of age, respectively. The relative age of 9.87 is the ratio of a firm's age at the 90th percentile to a firm's age at the 10th percentile. The relative age of 3.18 is the ratio of a firm's age at the 75th percentile to a firm's age at the 25th percentile.

The results of our analysis support the findings of Cloyne et al. (2018), demonstrating that contractionary monetary policy shocks indeed have a more substantial impact on younger firms. These findings align with the argument that younger firms, due to their higher reliance on external financing, are more susceptible to changes in monetary policy, which in turn affects their productivity and market dynamics.

5 Conclusion

This study elucidates the supply-side effects of monetary policy interventions on capital misallocation, a domain less frequently explored than the demand-side impacts. Utilizing data from the Compustat database and high-frequency financial market information, we identify monetary policy shocks through an instrumental variable technique and a local projections–instrumental variables (LP-IV) approach. Our findings indicate that a 100 basis point increase in the two-year Treasury rate results in a 2% rise in capital misallocation and a more than 1% reduction in efficiency, with these effects magnified when both capital and labor distortions are considered.

Our research shows that tighter monetary policy increases resource misallocation, reducing allocative efficiency. We also investigate how monetary policy shocks affect TFPR, using firm characteristics as proxies for financial frictions. Our findings reveal that young, small, and low net worth firms are more negatively impacted by contractionary policy shocks. This suggests that such policies exacerbate financial frictions, leading to greater resource misallocation and lower economic efficiency.

The employment of high-frequency financial market data to identify monetary policy shocks significantly strengthens the validity of our results, establishing a causal relationship between monetary policy actions and capital misallocation. This methodological approach enables a precise capture of the dynamic response of TFPR to monetary policy fluctuations, highlighting the differential impacts across various firm categories.

Our findings underscore the importance for policymakers to consider the supply-side repercussions of monetary policy. By understanding the heterogeneous effects on firms of different sizes and characteristics, policymakers can design more effective interventions to mitigate adverse impacts on capital allocation and economic efficiency. Future research should continue to investigate the intricate interplay between monetary policy and firm heterogeneity to further enhance policy effectiveness.

This study contributes to the literature by providing empirical evidence on the adverse supply-side effects of monetary policy on capital misallocation and economic efficiency, offering valuable insights for both academics and policymakers in the ongoing discourse on optimal monetary policy design.

REFERENCES

Alam, M. J. (2020). Capital Misallocation: Cyclicality and Sources. *Journal of Economic Dynamics and Control 112*(C).

Albrizio, S., B. González, and D. Khametshin (2023, January). A Tale of Two Margins: Monetary Policy and Capital Misallocation.

Asker, J., A. Collard-Wexler, and J. D. Loecker (2014, October). Dynamic Inputs and Resource (Mis)Allocation. *Journal of Political Economy 122*(5), pp. 1013–1063.

Baqaee, D. R., E. Farhi, and K. Sangani (2024). The Supply-Side Effects of Monetary Policy. *Journal of Political Economy 132*(4), 1065–1112.

Bauer, M. D. and E. T. Swanson (2023, March). An Alternative Explanation for the "Fed Information Effect". *American Economic Review 113*(3), 664–700.

Cloyne, J., C. Ferreira, M. Froemel, and P. Surico (2018, December). Monetary Policy, Corporate Finance and Investment. NBER Working Papers 25366, National Bureau of Economic Research, Inc.

Crouzet, N. and N. R. Mehrotra (2020, November). Small and Large Firms over the Business Cycle. *American Economic Review 110*(11), 3549–3601.

David, J. M., H. A. Hopenhayn, and V. Venkateswaran (2016, February). Information, Misallocation, and Aggregate Productivity. *Quarterly Journal of Economics 131*(2), 943–1005.

David, J. M. and V. Venkateswaran (2017, February). The Sources of Capital Misallocation. NBER Working Papers 23129, National Bureau of Economic Research, Inc.

David, J. M. and V. Venkateswaran (2019, July). The sources of capital misallocation. *American Economic Review 109*(7), 2531–67.

Gertler, M. and S. Gilchrist (1994, 05). Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms. *The Quarterly Journal of Economics 109*(2), 309–340.

Gertler, M. and P. Karadi (2015, January). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

González, B., G. Nuño, D. Thaler, and S. Albrizio (2024, January). Firm Heterogeneity, Capital Misallocation and Optimal Monetary Policy. ECB Working Paper No. 2024/2890, European Central Bank (ECB).

Gopinath, G., S. Kalemli-Ozcan, L. Karabarbounis, and C. Villegas-Sanchez (2017, November). Capital Allocation and Productivity in South Europe. *Quarterly Journal of Economics 132*(4), 1915–1967.

Gu, Y. and S. R. Singh (2024, February). Distribution of Market Power, Endogenous Growth, and Monetary Policy.

Hsieh, C.-T. and P. J. Klenow (2009, November). Misallocation and Manufacturing TFP in China and India. *Quarterly Journal of Economics 124*(4), 1403–1448.

Jarocinski, M. and P. Karadi (2020, April). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics 12*(2), 1–43.

Jarociński, M. and P. Karadi (2020, April). Deconstructing monetary policy surprises–the role of information shocks. *American Economic Journal: Macroeconomics 12*(2), 1–43.

Jeenas, P. (2018, 01). Monetary policy shocks, financial structure, and firm activity: A panel approach. *SSRN Electronic Journal*.

Jordà, O., M. Schularick, and A. M. Taylor (2020, June). The Effects of Quasi-Random Monetary Experiments. *Journal of Monetary Economics 112*, 22–40.

Jordà, Ò., S. R. Singh, and A. M. Taylor (2023, May). The Long-Run Effects of Monetary Policy. Working Paper 2020-01, Federal Reserve Bank of San Francisco.

Kehrig, M. (2011, May). The Cyclicality of Productivity Dispersion. Working Papers 11-15, Center for Economic Studies, U.S. Census Bureau.

Kehrig, M. and N. Vincent (2017, February). Do Firms Mitigate or Magnify Capital Misallocation? Evidence from Planet-Level Data. CESifo Working Paper Series 6401, CESifo Group Munich.

Kudlyak, M. and J. M. Sanchez (2017). Revisiting the behavior of small and large firms during the 2008 financial crisis. *Journal of Economic Dynamics and Control 77*, 48 – 69.

Meier, M. and T. Reinelt (2024). Monetary Policy, Markup Dispersion, and Aggregate TFP. *Review of Economics and Statistics 106*(4), 1012–1027.

Midrigan, V. and D. Y. Xu (2014, February). Finance and Misallocation: Evidence from Plant-Level Data. *American Economic Review 104*(2), 422–58.

Moll, B. (2014, October). Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation? *American Economic Review 104*(10), 3186–3221.

Nakamura, E. and J. Steinsson (2018, 01). High-Frequency Identification of Monetary Non-Neutrality: The Information Effect. *The Quarterly Journal of Economics 133*(3), 1283–1330.

Ottonello, P. and T. Winberry (2020, November). Financial Heterogeneity and the Investment Channel of Monetary Policy. *Econometrica 88*(6), 2473–2502.

Peters, M. (2018). Heterogeneous Markups, Growth and Endogenous Misallocation. Technical report, Yale University.

Peters, M. (2020). Heterogeneous Markups, Growth, and Endogenous Misallocation. *Econometrica 88*(5), 2037–2073.

Restuccia, D. and R. Rogerson (2008, October). Policy Distortions and Aggregate Productivity with Heterogeneous Plants. *Review of Economic Dynamics 11*(4), 707–720.

Romer, C. D. and D. H. Romer (2004, September). A new measure of monetary shocks: Derivation and implications. *American Economic Review 94*(4), 1055–1084.

Song, Z. M. and G. L. Wu (2015, January). Indentifying Capital Misallocation. Technical report, University of Chicago.

Wieland, J. F. and M. Yang (2020, February). Financial Dampening. *Journal of Money, Credit and Banking 52*(1), 79–113.

Appendix A: Variable Definitions, Sources, and Data Construction

Gross Output, Y_{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.

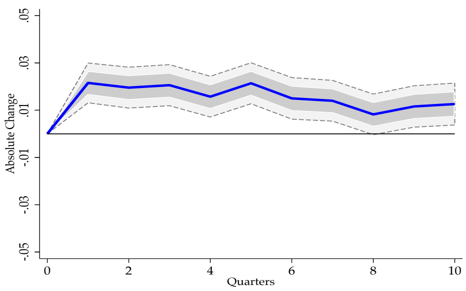
Capital, K_{si}: We follow Ottonello and Winberry (2020) to measure capital stock using the Compustat database. For each firm, we set the first value of k_{it+1} to be the level of gross plant, property, and equipment (`ppegtq`) in the first period in which this variable is reported in Compustat. From this period onwards, we compute the evolution of k_{it+1} using the changes of net plant, property, and equipment (`ppentq`), which is a measure of net investment with significantly more observations than `ppegtq` (net of depreciation). 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.

