Essays in Macroeconomics

by

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Submitted to the Faculty of the Department of Economics
on March 31, 2024
in partial fulfillment of the requirements for the degree of
Doctor of Philosophy

Morrissey Graduate School of Arts and Sciences
Boston College
2024

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Abstract

This dissertation comprises three self-contained essays that investigate how micro-level frictions affect firms' operational decisions and investors' behavior, evaluating their respective costs or benefits for the overall economy.

In the first chapter, "Customer Capital and The Aggregate Effect of Short-Termism", joint work with M. Errico and A. Lavia, we study the impact of short-termism on firms' pricing decisions and quantify the potential costs for consumers in term of welfare. Managers face continuous pressure to meet short-term forecasts and targets, which can impact their investment in customer capital and pricing decisions. Using data on U.S. public companies together with IBES analysts' forecasts, we find that firms that just meet analysts' profit forecasts have average markup growth of 0.8% higher than firms that just miss targets, suggesting opportunistic markup manipulation. To assess the aggregate economic implications of short-termism, we develop and estimate a quantitative heterogeneous firm model that incorporates short-term frictions and endogenous markups resulting from customer accumulation. In the model, short-termism solves an agency conflict between manager and shareholders, resulting in higher markups and lower customer capital stock. We find that, on average, firms increase markups by 8% due to short-termism, generating $38 million of additional annual profits. At the macro level, the distortion reduces consumers' welfare by 4% and lowers the total market capitalization by $3.1 trillion on average.

In the second chapter, "Strategic Investors and Exchange Rate Dynamics", joint work with M. Errico, we study how the exchange rate dynamics are influenced by the presence of heterogeneous investors with varying degrees of price impact. Leveraging data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions, we show that foreign exchange rate markets display a significant level of concentration,

and investors' price impact is stronger in more concentrated markets. We develop a monetary model of exchange rate determination that incorporates heterogeneous investors with different degrees of price impact. We show that the presence of price impact amplifies the exchange rate's response to non-fundamental shocks while dampening its response to fundamental shocks. As a result, investors' price impact contributes to the disconnect of exchange rates from fundamentals and the excess volatility of exchange rates. We provide empirical evidence in line with our theoretical predictions, using data on trading volume concentration from the US CFTC foreign exchange rate market for 10 currencies spanning from 2006 to 2016. Additionally, we extend our framework to account for information heterogeneity among investors, which presents a competing dimension of heterogeneity with qualitatively similar implications for exchange rate dynamics. Both dimensions of heterogeneity are quantitatively relevant, with the heterogeneity in price impact accounting for 62% of the additional volatility and 35% of the additional disconnect attributed to investors' heterogeneity.

In the third chapter, "Firms' Investment and Central Bank Communication: The Role of Financial Heterogeneity", I study how financial frictions impact the transmission of monetary policy to investment. Monetary policy affects firms' capital investment through two distinct channels: the pure monetary channel, which operates through changes in interest rates, and the information channel, which operates through changes in investors' beliefs about the economic outlook and future policy rates. I show that the role of financial frictions for monetary policy transmission hinges crucially on specific channel. Using Compustat data, I find that firms with high leverage are more sensitive to pure monetary shocks but are less sensitive to Fed information shocks. Finally, I develop a dynamic general equilibrium model with firm idiosyncratic productivity, real and financial frictions to rationalize the empirical findings and study aggregate implications.

Acknowledgments

I would like to express my deepest gratitude to my advisors, Ryan, Stephen, Fabio, and Rosen, for their unwavering support and guidance throughout my academic journey. Their invaluable insights, encouragement, and constructive criticism have helped me develop the necessary skills and knowledge to complete this dissertation. I am truly grateful for their patience, firm guidance, and mentorship, which have been essential to my success. Their passion for research and commitment to excellence have been a constant source of inspiration, and I feel incredibly fortunate to have had the opportunity to work with them.

During my time in Boston, I have been incredibly fortunate to form meaningful and lasting friendships with many people both within and outside the Ph.D. program. From the late-night dinners and Sunday lunches to the karaoke sessions and parties, I have shared unforgettable moments with all of you. A special thank you goes to Pietro, Alessandro, Simone, Marius, and Vera for everything you have done throughout these years. This program would never have been the same without your friendship, support, and the wonderful experiences we created together.

I want to dedicate an entire paragraph to thank Marco, my roommate, classmate, coauthor, and above all, cherished friend. Your unwavering companionship throughout this journey has been invaluable. From the countless wonderful meals we cooked and shared, to the late-night brainstorming sessions, deep discussions, and bursts of creativity in our joint projects, every moment has been a testament to your incredible support and friendship. I am profoundly grateful for your presence in my life, and I couldn't have asked for a better partner on this journey.

There are not enough words to express my gratitude to my partner and future wife, Iolanda. Your constant support, patience, and unwavering love have been my anchor through this journey. Your belief in me has given me strength during the toughest times, and your joy has amplified every success. Finally, I would like to thank my family and friends in Italy for their support and friendship throughout these years.

Persevera et vince.

This work is dedicated to my family.

Contents

Chapter I

Customer Capital and The Aggregate Effect of Short-Termism

1 Introduction

The model of corporate governance holds substantial influence over company operational choices, thereby potentially impacting the broader aggregate economy. The Anglo-Saxon model of corporate governance, common in the United States and the United Kingdom, is often noted to encourage efficient resource allocation, well-informed investment choices, and effective corporate governance through its promotion of market liquidity, distributed ownership, transparent reporting, and managerial discipline (Shleifer and Vishny, 1997; Burkart et al., 1997; Dewatripont and Maskin, 1995).[1] Nonetheless, this model puts emphasis on achieving short-term financial goal, which may affect long-term corporate investment and business development (Terry, 2022; Fama, 1980; Demsetz, 1983).

In this paper, we study how the tendency to prioritize short-term profits, typical of the Anglo-Saxon model of corporate governance, impacts firms' investment decisions in customer capital, pricing and, ultimately consumer welfare. Firm performance is routinely scrutinized and compared to analysts' profit forecasts, generating pressure on managers to meet short-term profit targets (Graham et al., 2005).[2] In a corporate governance model based on achieving short-term financial targets, this may lead managers to put less importance on

[1] The Anglo-Saxon model of corporate governance opposes other approaches, such as the Continental Europe model or the Japanese model, in which ownership is more concentrated and the focus is not on achieving short-term financial goals (La Porta et al., 1999; Hoshi et al., 1991; Demsetz and Lehn, 1985).

[2] Notably, a recent survey found that approximately 90% of US-based managers report experiencing pressure to meet short-term profit targets (Graham et al., 2005).

long-term business development, increasing markups to boost immediate profitability, but leading to reduced investment in customer capital and long-term value.[3]

In the data, firm profits bunch just above analysts' forecasts and relatively few firms display narrow misses, suggesting some form of systematic pressure to meet short-term profit forecasts. Using data on quarterly analyst earnings forecasts from IBES for the universe of U.S. public firms from 1990 to 2018, we compute profit forecast errors at the firm-quarter level as the difference between realized profits and the median analysts' forecast. We show that the distribution of forecast errors exhibits are bunched at small positive values. This evidence suggests firms care about meeting analysts' forecasts, opening up the possibility of some form of systematic opportunistic behavior to meet profit forecasts.

We document a systematic positive local differences in markup growth between firms that just meeting and just missing analysts' forecasts. Pressured to hit analysts' forecasts, managers may opportunistically raise markups to increase profits and meet short-term targets. By combining balance sheet information from Compustat and IBES data on analysts' forecasts, we find that firms that just meet analysts' forecasts exhibit an average markup growth 0.8 p.p. higher than firms that just miss their target, indicative of opportunistic markup manipulation. The magnitude of this discontinuity in markup growth is substantial when compared to the average and median absolute markup growth rates (8.3% and 3.2%, respectively). Additionally, we provide evidence that markup manipulation occurs through adjustments in prices rather than cost reductions.