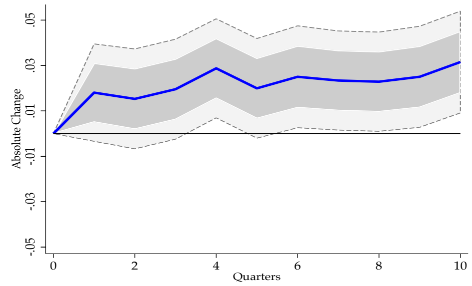
Appendix B: Results without Analytical Weights

Figure A1: Dynamic effects of contractionary policy shocks on economic performance indicator

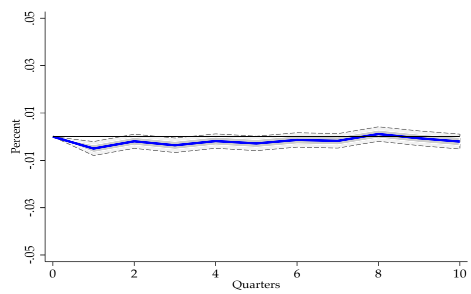
(a) SD of TFPR



(b) SD of TFPQ



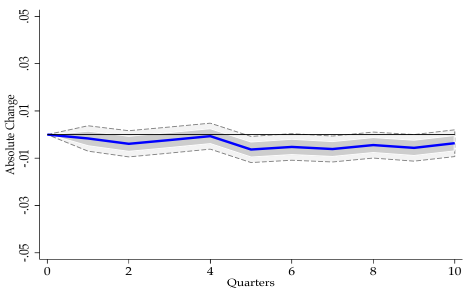
(c) Efficiency



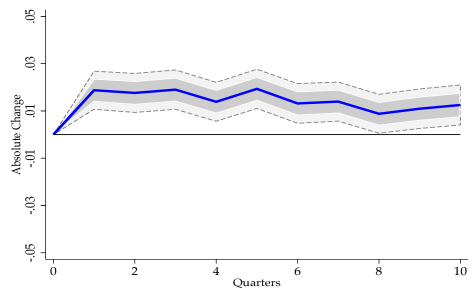
Note: The figures display the effects of contractionary policy shocks on economic performance indicators. Panel (a) shows the standard deviation of TFPR, while panel (b) shows the standard deviation of TFPQ. Panel (c) depicts the efficiency measure. The shaded areas in each panel represent the 68% and 90% error bands. The analysis includes industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included.

Figure A2: Dynamic effects of contractionary policy shocks on sources of capital misallocation

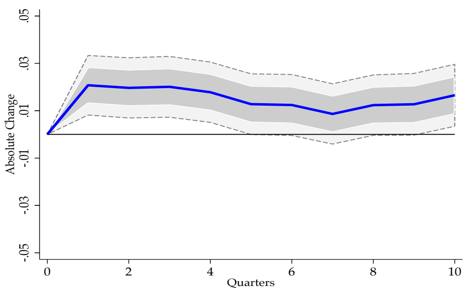
(a) Correlated Distortion (Sales)



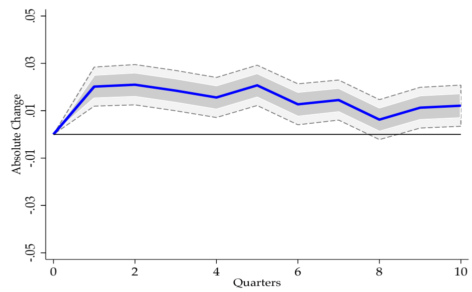
(b) Random Distortion (Sales)



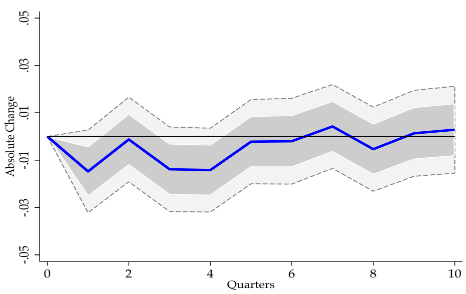
(c) Correlated Distortion (Age)



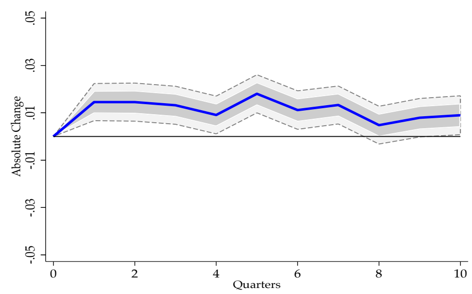
(d) Random Distortion (Age)



(e) Correlated Distortion (Net Worth)



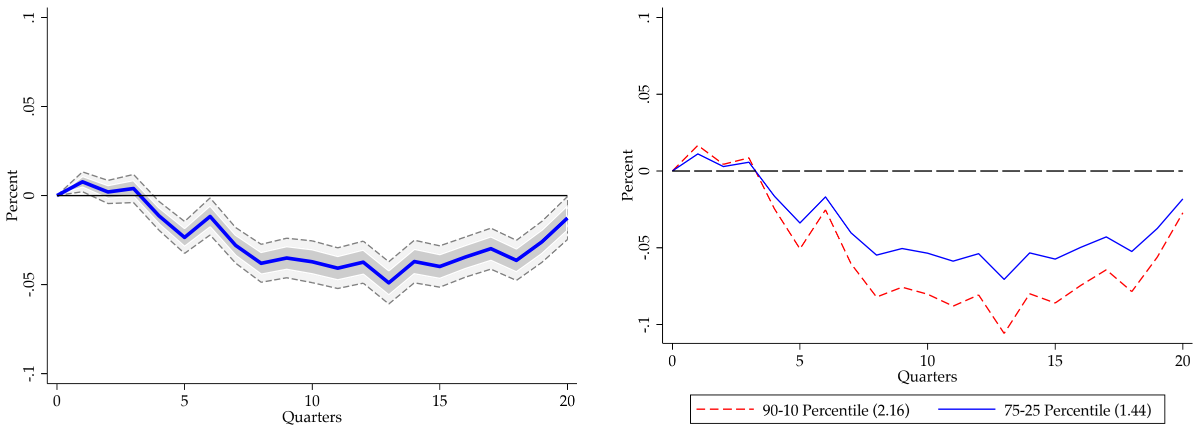
(f) Random Distortion (Net Worth)



Note: The figures illustrate the impact of contractionary policy shocks on capital misallocation across different sources. Panel (a) shows correlated distortion by sales, and panel (b) shows random distortion by sales. Panel (c) and (d) present correlated and random distortions by age, respectively. Panel (e) shows correlated distortion by net worth, and panel (f) shows random distortion by net worth. Panel (g) shows correlated distortion based on total factor productivity (TFPQ), while panel (h) presents random distortion based on TFPQ. The shaded areas represent 68% and 90% error bands. Industry and quarter fixed effects, along with lagged macroeconomic controls (GDP growth and excess bond premium), are included.

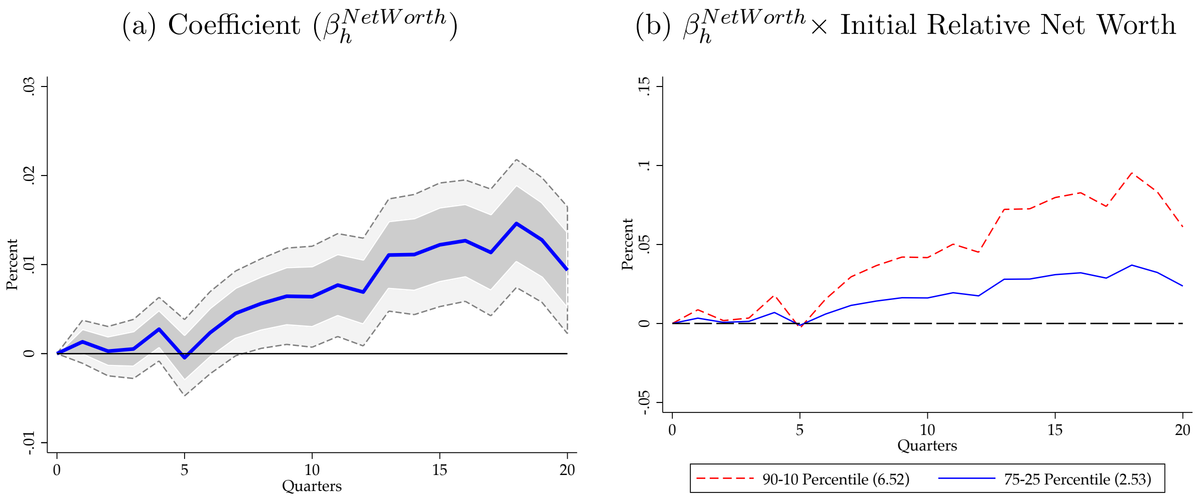
Figure A3: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{TFPR}) (b) $\beta_h^{TFPR} \times$ Initial Relative TFPR



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{TFPR} over quarters h for TFPR, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{TFPR}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{TFPR} \times$ Initial Relative TFPR, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of TFPR, respectively. The relative TFPR of 2.16 is the ratio of a firm's TFPR at the 90th percentile to a firm's TFPR at the 10th percentile. The relative TFPR of 1.44 is the ratio of a firm's TFPR at the 75th percentile to a firm's TFPR at the 25th percentile.