We use a model in the spirit of Terry (2022) to rationalize micro-level short-termism, and quantify its effects on pricing and welfare. Our empirical evidence serves as a detection mechanism for identifying the presence of opportunistic manipulation in markups consistent

[3] Short-termism has been linked to negative effects on investment in research and development, lower productivity, financial stability, and negative effects on long-term performance (Terry, 2022; Celik and Tian, 2022; Bertomeu et al., 2022).

with the existence of short-term pressure. Because our results only offer suggestive evidence of a local effect around the median analysts' forecast, they cannot be causally interpreted as the mean effect of short-termism on markups. Hence the need for a quantitative model that allows us to directly quantify the effects of short-termism, considering also aggregation and equilibrium forces.

We first develop a two-period model with short-term costs of meeting profit target and customer capital accumulation to qualitatively understand how short-termism influences firms' pricing and markups decisions. Firms sell a differentiated product facing a dynamic demand due to the presence of a customer capital accumulation process. Pricing decisions are forward-looking, as they influence current profits but also future customer capital (Foster et al., 2016; Gilchrist et al., 2017; Moreira, 2016). Private empire building motives push managers towards lowering today's markup to increase future customer capital, over-investing from the perspective of the firm's shareholders. To maximize shareholders' value, the board of directors introduces a cost for failing to meet profit expectations, disciplining managerial behavior and offsetting the agency conflict. Thus, short-termism emerges optimally as a corrective mechanism (Terry, 2022). The key implication is that firms seize the opportunity to raise their markup to increase current profits, and cut the costs associated with missing short-term analysts' forecasts. This strategy is inherently short-term in nature, as it sacrifices long-term growth and customer acquisition opportunities.

We embed the key mechanism of the simple model into a quantitative dynamic heterogeneous firm model to quantify the effects of short-termism on the aggregate economy. We extend the simple model and introduce heterogeneous firms' with idiosyncratic productivity and idiosyncratic demand shocks. Firms are run by risk-neutral managers who observe both productivity and demand shocks, and set prices and may engage in accrual manipulation to maximize their current private utility. Rational analysts forecast firms' profit having full knowledge of managers' incentive and firm current customer capital, but don't observe productivity and demand shocks. Shareholders observe analysts' forecasts and imposes an optimal cost on managers if analysts' forecasts are not met. Short-term incentives increase markup levels, causing excess volatility in markups and misallocation.

We estimate 7 parameters of the model with Simulated Methods of Moments (SMM). We target 12 moments computed from quarterly Compustat/IBES merged data using data spanning from 2003 to 2018, which corresponds to the period following the implementation of the Sarbanes-Oxley (SOX) Act in 2002. Parameters governing firm heterogeneity are identified targeting moments such as the correlation matrix between markup growth, profit growth, sales growth. Short-termism parameters and manager's private benefit are estimated targeting the forecast error at a quarterly frequency, the probability of meeting forecasters' expectations, and the probability of "just" meeting analysts' forecasts. Lastly, we target the average markup in the model to calibrate the elasticity of demand with respect to price. The estimation process yields a good overall fit in matching closely targeted moments. Moreover, the estimated model is able to replicate untargeted moments in the data such as the cross-sectional relationship between the probability of meeting analysts' forecasts and firm size or markup growth.

We use the estimated model to run counterfactuals to quantify the impact of short-termism on firms' pricing behavior and the aggregate economy. We show that, for a given customer base, short-termism prompts firms to increase their markups, leading to an immediate benefit for shareholders. At the firm level, the baseline model estimates an 8.04% rise in markups due to short-termism, which, in turn, increases firm profits by 5.76% on average. For some comparison, the mean quarterly firm profits reported in Compustat in 2019 is approximately $700 millions, meaning that, on average, each firm generates $38 millions of additional profits every quarter due to short-termism. Furthermore, at the aggregate level, we estimate a welfare loss of approximately 4% in terms of higher costs of living and consumption-equivalent welfare, figure in line with the quantitative estimates of other phenomena such as gains from trade or the welfare cost of business cycles. Additionally, although firms individually generate more profits, short-termism reduces customer accumulation, thereby shifting the size of firms across the distribution. This distributional effect leads to an 9.17% decrease in the total market capitalization, equivalent to a loss of approximately $3.1 trillions based on the overall annual capitalization of Compustat firms ($34 trillions). Overall, our results suggest that models of corporate governance implying strong emphasis on short-term goals, while closely associated with highly liquid and transparent capital markets, come at the cost of non-negligible welfare losses that might be relevant to regulators and policy makers.

We explore the robustness of our results conducting a wide range of alternative quantitative exercises. We examine changes to modeling assumptions such as a private benefit linked to revenues, rather than sales, or decreasing accrual costs in firm size. The latter (former) specification estimates an increase in markup of about 7% (12%) and a welfare loss of 4% (6%). Overall, we find that the qualitative predictions are similar across specification, but with varying quantitative magnitudes.

Literature. Our work relates to the literature that examines the effects of short-termism. At the micro-level, short-termism impacts managerial decisions in profits reporting not only via accounting and accrual manipulation, but also through operational decisions such as altering sales and shipment schedules (Fudenberg and Tirole, 1995), modifying pricing and cutting discretionary expenses (Bhojraj et al., 2009; Zhang and Gimeno, 2016, 2010; Roychowdhury, 2006), and delaying or reducing research and development (R&D) (Terry, 2022; Corredoira et al., 2021; Bebchuk and Stole, 1993). Relative to this literature, we provide novel evidence on markup manipulation using the universe of U.S. public companies and not specific industries such as airlines or electricity markets. Moreover, at the macro-level, Terry (2022) and Celik and Tian (2022) show that short-termism and agency conflicts between managers and shareholders resulting in opportunistic cuts to R&D expenditure have significant effects on long-term growth. Bertomeu et al. (2022) show that managers strategically concealing information to beat earnings forecasters result in market uncertainty. Our study complements this literature by exploring how the presence of short-termism affects customer accumulation, average markups and, ultimately, consumer welfare.[4]

Our work also contributes to the theoretical literature on modeling firm heterogeneity and frictions to study aggregate fluctuations. We extend an endogenous customer capital model incorporating short-term frictions to explore the effects of short-termism on pricing behavior and welfare. On one hand, our model relies on a customer capital accumulation process as in Foster et al. (2016), which have been used in macroeconomic models (Gourio and Rudanko, 2014; Ravn et al., 2008), models of firms' dynamics and business dynamism (Moreira, 2016; Foster et al., 2016; Bornstein, 2021), with financial frictions (Gilchrist and Zakrajšek, 2012). On the other hand, we model short-termism based on Terry (2022) and Celik and Tian (2022), who incorporate short-termism into an endogenous growth model to study its long-term effects. Our model differs from theirs due to the inclusion of an endogenous customer capital accumulation process and markup.

The remainder of the paper is organized as follows. Section 2 present empirical evidence on the relationship between short-termism and opportunistic markup manipulation. Section 3 presents a simple short-termism model. Section 4 introduces our quantitative model. Section 5 estimates the impact of short-termism. Section 6 concludes. Online appendices contain details on the data (Appendix E), the empirical robustness (Appendix B), the simple model (Appendix C), and the estimation and quantitative analysis (Appendix D).

[4] The effects of short-termism on markup dynamics and its excess volatility also relates to the markup and misallocation literature (Edmond et al., 2023; Baqaee and Farhi, 2020; Hsieh and Klenow, 2009).

2 Empirics

In this section, we present empirical evidence on the relationship between short-termism and markup growth. We begin by discussing our dataset and measurement approach for markups and short-termism. We show the presence of an abnormal bunching of firms just meeting analysts' forecasts, suggesting that managers are focused on meeting short-term targets. We then show that firms just meeting profits forecasts have higher markup growth than those just missing their targets.

2.1 Dataset and measurement

The empirical analysis in this paper is based on two main datasets. We use quarterly-level information from Compustat, which includes disaggregated data on various firm-level variables, allowing us to construct various measures of markup. The second dataset is the Institutional Broker's Estimate System (IBES) database, which provides profit forecasts and "Street" realized profits at the firm-analyst-quarter level. The two datasets are merged to create a panel of around 2200 firms from 1990-Q1 to 2018-Q4 with quarterly information on analysts' forecasts, earning realizations, markup and several other firm-level variables. We briefly summarize how we construct the variable markup and measure short-termism below. Appendix E provides additional information on the data sources, the construction and cleaning of the sample, and descriptive statistics of the main variables used in the analysis.

Quarterly firm-level markup growth. We estimate markups using Compustat data and following Hall (1988), De Loecker and Warzynski (2012), De Loecker et al. (2020) (henceforth DEU). We assume a Cobb-Douglas production function and define our main measure of markup for firm i, in sector s at quarter t as:

$$\mu_{ist} = \widehat{\theta}^{V}_{st} \frac{P_{ist} Q_{ist}}{P^{V}_{ist} Q^{V}_{ist}}, \tag{1}$$

where $\widehat{\theta}_{st}$ is the estimated sectoral output elasticity of variable input V in sector s at time t, and $\frac{P_{ist}Q_{ist}}{P^{V}_{ist}Q^{V}_{ist}}$ is the revenue share of variable input V of firm i at time t. We adopt the methodology proposed by DEU to estimate production function and output elasticity using Compustat data. Specifically, we use the cost of goods sold (*cogs* in Compustat) as variable input and measure revenues with total quarterly sales (*saleq* in Compustat). Sectors are defined at the 2-digit NAICS level.

To test the robustness of our results, we consider alternative measures of markups: (i) we estimate markups using the cost of goods sold plus overhead costs as variable input ($cogs + xsga$ in Compustat); (ii) we demean our preferred measure of markup at the sector-quarter level to make markups independent of output elasticities (Meier and Reinelt, 2022); and (iii) we proxy markups with the gross margin, defined as $\mu_{it} = 1 - \frac{\text{Variable Costs}_{it}}{\text{Revenues}_{it}}$, where variable costs are the cost of goods sold and revenues are total sales. Appendix E provides further details on the estimation and measures of markup.

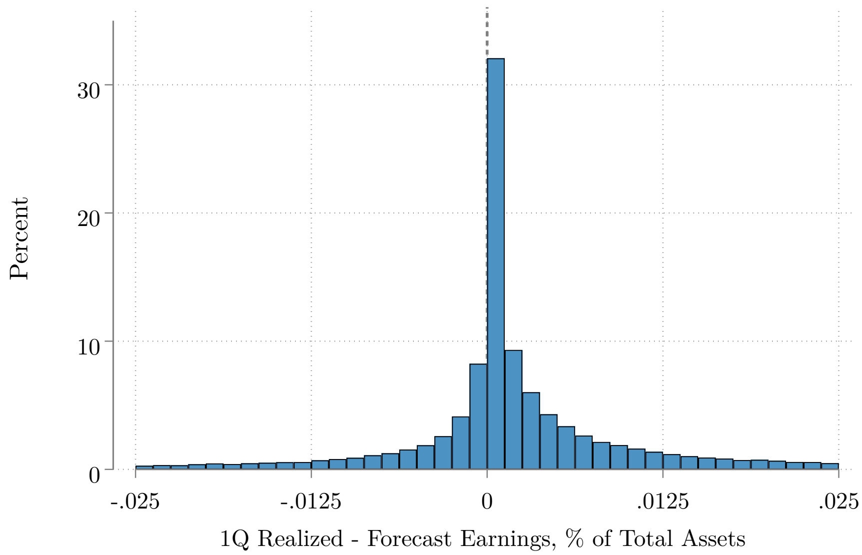
Forecast error. We follow Terry (2022) and use IBES profits forecasts and realized earnings to construct our main measure of the one-quarter forecast error for firm i at quarter t:

$$\text{Forecast Errors}_{it} \equiv fe_{it} = \frac{\text{Realized Earnings}_{it} - \text{Consensus}_{it}}{\text{Total Assets}_{it}}, \tag{2}$$

where Realized Earnings is the IBES Street quarterly earnings, and the consensus forecast measure (Consensus_{it}) is the median across analysts of one-quarter horizon forecasts of dollar earnings. To account for differences in firm size, we scale the forecast error by the size of the firm measured by total assets (*atq* in Compustat).

To test the robustness of our results, we construct alternative measures of forecast errors

Figure 1: Forecast Error Distribution of U.S. Non-Financial Firms (1990-2018)



Notes: The Figure plots the histogram of the forecast errors drawn from a 1990-2018 sample of 2,205 U.S.-based public, non-financial firms for a total of 86,122 firm-quarter observation. The histogram does not include the top 5% and the bottom 5% of the forecast error distribution. Realized profits are quarterly earnings; forecast profits are the median analyst forecasts at quarterly frequency. Profits and analyst forecasts are from IBES. Forecast errors are computed as the difference between realized profits and forecast profits, and expressed as percentage of total assets. Total assets are from Compustat. See Appendix E for additional details on data and measure construction.

rescaling the difference between realized earning and analyst consensus by other measure of firm size such as market value (Compustat variable *prccq*, i.e. price per share) or lagged sales (Compustat variable *saleq*). Appendix E provides further details on the construction of the forecast error measures.

2.2 Discontinuity at the Zero Forecast Error Threshold

We show that firms which slightly exceed analysts' forecasts experience higher growth in markups compared to firms that narrowly miss their earnings targets.

Figure 1 suggests the existence of pressure to hit profit targets in the short-run. We

Table 1: Discontinuity in Markup, Sales and Costs Growth

	(1) Δ% Markup	(2) Δ% Sales	(3) Δ% Costs
Mean Change at Cutoff (p.p.)	0.793***	1.065***	0.270*
	(0.116)	(0.177)	(0.155)
Standardized (p.p.)	4.822	5.098	1.303
Firm, Quarter FEs	Yes	Yes	Yes
Mean $\lvert\Delta \log \mu\rvert$ (p.p.)	8.351	13.560	13.616
Median $\lvert\Delta \log \mu\rvert$ (p.p.)	3.276	7.907	8.027
Observations	76087	76255	76069

Notes: The Table reports the estimated discontinuity in markup growth,sales growth and cost growth (in p.p.) for firms just hitting analysts' forecasts. We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is markup growth in column (1), sales growth in colun (2), cost of goods sold in column (3), all at the firm-quarter level, and the running variable is forecast error, fe_{it}. Markups are estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. All of these estmation control for firm and time fixed effects. The table reports also the estimated discontinuity in markup growth (in p.p.) after standardizing the outcome variable by its mean and standard deviation. Mean (median) refer to the average (median) of the absolute markup growth rates. Standard errors, clustered at the firm level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

plot the distribution of forecast errors, fe_{it}, and identify a bunching of firm profits at zero or just above forecasts while relatively fewer firms display narrow misses of expected profits. Quantitatively, 11% (18%) of all firm-quarter observations exhibit a forecast error greater than zero and lower than 0.01% (0.05%). Profit bunching supports the idea that firms may actively try to avoid small negative forecast errors. Figure 20 in Appendix E shows that the bunching pattern described in Figure 1 is robust to the other measures of forecast error constructed.[5]

Motivated by this evidence, we compare firms around the zero forecast error threshold and show that firms just meeting analysts forecasts differ in their markup behavior from firms just missing. We apply the following regression discontinuity design:

[5] More generally, bunching behaviors have been documented in multiple contexts. See Terry (2022) for a recent overview.

$$X_{it} = \alpha + \beta fe_{it} + \gamma fe_{it}\mathbb{1}(fe_{it} \geq 0) + \delta\mathbb{1}(fe_{it} \geq 0) + \eta_i + \nu_t + \varepsilon_{it}, \tag{3}$$

where X_{it} is our outcome of interest – quarterly markup growth defined as $\Delta \log \mu_{i,t} = \log(\mu_{i,t}) - \log(\mu_{i,t-1})$ – for firm i at quarter t, and fe_{it} is the corresponding forecast error. We follow Terry (2022) and estimate Equation (3) by demeaning the dependent variable by firm and then quarter in order to control for constant heterogeneity across firms and business cycle fluctuations. δ is the parameter of interest, capturing the average local difference in markup growth between firms that just hit profit targets and those that just missed them.