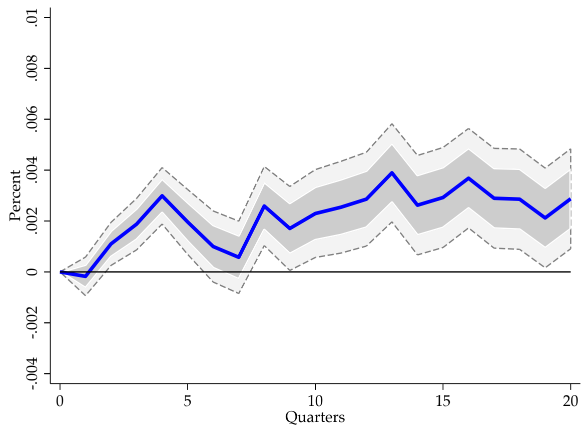
Figure A4: Effects of contractionary policy shocks on TFPR



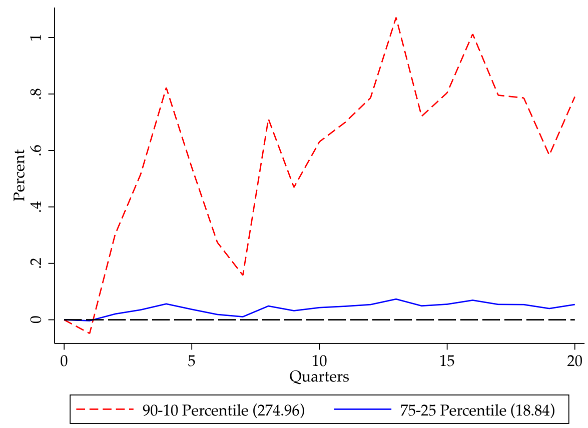
Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient $\beta_h^{NetWorth}$ over quarters h for net worth, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient $\beta_h^{NetWorth}$, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{NetWorth}$ $\times$ Initial Relative Net Worth, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of net worth, respectively. The relative net worth of 6.52 is the ratio of a firm's net worth at the 90th percentile to a firm's net worth at the 10th percentile. The relative net worth of 2.53 is the ratio of a firm's net worth at the 75th percentile to a firm's net worth at the 25th percentile.

Figure A5: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{Size})

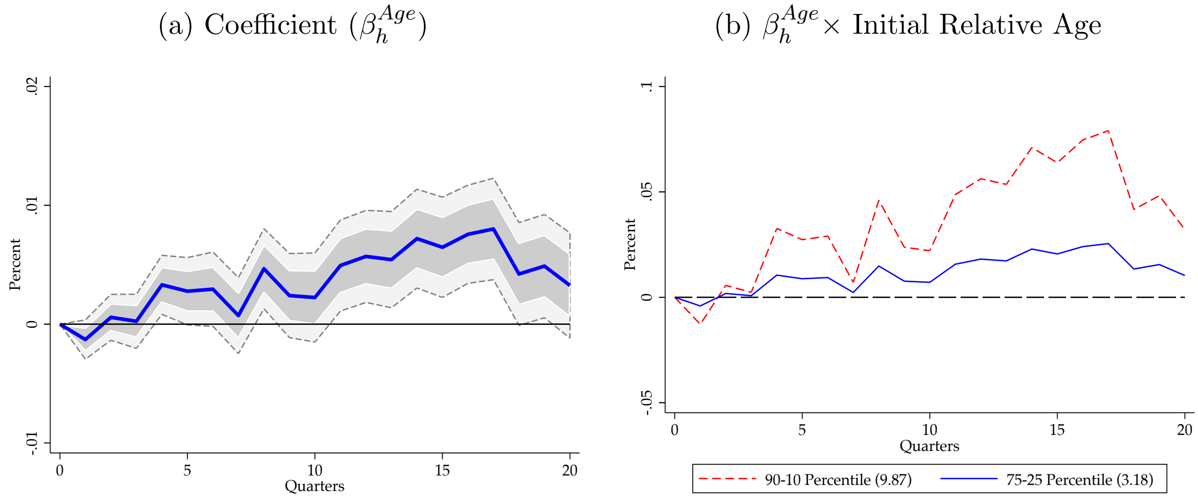


(b) $\beta_h^{Size} \times$ Initial Relative Size



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{Size} over quarters h for size, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{Size}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{Size} \times$ Initial Relative Size, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of size, respectively. The relative size of 274.96 is the ratio of a firm's size at the 90th percentile to a firm's size at the 10th percentile. The relative size of 18.84 is the ratio of a firm's size at the 75th percentile to a firm's size at the 25th percentile.

Figure A6: Effects of contractionary policy shocks on TFPR



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{Age} over quarters h for age, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{Age}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{Age} \times$ Initial Relative Age, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of age, respectively. The relative age of 9.87 is the ratio of a firm's age at the 90th percentile to a firm's age at the 10th percentile. The relative age of 3.18 is the ratio of a firm's age at the 75th percentile to a firm's age at the 25th percentile.

Appendix C: Alternative Assumption: $\tau_{si}^L = \tau_{si}^K$

For this section, to calculate TFPR, we use **Assumption 1:** Labor and capital distortions are equal ($\tau_{si}^L = \tau_{si}^K$). This appendix includes the following key components:

1. **Descriptive Statistics of Economic Performance Indicators**: This section provides a detailed summary of various economic performance indicators under the assumption that labor and capital distortions are equal. It highlights the means and standard deviations of metrics such as MRPK, TFPR, TFPQ, efficiency, and both correlated and random distortions.

- **Table A1**: This table provides the descriptive statistics of various economic performance indicators under Assumption 1, where labor and capital distortions are equal.

2. **Economic Performance Indicators Over Time**: Graphs in this section illustrate the temporal patterns of key economic performance indicators, including MRPK, TFPR, efficiency, and random distortions. The figures compare these indicators during recession and non-recession periods to highlight the impact of economic downturns on resource allocation and efficiency.

- **Figure A7**: This figure shows the economic performance indicators over time under Assumption 1, highlighting trends during recession and non-recession periods.

3. **Cyclical Components of Economic Performance Indicators**: This section presents the cyclical components of the economic performance indicators, showing how they fluctuate over different economic cycles. The figures demonstrate the variations in MRPK, TFPR, random distortions, and efficiency across various economic conditions, with particular attention to recession periods.

- **Figure A8**: This figure presents the cyclical components of various economic performance indicators under Assumption 1, focusing on fluctuations during different economic cycles.

4. **Dynamic Effects of Contractionary Policy Shocks on Economic Performance Indicators**: This section explores the dynamic impact of contractionary policy shocks on

various economic performance indicators. It examines how such shocks influence the standard deviations of TFPR and TFPQ, as well as overall efficiency, over different time horizons.

- **Figure A9**: This figure illustrates the dynamic effects of contractionary policy shocks on economic performance indicators, focusing on the standard deviations of TFPR and TFPQ, as well as efficiency measures over time.

5. **Dynamic Effects of Contractionary Policy Shocks on Sources of Capital Misallocation**: This section investigates the dynamic impact of contractionary policy shocks on the sources of capital misallocation. It analyzes how such shocks affect correlated and random distortions in sales, age, and net worth over different time horizons.

- **Figure ??**: This figure illustrates the dynamic effects of contractionary policy shocks on sources of capital misallocation, focusing on correlated and random distortions in sales, age, and net worth.

6. **TFPR and Firm Characteristics**: This section examines the relationship between TFPR and various firm characteristics, such as firm size, age, markups, and net worth. The figures illustrate how TFPR varies across different percentiles of these characteristics, providing insights into the efficiency and productivity differences among firms with varying attributes.

- **Figure A11**: This figure illustrates the relationship between TFPR and various firm characteristics under Assumption 1, showing variations across different percentiles of firm size, age, markups, and R&D expenditures.

7. **Effects of Contractionary Policy Shocks on TFPR**: This section explores the dynamic impact of contractionary policy shocks on TFPR. It examines the coefficients of TFPR over different time horizons, as well as the interaction with initial relative TFPR.

- **Figure A12**: This figure illustrates the dynamic effects of contractionary policy shocks on TFPR, focusing on the coefficient β_h^{TFPR} and its interaction with initial relative TFPR.

8. **Effects of Contractionary Policy Shocks on TFPR by Net Worth**: This section explores the dynamic impact of contractionary policy shocks on TFPR, focusing on the coefficient $\beta_h^{NetWorth}$ and its interaction with initial relative net worth.

- **Figure A13**: This figure illustrates the effects of contractionary policy shocks on TFPR by net worth, showing the coefficient $\beta_h^{NetWorth}$ and its interaction with initial relative net worth.

9. **Effects of Contractionary Policy Shocks on TFPR by Firm Size**: This section explores the dynamic impact of contractionary policy shocks on TFPR, focusing on the coefficient β_h^{Size} and its interaction with initial relative size.

- **Figure A14**: This figure illustrates the effects of contractionary policy shocks on TFPR by firm size, showing the coefficient β_h^{Size} and its interaction with initial relative size.

10. **Effects of Contractionary Policy Shocks on TFPR by Firm Age**: This section explores the dynamic impact of contractionary policy shocks on TFPR, focusing on the coefficient β_h^{Age} and its interaction with initial relative age.

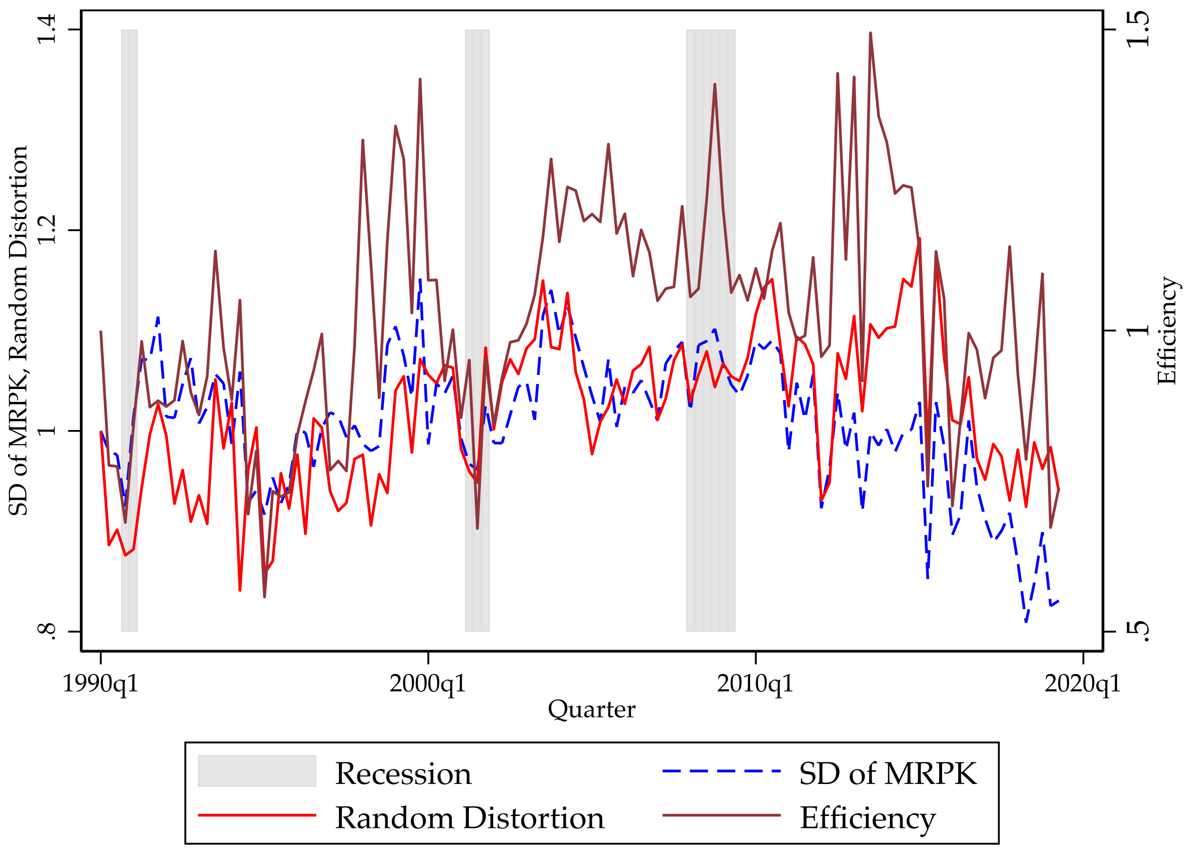
- **Figure A15**: This figure illustrates the effects of contractionary policy shocks on TFPR by firm age, showing the coefficient β_h^{Age} and its interaction with initial relative age.

Table A1: Descriptive statistics of economic performance indicators

	Obs	Mean	SD	Min	Max
Standard deviation of MRPK	6709	0.87	0.27	0.21	2.39
Standard deviation of TFPR	6709	0.87	0.27	0.21	2.39
Standard deviation of TFPQ	6709	1.34	0.32	0.40	3.05
Efficiency	6709	-0.26	0.28	-4.79	-0.01
Correlated Distortion (Sales Coefficients)	6709	-0.03	0.11	-0.67	1.22
Random Distortion (Sales Coefficients)	6709	0.84	0.26	0.19	2.34
Correlated Distortion (Age Coefficients)	6709	-0.06	0.23	-3.54	1.97
Random Distortion (Age Coefficients)	6709	0.85	0.27	0.19	2.12
Correlated Distortion (Net Worth Coefficients)	6709	-0.47	0.36	-3.35	2.05
Random Distortion (Net Worth Coefficients)	6709	0.77	0.25	0.14	1.97
Correlated Distortion (TFPQ Coefficients)	6709	0.36	0.16	-0.41	1.30
Random Distortion (TFPQ Coefficients)	6709	0.68	0.17	0.13	1.41

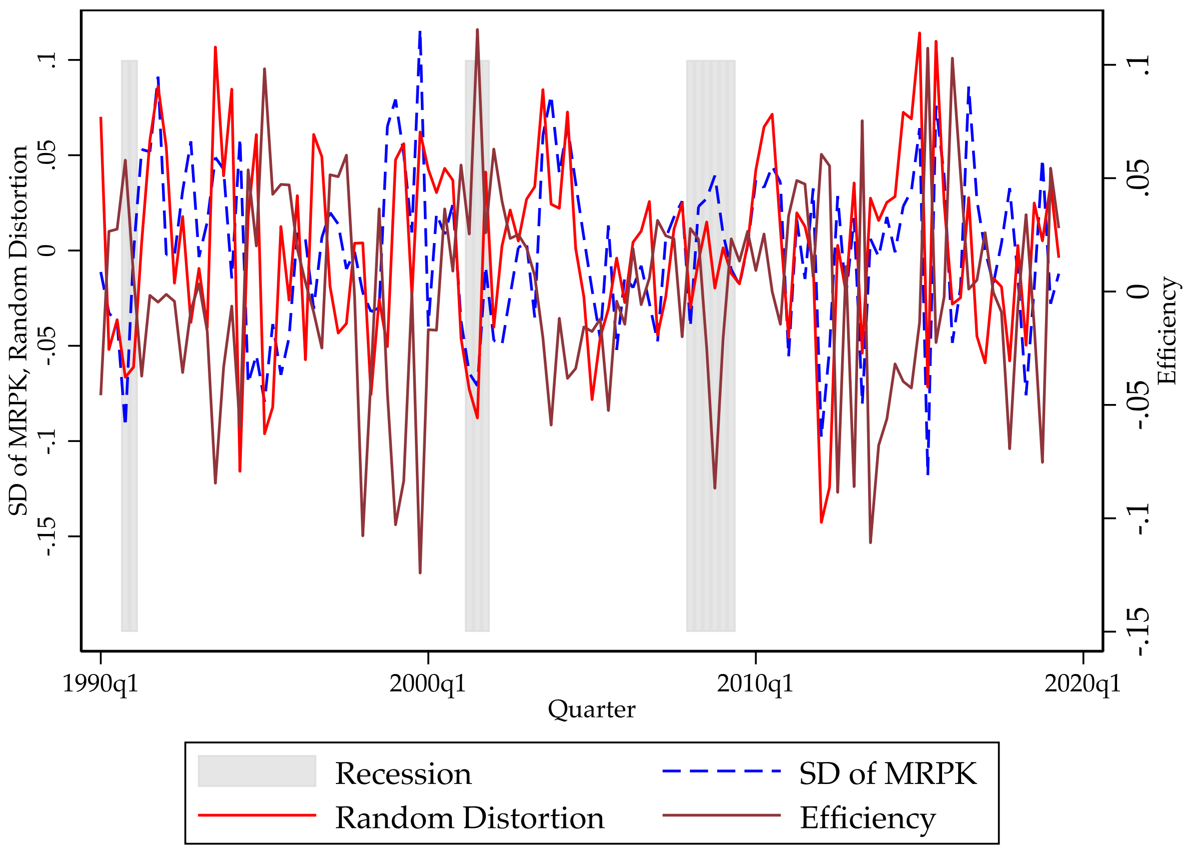
Note: This table provides the descriptive statistics of various economic performance indicators for the first assumption regarding labor and capital distortions. The first assumption considers that labor and capital distortions are equal.