Table 1 reveals that, on average, markup growth is 0.8 p.p. higher for firms just meeting the analysts' forecasts compared to firms that just miss. The positive discontinuity in markup growth around the zero forecast error threshold is quantitatively large if compared to the average and median absolute markup growth rate (8.3% and 3.2%, respectively).[6]

How do firms increase markup? Column (2) and (3) of Table 1 presents evidence that the higher markup growth for firms just meeting analysts' forecasts is driven by higher sales growth rather than negative cost growth. In detail, we re-estimate Equation (3) using the growth rate of sales and costs at the firm-quarter level as the outcome variable X_{it}.[7] Column (2) shows that the growth rate of sales is 1.1% higher for firms just meeting forecasters' expectations, while Column (3) shows that the growth rate of costs is 0.27% higher but only weakly significant at the 10% level. The estimated discontinuities in markup growth suggest evidence that are consistent with the idea that firms may tend to increase their markups to avoid small target misses, and the boost in markup growth is primarily driven

[6] Table 1 also shows that the discontinuity in markup growth is equivalent to an increase relative to one standard deviation of about 5%.

[7] The growth rate of sales is calculated as the log difference in total sales (Compustat variable *saleq*) at the firm-quarter level, while the growth rate of costs is computed similarly using the cost of goods sold (Compustat variable *cosg*).

by price growth rather than cost reduction.

Importantly, the discontinuities in Table 1 do not present causal results, but an endogenous detection mechanism (Terry, 2022).[8] Moreover, ever if they had a causal interpretation such disaggregated reduced-form facts represent local effects, and cannot be interpreted as the total effect of short-term incentives. After discussing the robustness of the empirical results, we build a quantitative model with the exact goal of quantifying the effects of short-termism.

Robustness check. We undertake a series of robustness checks. Specifically, we use different measures of markup, forecast errors and costs, as well as different model specifications. Moreover, we study how the discontinuity behaves across firms and sectors. These robustness checks provide additional insights and further support for our primary analysis.

Table 9 in Appendix B shows that the estimated discontinuity in markup growth is robust to the measure of markup used. We estimate markups using Equation (1) and the cost of good sold plus overhead costs as variable input ($cogs + xsga$ in Compustat). Alternatively, we use our preferred measure of markup and demean it at the sector-quarter level to obtain a measure of markup that is independent of output elasticity.[9] Lastly, we use the gross profit margin as alternative measure of profitability. Independently of the measure of markup used, markup growth is higher for firms just meeting forecasts and quantitatively similar to the discontinuity estimated using our preferred measure of markup.[10] Similarly, Table 10 in Appendix B shows that the estimated discontinuity in markup growth is robust

[8] The accounting literature has also documented similar discounted around the zero forecast error threshold, including "operational manipulation" such as changes in pricing, costs and markup. See Zhang and Gimeno (2016, 2010); Roychowdhury (2006); Laverty (1996).

[9] A measure of markup independent of output elasticity abstracts away from the empirical challenges to identify output elasticities that many have recently emphasized, see Bond et al. (2021) among others.

[10] Table 15 in Appendix B shows that the estimated discontinuity in costs growth for firms just meeting analysts' forecasts is positive and statistically not different from zero when costs are defined as cost of good sold plus overhead costs, suggesting that overhead costs are less sensitive than the production costs, in line with Terry (2022).

to the definition of forecast errors, as we scale the difference between realized profits and the median analysts forecast by firms' market value or by lagged total sales. The estimated discontinuity is 0.76% and 0.96%, respectively, quantitatively close to the main specification in Table 1.[11]

We test whether changes in markup growth are due to movements in inventories, as revenues and costs are reported in different periods. We first project markup growth on inventory growth and used the unexplained component as dependent variable in Equation (3). Table 11 in Appendix B shows that the discontinuity in the unexplained part of markup growth survives both qualitatively and quantitatively, and is again robust to the definition of markup and forecast errors.

We also explore whether the magnitude of the discontinuity correlates with several variables across sectors or along the firm distribution. Table 12 in Appendix B shows that the discontinuity is increasing in sectors with lower levels of inventories, in line with Table 11. Similarly, the discontinuity is increasing in more concentrated sectors (higher HHI index), among firms with higher markup levels, and decreasing in the sectoral elasticity of substitution, consistent with the idea that firms with more market power may have more room to move markup to meet analysts' forecasts. Moreover, as we would expected, the discontinuity is increasing in sectors that exhibit higher price adjustment frequency.[12] Lastly, Table 13 in Appendix B shows that the discontinuity is higher for firms that are less (geographically and industrially) diversified, in line with the idea that diversification can reduce short-termism by providing managers with more flexibility to make long-term investments without being overly reliant on any single product market (Hoberg and Phillips,

[11] Moreover, Table 14 in Appendix B show that markup growth is driven by sales growth and not by cost reduction using alternative definitions of forecast errors, qualitatively confirming the results from the main specification.

[12] We kindly thank Micheal Weber for sharing with us the sectoral frequencies of price adjustment (Pasten et al., 2020).

2010; Morck et al., 1990).[13]

On the technical side, we use a 32-quarter rolling window approach to check whether the discontinuity is influenced by specific time periods. Figure 21 in Appendix B illustrates that the estimated discontinuity in markup growth does not seem to be driven by any particular time period and exhibits some countercyclicality. This finding suggests that the observed markup growth discontinuity is not solely attributable to specific economic conditions but holds across different periods.[14]

Furthermore, Figure 21 also demonstrates the robustness of the estimated discontinuity to the choice of bandwidth in the local linear regression discontinuity estimator of Equation (3). In our main specification, we utilize an optimal bandwidth of 0.037, in accordance with state-of-the-art regression discontinuity estimation techniques (Calonico et al., 2020). Importantly, we find that the estimated discontinuity remains quantitatively stable within a bandwidth range of $[0.02, 0.05]$.

3 A simple model of pricing and short-termism

We develop a two-period, partial equilibrium model with short-term frictions and endogenous markup due to customer accumulation to qualitatively explain the key mechanisms and implications of short-term pressure on pricing and markups.

We consider a firm that produces and sells a differentiated product, facing a dynamic demand due to the presence of a demand accumulation process (Foster et al., 2016; Gilchrist et al., 2017; Moreira, 2016). Firms' decisions are taken by a manager with private empire

[13] We kindly thank Jaeho Choi for sharing with us their measures of diversification (Choi et al., 2021).

[14] Nevertheless, Table 16 in Appendix B documents that the discontinuity in markup growth is statistically larger during periods of recession compared to periods of economic boom (1.7% during recessionary periods, 0.7% during economic booms), suggesting that the impact of hitting analysts' forecasts on markup growth is more pronounced and economically meaningful during economic downturns. Figure 22 and Table 17 in Appendix B show that the same qualitative patterns hold for sales and cost growth.

building motives. The manage lowers markup below the firm optimal level because he faces additional private benefits from increasing firm' size. To offset private benefits, the board of directors discipline managerial behavior introducing optimal short term incentives, i.e. costs for failing to meet profit expectations (Terry, 2022).

3.1 Environment

Consider a single firm that operates two periods, denoted as t (today) and $t+1$ (tomorrow), producing a differentiated product using a linear technology with constant marginal cost, c. The firm faces an isoelastic demand curve with a price elasticity $\eta > 1$ and generates profits by selling its output in both periods at a specific price.

The amount of product that the firm sells today y_t depends on the stock of existing customers $\bar{b}$ the firm has, and the price p_t per unit of output optimally charged by the management:

$$y_t = \bar{b}^{\theta} p_t^{-\eta}. \tag{4}$$

Tomorrow, the firm sells the output y_{t+1} at the optimal price $\bar{p} = \frac{\eta}{\eta-1}c$ which is the price that the firm would choose to maximize current profits.[15] Hence, the total profits in period $t+1$ depends solely on the stock of customers that the firm will have tomorrow b_{t+1}, which, in turn, we assume depends on the total revenues generated by the firm in the current period $p_t y_t$,

$$b_{t+1} = \delta p_t y_t, \tag{5}$$

where $\delta \in (0,1)$ is the fraction of revenues that translate in the stock of customers tomorrow. By increasing revenues today, the firm can acquire new customer capital and expand future demand, thus impacting future profits.[16]

[15] More precisely, $\bar{p}$ is the price that solves the firm's profit maximization in a static context.

[16] This functional form follows the specification as outlined in Foster et al. (2016) and Moreira (2016).

Given the real interest rate R, firm value $V(p_t)$ is the sum of the stream of discounted profits today and tomorrow:

$$V(p_t) = (p_t - c)\bar{b}^\theta p_t^{-\eta} + \frac{1}{R}(\bar{p} - c)\frac{(\delta\bar{b}^\theta)^\theta}{\bar{p}^\eta} p_t^{(1-\eta)\theta}. \tag{6}$$

Compared to a static model, the price charged by the firm influences the total revenues the firms generate in the current period, as well as the stock of customers the firm serves tomorrow b_{t+1}. At the optimum, the choice of the price p_t balances the trade-off between charging a higher price today to leverage the inelastic part of demand (harvesting motive) and lowering the price to attract more customers tomorrow (investing motive).

Today's profits are net cash flow plus accounting noise, ν_t:

$$\Pi_t = (p_t - c)y_t + \nu_t, \quad \nu_t \sim N(0, \sigma_\nu^2), \tag{7}$$

where noise ν_t, with CDF F_ν and PDF f_ν, is unobservable before price is chosen. Outside analysts observe the stock of firms' customers and make a profit forecast Π_t^f.

A risk-neutral manager optimally sets the price p_t to maximize his utility function, which is a weighted sum of the firm's value function and a personal benefit ϕ_e from expanding the company size arising from their private empire building motifs. The board of directors introduces a cost to the manager's utility that depends on the difference between the actual profits realized Π_t and an expected profit target Π_t^f set by the outside analyst, to discipline the manager's behavior and align it with the firm's interests (Terry, 2022).

Given analysts' forecast and board controls, the manager's objective solves:

$$V^M\Big(p_t|\Pi_t^f, \theta_\pi\Big) = (p_t - c)\bar{b}^\theta p_t^{-\eta} + \phi_e y_t - \theta_\pi y_t \mathbb{P}\Big(\Pi_t < \Pi_t^f\Big) + \frac{1}{R}(\bar{p} - c)\frac{(\delta\bar{b}^\theta)^\theta}{\bar{p}^\eta} p_t^{(1-\eta)\theta}, \tag{8}$$

where the cost of missing profit targets, $\theta_\pi y_t \mathbb{P}\Big(\Pi_t < \Pi_t^f\Big)$ is also increasing in the size of the firm. The cost of missing profit targets represents the short-term friction into the model, as the manager has an incentive to prioritize meeting the profit target over maximizing their private benefit in the current period.

An equilibrium with rational expectations and optimal short-termism frictions in this simple model requires that: *i*) the manager determines a price today to maximize his utility conditional to the analyst's forecasts and short-term costs; *ii*) the analysts' forecast are rational given what the analysts' information set; *iii*) the board of director sets the optimal short-term cost to maximize firm value given manager's decision.

3.2 Optimal pricing decisions and short-term costs

Optimal managers' pricing decisions and short-term costs are pin down by the first-order condition with respect to p_t and θ_π.

Corrective effects of short-termism. Given manager choice, the board of directors choose the optimal short-term cost to maximize firm value which is given by the equation:[17]

$$\theta_\pi^* = \phi_e \left[\mathbb{P}\Big(\Pi_t < \Pi_t^f\Big) + \frac{p_t}{\eta} f_\nu \frac{\partial \Pi_t}{\partial p_t} \right]^{-1}. \tag{9}$$

The introduction of short-termism costs is designed to align managers' incentives with the overall goals of the firm and mitigate the potential negative impact of their private benefits. The optimal level of short-termism costs depends on two factors. Firstly, the private benefit of the manager, denoted as ϕ_e, positively influences the optimal level of short-termism costs. A higher private benefit increases the manager's inclination to prioritize current price reduction at the expense of current profits. As a result, the board of directors needs to

[17] Derivations in the Appendix C.

implement more stringent measures to restore the optimal value of the firm. Secondly, the probability of meeting short-term earnings forecasts has a negative impact on the optimal level of short-termism costs. A higher probability of meeting expectations reduces the need for aggressive corrective actions. When the probability of meeting forecasts is higher, the board of directors can afford to impose lower short-termism costs, as the manager's behavior is already aligned with achieving the desired profit targets.[18]

Optimal pricing decisions. Given analyst's forecasts Π_t^f and short-term cost θ_π, the optimal pricing decision taken by the manager is given by the following Euler equation:[19]

$$\left(1-\eta\frac{p_t-c}{p_t}\right)-\frac{\eta}{p_t}\phi_e+\left[\theta_\pi\mathbb{P}\left(\Pi_t<\Pi_t^f\right)+\theta_\pi f_\nu\frac{\partial\Pi_t}{\partial p_t}\right]=\frac{1}{R}(\bar{p}-c)\frac{\left(\delta\bar{b}^\theta\right)^\theta}{\bar{p}^\eta}(\eta-1)\theta p_t^{(1-\eta)(\theta-1)}. \tag{10}$$

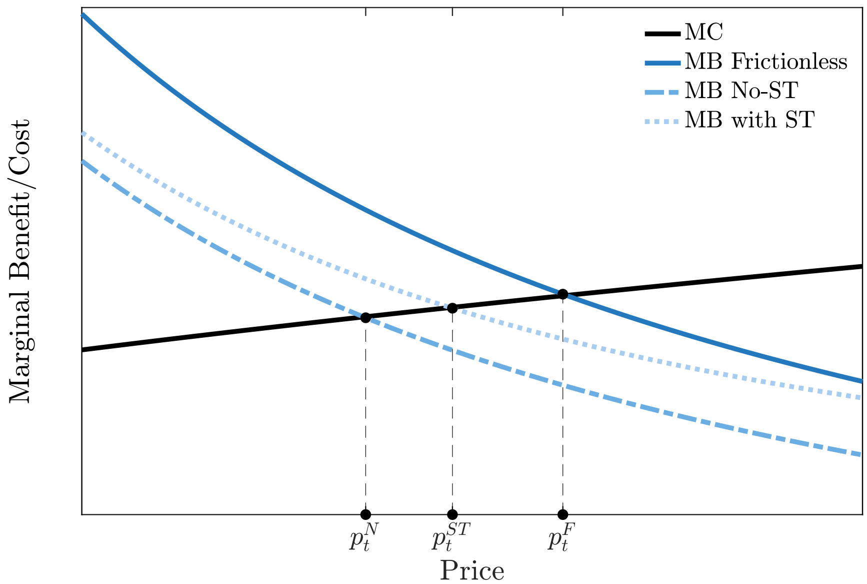
Equation 10 states that at the optimum, the manager sets the price p_t to equate the marginal benefit (on the left-hand side) with the marginal cost of increasing the price today (on the right-hand side). The marginal cost of increasing the price is determined by the fact that higher prices reduce the customer base for tomorrow, thereby reducing next period's profits. Conversely, the marginal benefit of increasing the price is determined by three terms. The first term represents the marginal profit gained from increasing the current price by one unit today, $\frac{\partial\Pi_t}{\partial p_t}$.[20] The second term is the marginal benefit received by the manager from increasing the price today, which reduces the marginal benefit of increasing current price and prompts the firm to lower the price of its current output. Finally, the last term represents the marginal benefit obtained from meeting short-term expectations, which

[18] The board has an incentive to raise θ_π up to an optimal value of θ_π^* beyond which the cost imposed by the board becomes excessively high. After this value point, the short-term cost becomes counter-productive and negatively impacts the firm's value. The manager may be discouraged from pursuing profit-maximizing pricing decisions due to the excessive penalties imposed by the board.

[19] Derivations in the Appendix C.

[20] In a static profit maximization problem this term is set to 0 optimally by the firm.