Figure A7: Economic performance indicators over time



Note: This figure provides the various economic performance indicators for the first assumption regarding labor and capital distortions. The first assumption considers that labor and capital distortions are equal. The shaded regions represent periods of recession.

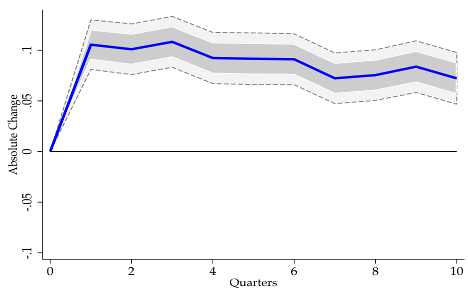
Figure A8: Cyclical components of economic performance indicators



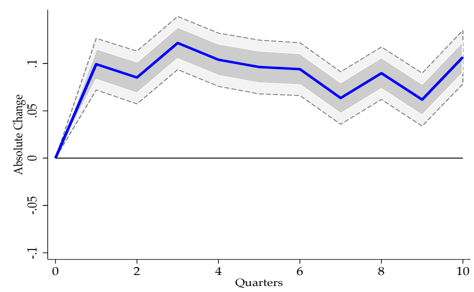
Note: This figure provides the cyclical components of various economic performance indicators for the first assumption regarding labor and capital distortions. The first assumption considers that labor and capital distortions are equal.

Figure A9: Dynamic effects of contractionary policy shocks on economic performance indicator

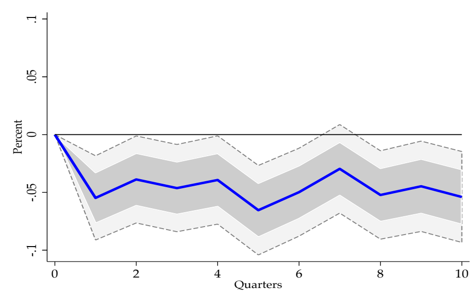
(a) SD of TFPR



(b) SD of TFPQ



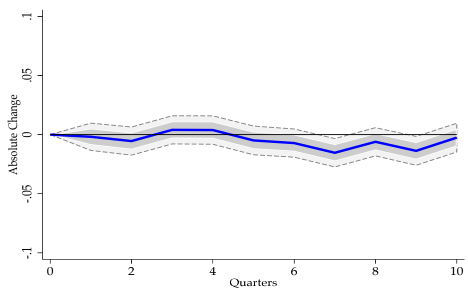
(c) Efficiency



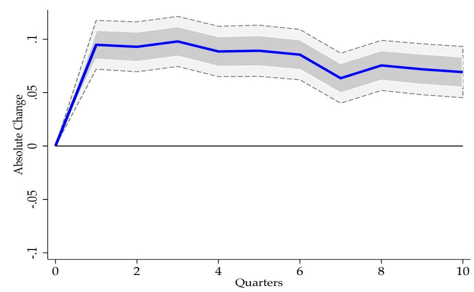
Note: The figures display the effects of contractionary policy shocks on economic performance indicators. Panel (a) shows the standard deviation of TFPR, while panel (b) shows the standard deviation of TFPQ. Panel (c) depicts the efficiency measure. The shaded areas in each panel represent the 68% and 90% error bands. The analysis includes industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included.

Figure A10: Dynamic effects of contractionary policy shocks on sources of capital misallocation

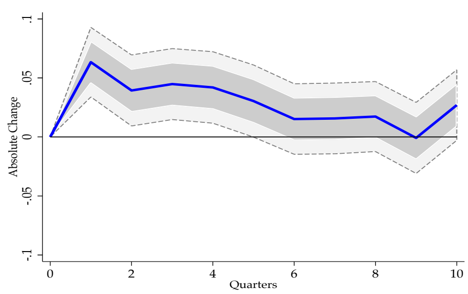
(a) Correlated Distortion (Sales)



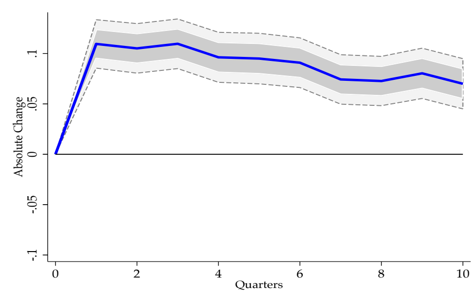
(b) Random Distortion (Sales)



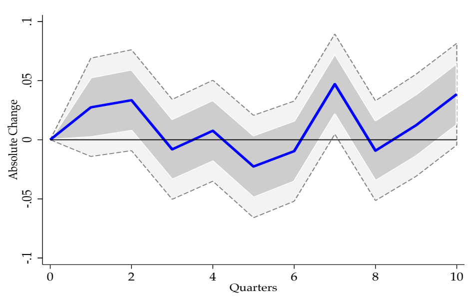
(c) Correlated Distortion (Age)



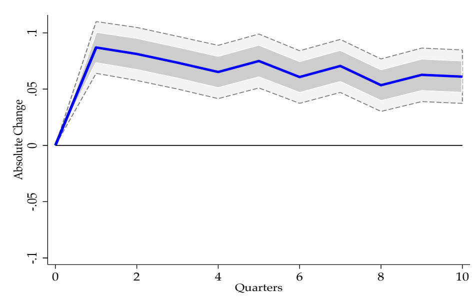
(d) Random Distortion (Age)



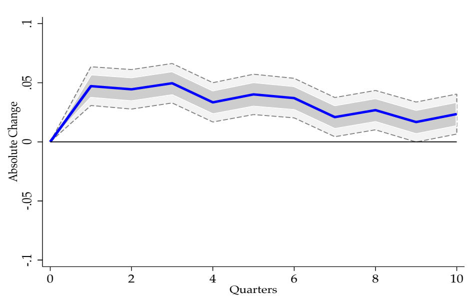
(e) Correlated Distortion (Net Worth)



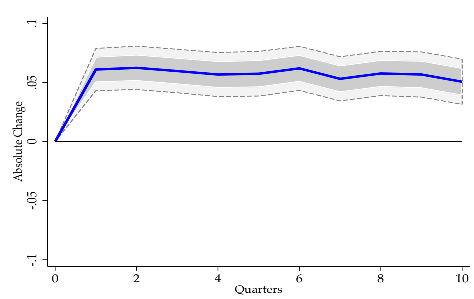
(f) Random Distortion (Net Worth)



(g) Correlated Distortion (TFPQ)

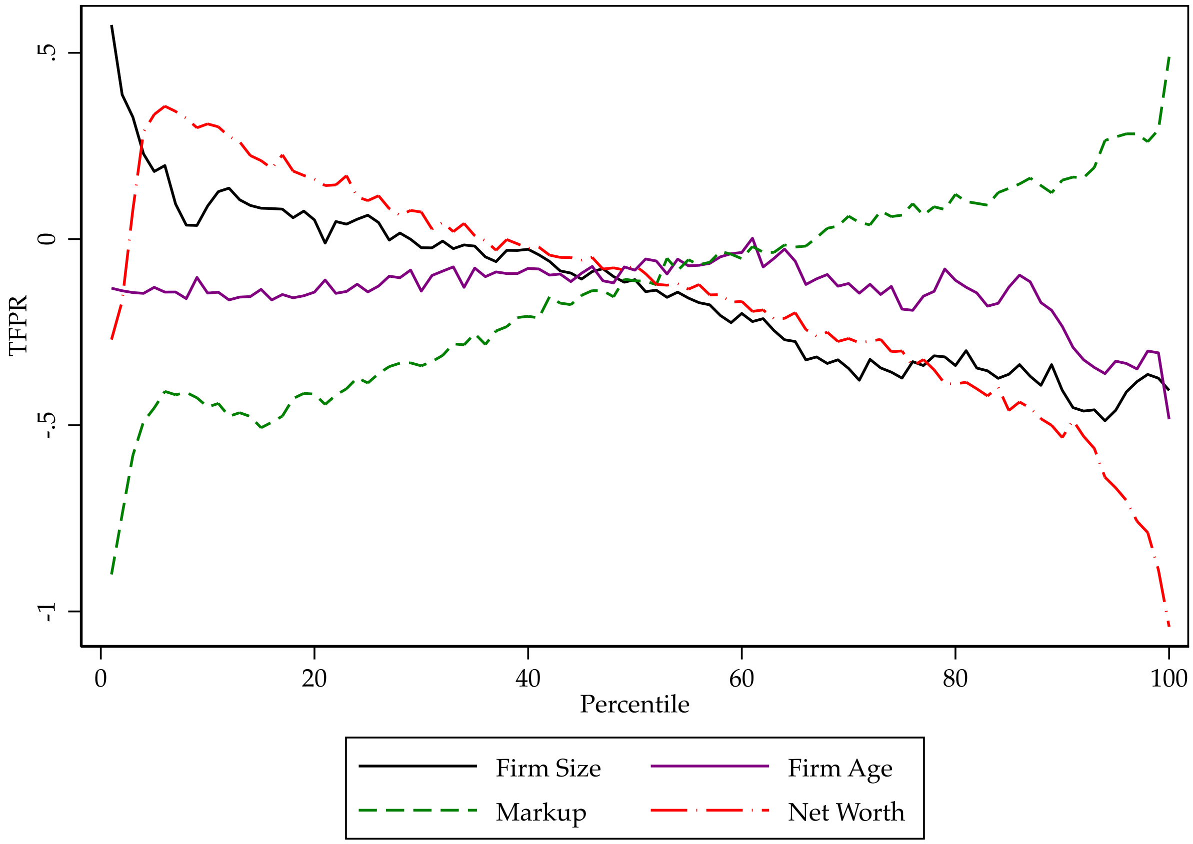


(h) Random Distortion (TFPQ)