Figure 2: Optimal pricing decisions



Notes: The figure shows the marginal cost (black line) and the marginal benefit (blue lines) of increasing price without agency conflict (dark blue line), without managers' short-termism pressure (medium blue line), and with manager short-term pressure (light blue line) as a function of current prices. The vertical lines represent the optimal level of price that equates marginal benefit marginal costs in each scenario. p_t^F is the price that maximize firm value without agency conflict; p_t^N is the price set by the manager with private benefit and no short-term costs; p_t^{ST} is the price that maximize manager value facing short-termism costs. θ_π is not optimal in the figure.

is positive when the board sets a cost for not meeting analysts' forecasts ($\theta_\pi > 0$), resulting in the manager choosing a higher price compared to the case without short-term costs.

Figure 2 plots the optimal pricing decision in the presence of and abstracting away from short-termism frictions for an illustrative parametrization. In the absence of short-term incentives ($\theta_\pi = 0$), the manager would choose a price level (p_t^N) lower than the one maximizing the firm's value (p_t^F), thus leaving room for the manager to increase firm value and profits by raising current prices.[21] This occurs because the existence of a private

[21] Two forces push the manager to set the price in the region where the marginal profit to price is positive. First, the presence of a dynamic customer base leads the manager to reduce prices to retain customers for tomorrow. Second, the manager' private benefit from increasing firm' size. Because of the downward demand, manager further reduces current prices.

benefit for the manager reduces the marginal benefit of increasing the price today and diminishes the incentives to extract value from the existing customer base. However, when short-termism frictions are introduced ($\theta_\pi > 0$), the board of directors optimally introduces a cost to adjust the manager's behavior and prevent significant deviations from the firm's value-maximizing pricing choice, resulting in the manager setting a higher optimal price ($p_t^{ST} > p_t^N$) and partially increasing firm value.

4 Quantitative model

We study the quantitative implications of the mechanism outline in the previous section in a discrete, infinite horizon, quantitative dynamic model with heterogeneity in idiosyncratic productivity, customer accumulation, short-term frictions and endogenous markups.

4.1 Heterogeneous firms

In each period, the economy is populated by a unit mass of firms, indexed by j, and each firm is managed by a risk-neutral manager whose decisions are influenced by a board of directors.

Demand and technology. Each firm produces a differentiated product and faces dynamic demand due to the accumulation of customer capital. At time t, each firm j faces the following isoelastic demand for its differentiated product (Foster et al., 2016; Gilchrist et al., 2017; Moreira, 2016):

$$y_{j,t} = z_{j,t} b_{j,t}^{\theta} p_{j,t}^{-\eta}, \qquad 0 < \theta < 1 \text{ and } \eta > 0, \tag{11}$$

where θ and η measure the elasticity of demand with respect to customer capital and the elasticity of demand with respect to price ($p_{j,t}$), respectively, $b_{j,t}$ the stock of customer capital, and $z_{j,t}$ the idiosyncratic demand shock. We assume that the demand shock is the combination of two i.i.d. idiosyncratic components, $\varepsilon_{j,t}$ and $\nu_{j,t}$. $\varepsilon_{j,t} \sim_{iid} N(0, \sigma_\varepsilon^2)$ is the exogenous part of the idiosyncratic demand shock that is observed by the manager, whereas $\nu_{j,t} \sim_{iid} N(0, \sigma_\nu^2)$ represent the the exogenous part of the idiosyncratic demand shock that is unobserved by the manager when making decisions.

Following Gilchrist et al. (2017), the customer capital evolves according to:

$$b_{j,t+1} = (1-\delta)b_{j,t} + \delta p_{j,t} y_{j,t}, \qquad 0 < \delta < 1, \tag{12}$$

where δ is the detachment rate of existing customers. The accumulation of customer capital captures the idea that by selling more today, businesses acquire customer capital and expand their future demand. Thus, prices are a tool to increase firms' existing customer base.[22] [23]

Firms produce a distinct consumption good, $y_{j,t}$, using a linear technology with labor, $l_{j,t}$, as the unique input. Firms hire labor from the labor market at a predetermined wage, w_t. The production function for a firm j is:

$$y_{j,t} = a_{j,t} l_{j,t}, \tag{13}$$

where $a_{j,t} \in \mathcal{A} \equiv \{a_1, a_2, ..., a_N\}$ is an idiosyncratic productivity shock which follows a discrete time first-order stationary Markov chain with transition probability $P(a_{j,t+1} = a_s | a_{j,t} = a_i) \equiv \pi_{i,s} \geq 0$, and $\sum_s^N \pi_{is} = 1, \forall i$. Importantly, we assume that the level of

[22] Price choices influence investment in new customers. Higher prices may increase profits, but they also reduce the number of customers in the future, highlighting the trade-off between short-term profit maximization and long-term customer base growth.

[23] Notice that the presence of customer capital makes the i.i.d. demand shock endogenously persistent due to its effects on the future customer capital.

idiosyncratic productivity, $a_{j,t}$, is observed by firms and their managers prior to making their decisions.[24]

Firm profits. The profits of firm j in period t are given by:

$$\Pi_{j,t} = p_{j,t} y_{j,t} - \frac{w_t}{a_{j,t}} y_{j,t} + m_{j,t}, \tag{14}$$

where $m_{j,t}$ denotes the accrual manipulation of reported profits.

Manager. A risk-neutral manager at each firm maximizes their utility by setting the price of the differentiated product, $p_{j,t}$, and determining the level of accrual manipulation, $m_{j,t}$. The manager receives a private benefit from expanding the company's size, $\phi_e \frac{y_{j,t}}{a_{j,t}}$, which encourages managers to lower prices.[25] Moreover, the manager incurs quadratic costs to manipulate the balance sheet and report higher quarterly earnings:

$$\Psi_{j,t} = \phi_m m_{j,t}^2, \tag{15}$$

where the accounting manipulation cost depends on the parameter ϕ_m, and it is marginally increasing in the level of accrual manipulation. Lastly, the manager faces a cost imposed by the board of directors if they fail to meet short-term analysts' forecasts. This cost is increasing in firm's size and depends on the parameter θ_π, which is optimally chosen by the

[24] According to Equation (13), the quantity of labor hired by each firm in a particular state depends solely on the realization of idiosyncratic productivity and the demand for the products it sells in the market.

[25] We scale the manager's private benefit by idiosyncratic productivity to interpret the parameter ϕ_e in terms of differences in wages.

board. Thus, the manager solves the following dynamic problem:

$$V^M\Big(a_{j,t},\varepsilon_{j,t},b_{j,t}|\theta_\pi,\Pi^f_{j,t}\Big)=\max_{\{p_{j,t},m_{j,t}\}}\Bigg\{\theta_d\Bigg(p_{j,t}y_{j,t}+m_{j,t}-\frac{w_t}{a_{j,t}}y_{j,t}\Bigg)+\phi_e\frac{y_{j,t}}{a_{j,t}}-\phi_m m^2_{j,t}$$
$$-\theta_\pi\frac{y_{j,t}}{a_{j,t}}\mathbb{P}\Big(\Pi_{j,t}<\Pi^f_{j,t}\Big)+\frac{1}{R_t}\mathbb{E}_tV^M\Big(a_{j,t+1},\varepsilon_{j,t+1},b_{j,t+1}|\theta_\pi,\Pi^f_{j,t}\Big)\Bigg\}, \tag{16}$$

where the first term represents the direct payoff of the manager from the firm, and the other terms represent the private payoff as described above.[26]

Analyst. Analysts are rational and seek to maximize their expected utility by accurately forecasting firms' profits. Analysts determine their optimal forecast, denoted as $\Pi^f_{j,t}$, based on the information available at time t. The analyst has access to information regarding the firm's customer base, $b_{j,t}$. However, the analyst does not observe the specific components of the demand shocks, $\varepsilon_{j,t}$ and $\nu_{j,t}$, and the firm's idiosyncratic productivity, $a_{j,t}$. Therefore, rational forecasts are:

$$\Pi^f_{j,t}=\arg\min_{\Pi^f_{j,t}}\mathbb{E}\Big[\Big(\Pi_{j,t}-\Pi^f_{j,t}\Big)^2|b_{j,t}\Big]=\mathbb{E}[\Pi_{j,t}|b_{j,t}]. \tag{17}$$

Board of directors. Given the manager's policies of prices, $p^*_{j,t}$, and accounting manipulation, $m^*_{j,t}$, the board of directors optimally sets a short-term cost, θ_π, to discipline the manager's behavior and align it with the firm's interests. Given managers' policies, the value of the firm is:

$$V^F(a_{j,t},\varepsilon_{j,t},b_{j,t})=\Bigg[p^*_{j,t}y^*_{j,t}-\frac{w_t}{a_{j,t}}y^*_{j,t}+\frac{1}{R_t}\mathbb{E}_tV^F\Big(a_{j,t+1},\varepsilon_{j,t+1},b^*_{j,t+1}\Big)\Bigg]. \tag{18}$$

[26] The parameter θ_d captures the fact that manager private payoff are proportional to the firm payout. Without loss of generality, we fix $\theta_d=1$ when solving and estimating the model.

Let Γ_h be the distribution over idiosyncratic productivity, $a_{j,t}$, demand shock, $\varepsilon_{j,t}$, and customer capital, $b_{j,t}$, that would prevail in the economy if managers interests align with the of the board. The board of directors of each firm commits to an optimal contracted level of short-term incentives, θ_π^*, to maximize the mean firm value weighted for the theoretical distribution, Γ_h. Hence, the board of directors sets θ_π to solve the following problem:

$$\theta_\pi^* = \arg\max_{\theta_\pi} \int V^F(a_{j,t}, \varepsilon_{j,t}, b_{j,t}) d\Gamma_h(a_{j,t}, \varepsilon_{j,t}, b_{j,t}). \tag{19}$$

The optimal level of short-term incentive arises as a result of a constrained maximization problem to restore the unconditional maximum firm value. Two points are worth mentioning. First, if there is no manager's private benefit ($\phi_e = 0$), the manager problem in Equation (16) boils down to the firm problem and the optimal level of short-term incentive is $\theta_\pi^* = 0$. Second, the choice of θ_π restores the unconditional maximum firm value without considering the effect on the distribution of firms in the economy. This approach is in line with the idea that shareholders act to maximize the value of the company at micro-level.

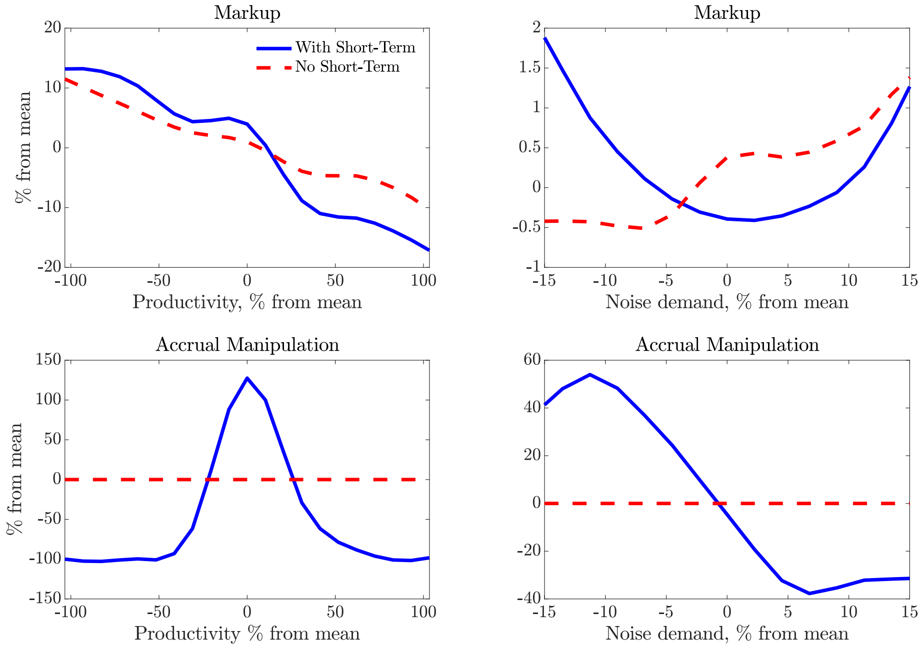
4.2 Equilibrium and Solution

An equilibrium in the model with rational expectations and optimal short-term costs is a set of policy functions, $p^*(a, \varepsilon, b)$ and $m^*(a, \varepsilon, b)$, manager and firm value functions, $V^M(a, \varepsilon, b)$, and $V^F(a, \varepsilon, b)$, optimal forecasts, Π^f, optimal short-term frictions ,θ_π^*, and a distribution of firms $\Gamma(a, \varepsilon, b)$, such that:

i) The manager sets $p^*(a, \varepsilon, b)$ and $m^*(a, \varepsilon, b)$ to solve Equation (16) conditional to the analyst's forecasts Π_t^f and short-term costs θ_π;

ii) The analysts forecasts $\Pi_t^f(\theta_\pi)$ solves Equation (17) conditional to the optimal manager policies, $p^*(a, \varepsilon, b)$ and $m^*(a, \varepsilon, b)$;

Figure 3: Manager Policies



Notes: The dotted red lines represent policy functions with no short-term incentives ($\theta_\pi = 0$), while the continuous blue lines represent policy functions with short-term incentives (θ_π^*). All policy functions are computed in percentage deviation from the average value in the stationary distribution. The top row of the figure shows the mean markup policies, and the bottom row shows manager accruals manipulation policies. The left column depicts mean policies over the idiosyncratic productivity grid as a percentage deviation from the mean, and the right column shows mean policies over the idiosyncratic demand grid. These policies are based on the parameterization of the model reported in table 2, and they are smoothed over the grid for clarity.

iii) The board of directors sets θ_π^* to solve Equation (18) conditional to optimal managers decisions, $p^*(a, \varepsilon, b)$ and $m^*(a, \varepsilon, b)$, and analysts' forecasts;

iv) The firm distribution $\Gamma(a, \varepsilon, b)$ is consistent with the idiosyncratic stochastic processes and managers' policy function, $p^*(a, \varepsilon, b)$ and $m^*(a, \varepsilon, b)$.

We solve the model numerically. Further details on the algorithm used in Appendix D.2.

4.3 Manager Policies

Figure 3 shows the managers' policy function for markup (top row) and accrual manipulation (bottom row) across idiosyncratic productivity (left column) and noisy demand (right column) to highlight the impact of short-termism on pricing and manipulation decisions. We compare optimal managers' decisions in a model with optimal short-term pressure ($\theta_\pi = \theta_\pi^*$) and without short-term pressure ($\theta_\pi = 0$), in deviation from their respective means.

In a model without short-termism (red dashed line), managers do not face any incentives to manipulate current profits, resulting in the absence of accrual manipulation and in a markup policy that aligns with standard models incorporating dynamic customer accumulation. In high productivity states, the marginal benefit of increasing prices is relatively lower, leading firms to reduce their markups below average and increase their investment in acquiring new customers. Conversely, in low productivity states investing in new customers becomes relatively more expensive. Hence, firms postpone investments in new customers and pushes their markups above average.

Demand shocks influence current revenues and, at the same time, future customer capital.[27] Consequently, following a negative demand shock, firms lower their markup below the average to mitigate persistent losses in customers and revenues. On the other hand, for high demand shocks, firms experience an increase in customer capital and profits. As a result, they optimally increase their markup above the average to boost profits without incurring a loss of customers.[28]

In a model with short-termism (blue solid line), managers face pressures to opportunis-

[27] Moreover, the presence of customer capital accumulation makes i.i.d. demand shock endogenously persistent. This implies that demand shocks have potentially long-lasting effects on firms' cash flow.

[28] Notice how markups are counter-cyclical in response to a productivity shock, whereas markups are pro-cyclical in response to a demand shock. This difference arises because we model firms' productivity to have no direct effect on customer accumulation.

tically change accruals and markups when close to meet analysts' forecasts, causing excess volatility in markups and misallocation.[29] As productivity shocks approach zero from the left, firms seize the opportunity to strategically raise their markup and increase accrual manipulation to enhance current profits and cut the costs associated with missing short-term targets. Figure 3 shows a noticeable spike in accrual manipulation and markup values just around the zero productivity.[30] This strategy is inherently short-term in nature, as it sacrifices long-term growth and customer acquisition opportunities. Differently, as demand shocks approach zero from the left, firms seize the opportunity to strategically increase accrual manipulation while lowering markups to enhance current profits and cut the costs associated with missing short-term targets. Negative demand shocks directly shrink the customer base, thus diminishing the likelihood of meeting future forecasts. Consequently, as demand shocks approach zero, firms have an additional incentive to maintain lower markups and preserve their customer base.