Note: The figures display the effects of contractionary policy shocks on sources of capital misallocation. We estimate the coefficient β_h^J over quarters h for the sources of capital misallocation, using Model 1 (refer to Model 1 for details). Panel (a) shows correlated distortion based on sales, while panel (b) shows random distortion based on sales. Panel (c) depicts correlated distortion based on age, and panel (d) depicts random distortion based on age. Panel (e) shows correlated distortion based on net worth, and panel (f) shows random distortion based on net worth. The shaded areas in each panel represent the 68% and 90% error bands. The analysis includes industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included.

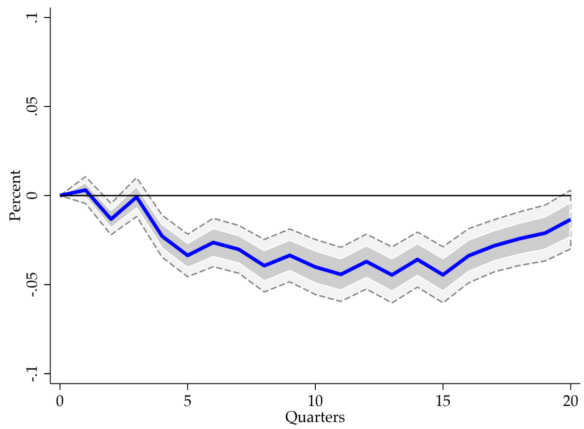
Figure A11: TFPR and firm characteristics



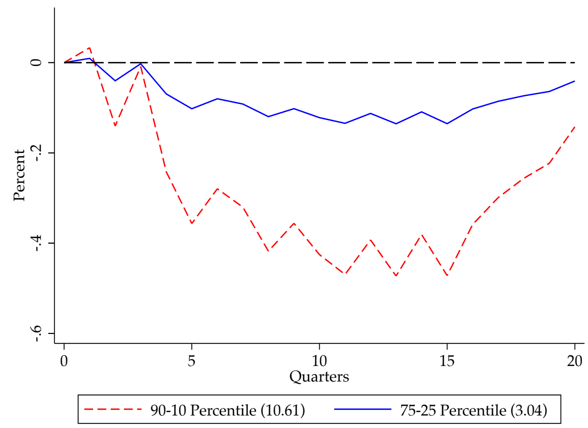
Note: The vertical axis shows the log ratio of $TFPR_{si}$ to $\overline{TFPR_s}$, while the horizontal axis represents the percentile of firm size, age, markups, and net worth to their industry average. This graph considers the first assumption.

Figure A12: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{TFPR})



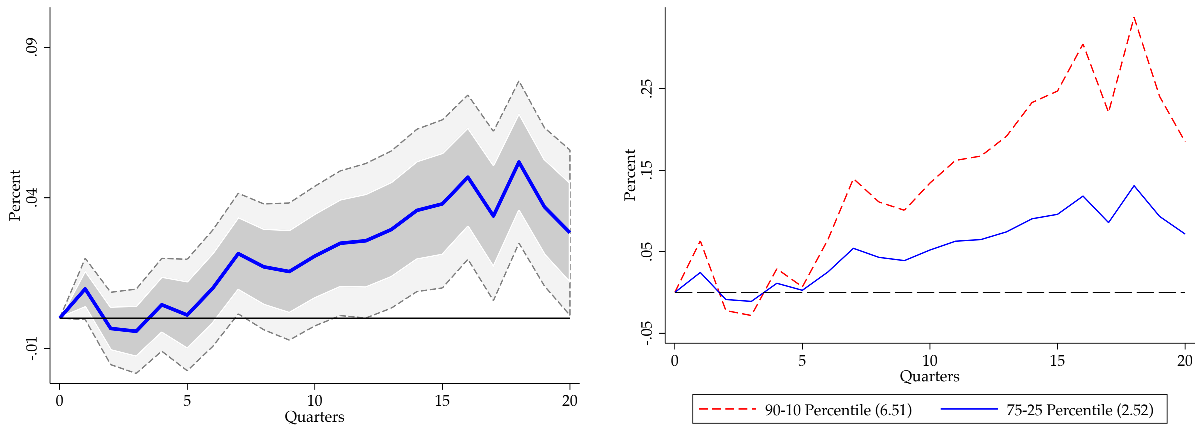
(b) $\beta_h^{TFPR} \times$ Initial Relative TFPR



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{TFPR} over quarters h for TFPR, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{TFPR}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{TFPR} \times$ Initial Relative TFPR, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of TFPR, respectively. The relative TFPR of 2.16 is the ratio of a firm's TFPR at the 90th percentile to a firm's TFPR at the 10th percentile. The relative TFPR of 1.44 is the ratio of a firm's TFPR at the 75th percentile to a firm's TFPR at the 25th percentile.

Figure A13: Effects of contractionary policy shocks on TFPR

(a) Coefficient ($\beta_h^{NetWorth}$) (b) $\beta_h^{NetWorth} \times$ Initial Relative Net Worth

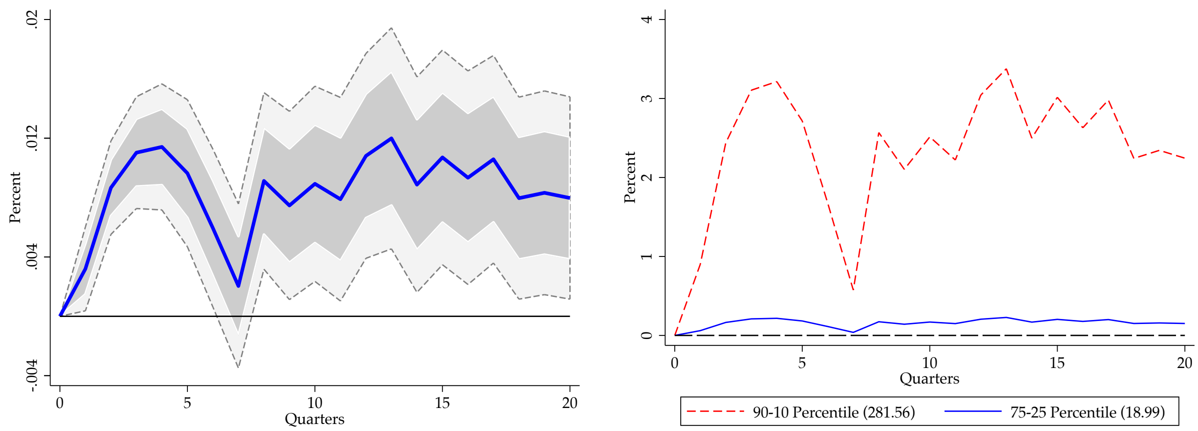


Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient $\beta_h^{NetWorth}$ over quarters h for net worth, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient $\beta_h^{NetWorth}$, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{NetWorth} \times$ Initial Relative Net Worth, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of net worth, respectively. The relative net worth of 6.52 is the ratio of a firm's net worth at the 90th percentile to a firm's net worth at the 10th percentile. The relative net worth of 2.53 is the ratio of a firm's net worth at the 75th percentile to a firm's net worth at the 25th percentile.

Figure A14: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{Size})

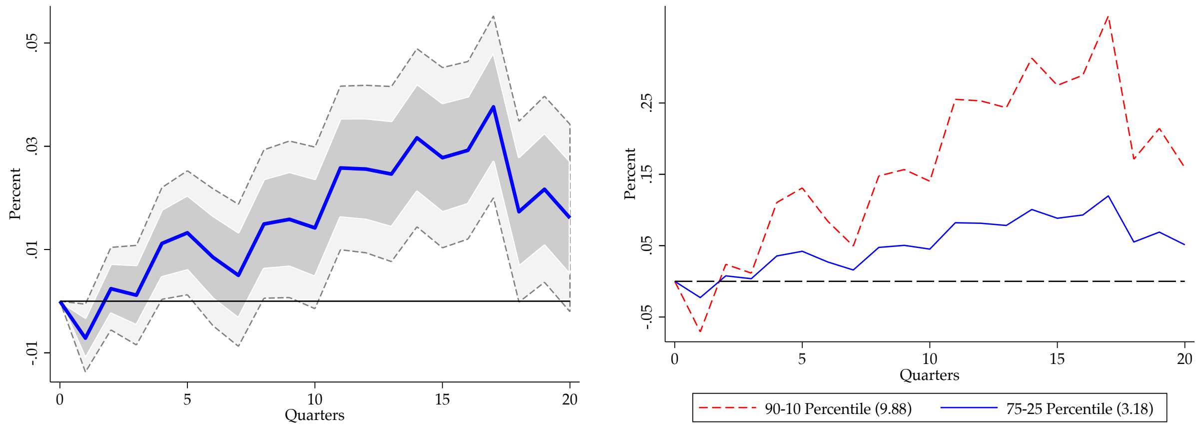
(b) $\beta_h^{Size} \times$ Initial Relative Size



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{Size} over quarters h for size, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{Size}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{Size} \times$ Initial Relative Size, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of size, respectively. The relative size of 274.96 is the ratio of a firm's size at the 90th percentile to a firm's size at the 10th percentile. The relative size of 18.84 is the ratio of a firm's size at the 75th percentile to a firm's size at the 25th percentile.

Figure A15: Effects of contractionary policy shocks on TFPR

(a) Coefficient (β_h^{Age}) (b) $\beta_h^{Age} \times$ Initial Relative Age



Note: The figures display the effects of contractionary policy shocks on TFPR. We estimate the coefficient β_h^{Age} over quarters h for age, using Model 2 (refer to Model 2 for details). Panel (a) shows the coefficient β_h^{Age}, with the shaded area representing the 68% and 90% error bands. We include industry and quarter fixed effects to account for time-invariant industry differences and quarter-specific shocks. Macroeconomic controls, such as GDP growth and excess bond premium, each lagged by four quarters, are also included. Panel (b) shows the $\beta_h^{Age} \times$ Initial Relative Age, with the red and blue lines representing the 90-10 percentile and 75-25 percentile ratios of age, respectively. The relative age of 9.87 is the ratio of a firm's age at the 90th percentile to a firm's age at the 10th percentile. The relative age of 3.18 is the ratio of a firm's age at the 75th percentile to a firm's age at the 25th percentile.

Appendix D: Markup Theory Test

The goal of our analysis is to empirically test the theoretical framework proposed by Baqaee et al. (2024), which predicts that a contractionary monetary shock leads to relative increases in TFPR of high-TFPR firms. To accomplish this, we employ the empirical methodology described in their work, focusing on within-industry local projection estimates to assess the impact of monetary policy shocks on firm-level productivity.

Following Baqaee et al. (2024), the core regression equation of interest is specified as:

$$\begin{aligned}\mathrm{Cov}_\lambda\left(-\frac{1}{\mathrm{TFPR}_{f,t}}, \Delta\log\mathrm{TFPR}_{f,t\to t+h}\right) &= a_i^h + \sum_{k=0}^{4} b_k^h \cdot \mathrm{MonetaryShock}_{t-k} \\ &+ \sum_{k=1}^{4} c_k^h \cdot \mathrm{Cov}_\lambda\left(-\frac{1}{\mathrm{TFPR}_{f,t}}, \Delta\log\mathrm{TFPR}_{f,t-k\to t}\right) + \epsilon_{i,t}^h\end{aligned}$$

The dependent variable on the left-hand side represents the sales-weighted covariance between the inverse of TFPR and changes in TFPR over a time horizon h, for firm f in industry i. This covariance provides a measure of how changes in TFPR are distributed across firms with differing productivity levels.

On the right-hand side, the independent variables consist of two key components:

- The first summation captures the effect of a contemporaneous and lagged series of monetary policy shocks, $\mathrm{MonetaryShock}_{t-k}$, which aims to quantify the response of firm-level TFPR to contractionary monetary policy at both time t and four previous periods ($t-1$ through $t-4$). These shocks are measured using three different measures (see the details in the next section).

- The second summation accounts for the lagged covariances between inverse TFPR and prior changes in TFPR over the previous four quarters. This inclusion allows for the capture of dynamic persistence in the relationship between firm-level productivity and previous shocks to productivity.

The parameters a_i^h denote industry-specific fixed effects, which control for time-invariant factors within each NAICS-3 industry that might affect the relationship between TFPR and monetary policy shocks. The error term $\epsilon_{i,t}^h$ captures any unexplained variation at the industry level, with standard errors clustered at the industry level to account for cross-sectional dependence and autocorrelation in the panel data.

The objective of this model is to assess whether contractionary monetary policy shocks lead to relative increases in the TFPR of high-TFPR firms. Based on Baqaee et al. (2024), we expect that the coefficients b_k^h associated with the monetary shocks will be positive, indicating that high-TFPR firms experience larger relative increases in productivity following a contractionary shock. Additionally, we control for potential persistence in productivity changes by including lagged covariances as additional explanatory variables.

The regression is estimated using a local projection method, allowing us to trace the dynamic response of firm-level productivity to monetary policy shocks over multiple horizons, ranging from $h = 0$ to $h = 12$. We use Driscoll-Kraay standard errors to address the potential issues of autocorrelation and heteroskedasticity across industries over time. The findings from this analysis will shed light on the differential effects of monetary policy across firms with varying levels of productivity.

Monetary Policy Shock Measures

In our empirical model, we employ three distinct measures of monetary policy shocks to capture the impact of contractionary shocks on firm-level Total Factor Productivity Revenue (TFPR):

- **High-Frequency Interest Rate Surprises**: This measure is based on unexpected changes in interest rates around Federal Open Market Committee (FOMC) meetings. By focusing on the unanticipated component of monetary policy announcements, this measure isolates the effects of monetary policy actions that are not anticipated by market participants, providing a cleaner identification of monetary shocks.

- **Poor Man's Monetary Shocks**: These shocks are constructed using publicly available macroeconomic data and are designed to capture shifts in monetary policy that may affect firms indirectly, through changes in financial conditions and aggregate demand. We employ the *poor man's* monetary policy shocks, following the approach of

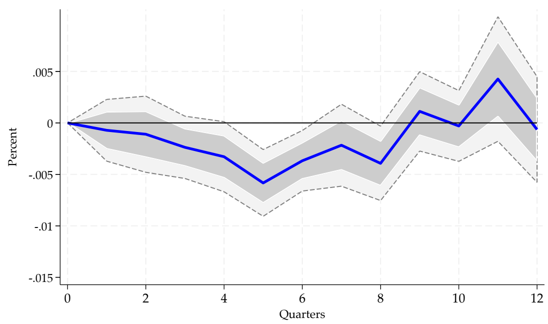
Jarocinski and Karadi (2020). This measure offers an alternative to more sophisticated identification methods, relying on simpler, easily replicable data sources.

- **Romer and Romer (2004) Monetary Shocks, Extended by Wieland and Yang (2020)**: This series builds on the influential work of Romer and Romer (2004), which identified exogenous shifts in U.S. monetary policy by examining Federal Reserve policy statements and actions. Wieland and Yang (2020) extended this series to cover up to 2007Q4, allowing us to analyze the effects of monetary policy shocks over a longer time frame. Specifically, for this research, the series covers data from 1990Q1 to 2007Q4, providing a robust identification of policy shocks by distinguishing between anticipated and unanticipated changes in monetary policy.

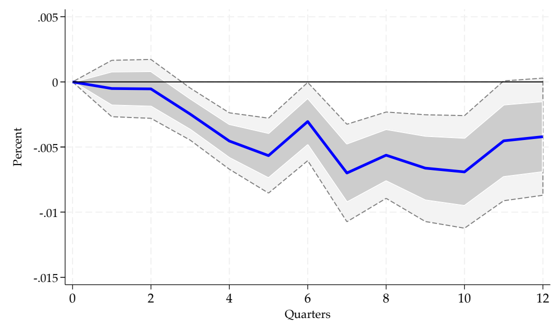
By utilizing these four measures, we aim to capture the full spectrum of monetary policy shocks and their differential effects on firm-level productivity. This approach allows us to test the robustness of our results across various shock identification strategies, ensuring that our findings are not driven by the specific choice of monetary shock measure.

The results depicted in Figure A16 suggest that, contrary to theoretical expectations, contractionary monetary shocks lead to relative *decreases* in TFPR for high-TFPR firms across all four measures of monetary policy shocks. This pattern is observed consistently across changes in two-year treasury rates, high-frequency interest rate surprises, poor man's monetary shocks, and the extended Romer and Romer shocks. Each measure demonstrates a similar trend of negative TFPR responses following monetary shocks over the 12-quarter horizon. This unexpected outcome challenges the hypothesis of a positive TFPR response to contractionary shocks and raises questions about the mechanisms through which monetary policy affects firm-level TFPR. Further investigation is needed to better understand the transmission channels of monetary shocks and their heterogeneous effects across firms.

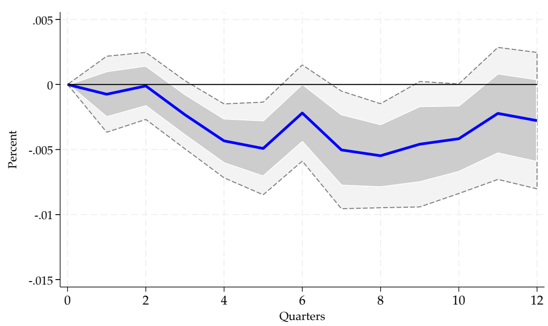
Figure A16: Dynamic Effects of Monetary Policy on TFPR



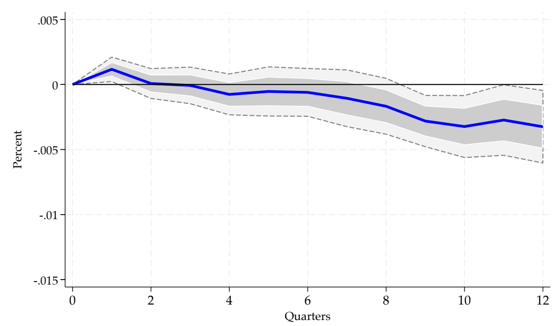
(a) LP-IV



(b) High-Frequency Interest Rate Surprises



(c) Poor Man's Monetary Shocks



(d) Romer and Romer Shocks (Extended)

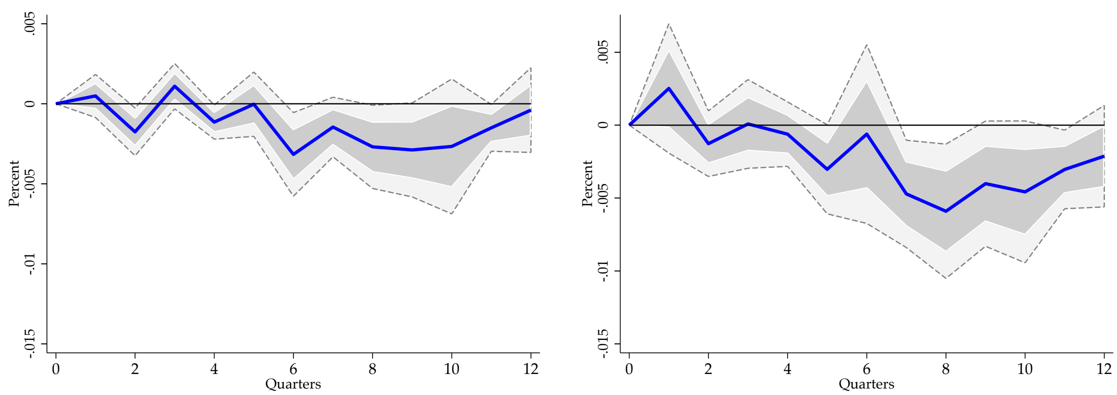
Note: This figure illustrates the dynamic effects of monetary policy shocks on TFPR over a 12-quarter horizon. Subfigure (a) depicts the response of two-year Treasury rates instrumented by Poor Man's Monetary Shocks (LP-IV method), while subfigure (b) captures the impact of High-Frequency Interest Rate Surprises. Subfigure (c) represents the effects of Poor Man's Monetary Shocks, and subfigure (d) shows the response to the Romer and Romer (2004) shocks extended by Wieland and Yang (2020), using data from 1990Q1 to 2007Q4. The solid blue line in each subfigure denotes the point estimate, while the shaded areas represent the 68% (dark gray) and 90% (light gray) confidence intervals, respectively. These plots allow for a comparison of how different monetary policy shocks influence firm-level productivity across time.

Extended Analysis and Robustness Check

To further validate the robustness of our findings, we extend the sample period to cover data from 1971Q4 to 2007Q4.[2] This extended period allows us to analyze the dynamic effects of monetary policy shocks over a broader historical context, providing an opportunity to assess whether the patterns observed in the original analysis hold over a longer time span. By including data from the 1970s and 1980s, when monetary policy regimes and macroeconomic conditions were markedly different from the 1990s and 2000s, we can ensure that our conclusions are not specific to the more recent period alone.

Figure A17 compares the results from the original sample period (1990Q1 to 2007Q4) with the extended period (1971Q4 to 2007Q4) using two key monetary policy shock measures: Two-Year Treasury Rates and Romer and Romer shocks. Despite the addition of earlier data, the results are remarkably consistent, indicating that contractionary monetary policy shocks continue to result in relative *decreases* in TFPR for high-TFPR firms.

Figure A17: Comparison of Dynamic Effects of Monetary Policy on TFPR (Extended Period)



(a) Two-Year Treasury Rates (b) Romer and Romer Shocks

Note: This figure compares the dynamic effects of monetary policy shocks on TFPR over an extended period (1971Q4 - 2007Q4). Subfigure (a) illustrates the response of Two-Year Treasury Rates, while subfigure (b) shows the response to Romer and Romer shocks, both over the extended sample. The solid blue line in each subfigure denotes the point estimate, and the shaded areas represent the 68% (dark gray) and 90% (light gray) confidence intervals. These plots confirm the robustness of our results, showing consistent patterns of TFPR responses across different time periods.

The inclusion of the extended period provides further justification for our findings in two

[2]Although Baqaee et al. (2024) use data from 1969 to 2007, we begin our analysis in 1971Q4 due to missing capital stock data for earlier periods.

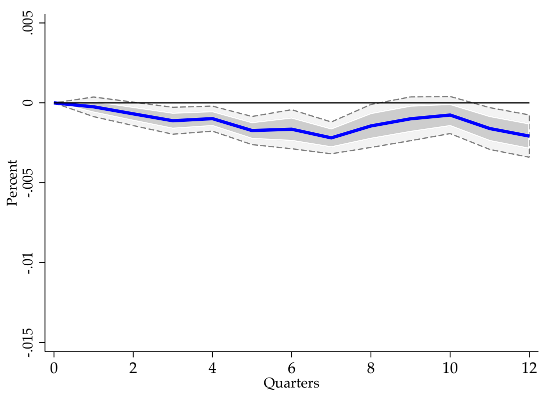
important ways:

1. **Broader historical coverage**: By incorporating data from earlier decades, we account for a wider range of macroeconomic conditions, including the high inflation environment of the 1970s and the subsequent monetary tightening. The consistency of the results across these different macroeconomic periods strengthens the generalizability of our conclusions.

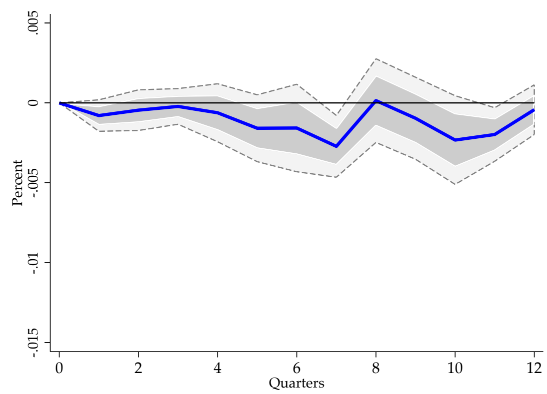
2. **Consistency with theoretical expectations**: While Baqaee et al. (2024) predicted that contractionary monetary shocks should lead to relative *increases* in TFPR for high-TFPR firms, our analysis consistently finds the opposite result across both time periods. This suggests that the transmission mechanism through which monetary policy affects firm-level productivity may be more complex than previously thought. The robustness of the results across different time horizons implies that further theoretical refinement may be necessary to fully understand the heterogeneous effects of monetary shocks.

In conclusion, the results obtained over the extended period further confirm that the relationship between monetary policy shocks and TFPR responses remains consistent over time. Despite the inclusion of data from earlier decades, our findings challenge the theoretical expectation of positive TFPR responses to contractionary monetary shocks and suggest that high-TFPR firms may experience relative declines in TFPR following such shocks. This highlights the need for further exploration into the transmission mechanisms of monetary policy and the factors that drive these heterogeneous effects across firms.

Figure A18: Comparison of Dynamic Effects of Monetary Policy on TFPR (Operating Income)



(a) Two-Year Treasury Rates



(b) Romer and Romer Shocks

Note: This figure compares the dynamic effects of monetary policy shocks on TFPR over an extended period (1971Q4 - 2007Q4). Subfigure (a) illustrates the response of Two-Year Treasury Rates, while subfigure (b) shows the response to Romer and Romer shocks, both over the extended sample. The solid blue line in each subfigure denotes the point estimate, and the shaded areas represent the 68% (dark gray) and 90% (light gray) confidence intervals. These plots confirm the robustness of our results, showing consistent patterns of TFPR responses across different time periods.