Finally, Figure 23 in Appendix D displays the distribution of managers' policy functions, providing insights into how short-termism affects the distribution of firms' choices across the states.[31] In the model with short-term costs, managers, on average, charge a higher level of markup to customers compared to the scenario without short-term costs (bottom left). As a consequence, in the absence of short-termism, firms are relatively larger due to their accumulated customer base (top left). The shift in the distribution is relevant for the quantification of the aggregate effects of short-termism, as shown in Section 5.

[29] See Edmond et al. (2023), Baqaee and Farhi (2020), Hsieh and Klenow (2009) and among others.

[30] Interestingly, the presence of short-term costs compels firms to reduce their markups by a greater extent during highly favorable economic states. This reduction in markups serves as a protective measure for managers, reducing the probability of firms failing to meet expectations in the future. As a result, the marginal benefit of investing in new customers is higher with short-term frictions, prompting firms to strategically invest in a relatively larger customer base during good states of the economy. This mechanism is unique to dynamic corporate finance model and it is similar to the case of equity issuance costs (Hennessy and Whited, 2007; Strebulaev et al., 2012).

[31] We compute the distribution of managers' policy functions for 3000 firms simulated over 50 quarters and average them over time.

5 Quantitative results

We present the quantitative results of the baseline model in this section. Section 5.1 discuss identification and the parameters' estimation in the model. Section 5.2 presents the quantitative impact of short-termism on firms' markup and welfare. Section 5.3 shows that our estimates are robustness to several specifications.

5.1 Estimating the model

We calibrate a set of parameters following previous works in the literature. Following Gilchrist et al. (2017), we set the parameter $\delta = 0.08$, which implies that only 8% of stock of customer capital is depreciated in a quarter, falling in the range of the annual estimates in Bornstein (2021) and Ravn et al. (2006). We normalize the equilibrium wage proportional to the demand elasticity with respect to prices $\frac{\eta-1}{\eta}$, and set the annual discount factor $\beta = 0.96$ (Moreira, 2016).

Simulated Method of Moments. We estimate the remaining 7 parameters in Table 2 using the Simulated Method of Moments (SMM).[32] We target a set of 12 empirical moments computed from quarterly Compustat/IBES merged data, selected based on prior studies in the literature. These moments are computed using data spanning from 2003 to 2018, which corresponds to the period following the implementation of the Sarbanes-Oxley (SOX) Act in 2002 (Terry, 2022). The dataset consists of approximately 48,016 firm-quarters of data from around 1,587 firms. Our targeted moments include the correlation matrix between markup growth, profit growth, sales growth, and forecast error at a quarterly frequency which are informative about the standard deviation and persistence of idiosyncratic productivity and

[32] The SMM approach is particularly advantageous when traditional estimation methods, such as maximum likelihood estimation, are impractical due to the complexity of the model's functional forms or the presence of non-linear relationships.

demand shocks. We also target the probability of meeting forecasters' expectations, defined as the percentage of firms that outperform forecasters in the simulated data. Moreover, we consider the probability of "just" meeting analysts' forecasts, defined as the ratio between the fraction of firms whose earnings beat forecasters by a maximum of 10% and the mass of firms located around the zero threshold within the 10% range in absolute value. These moments are informative about the observed jump at the zero threshold in forecasting errors documented in the empirical part above. Lastly, we target the average markup in the model to calibrate the elasticity of demand with respect to price.

We choose the optimal model parameter vector, θ, to make simulated model moments close to data moments. We estimate the optimal vector of parameters $\hat{\theta}_{\text{SMM}}$ such that:

$$\hat{\theta}_{\text{SMM}} = \theta : \min_{\theta} \quad \Big(m(\tilde{x} \mid \theta) - m(\tilde{x})\Big) W \Big(m(\tilde{x} \mid \theta) - m(\tilde{x})\Big)', \tag{20}$$

where $m(\tilde{x})$ is the data moment vector and $m(\tilde{x} \mid \theta)$ is the simulated model moment vector. We use the asymptotically efficient weighting matrix W, cluster standard errors by firm with the asymptotic formulas in Hansen and Lee (2019). We generate simulated data on 3,000 firms for 25 years with a burn-in-period of 50 quarters from the model for a given set of parameters. We compute the equivalent model moments from the simulated data and compare them to the true moments in the data. In estimating Equation (20), We employ a mix of stochastic optimization routine and non-stochastic search algorithm.

Identification. Figure 4 plots selected target moments that help for the identification of the agency cost parameter ϕ_e. The parameter ϕ_e captures the agency conflict between manager and shareholders and, thus, it increases the degree of short-termism in the model. With higher ϕ_e and, consequently, more short-termism, markups become more volatile as firms need to adjust their markup more frequently (top left). As short-termism increases

Table 2: Estimated parameters and moments

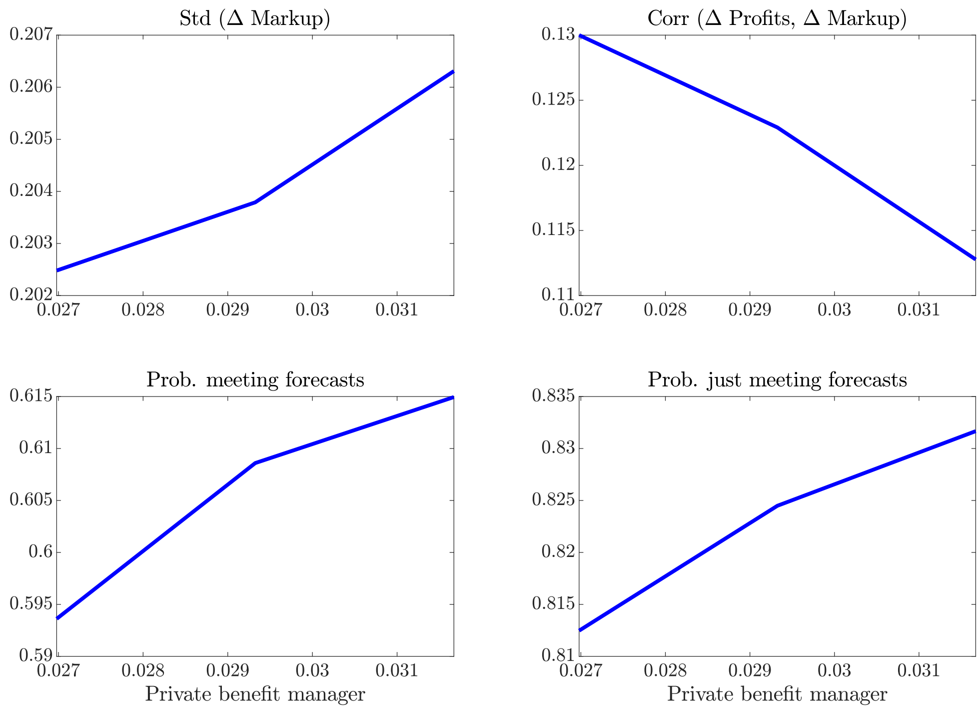
A. Estimated parameters	Symbol	Estimate	(Std. Error)
Price elasticity of demand	η	1.7270	0.0024
Persistence of idiosyncratic productivity	ρ_a	0.8433	0.0009
Std of idiosyncratic productivity	σ_a	0.1852	0.0004
Std of observed demand shock	σ_e	0.0751	0.0005
Std of unobserved demand shock	σ_u	0.0338	0.0001
Quadratic manipulation cost	ϕ_m	1.6319	0.0894
Private benefit manager	ϕ_e	0.0293	0.0016
B. Targeted moments	**Data**	**(Std. Error)**	**Model**
Std. deviation of sales growth	0.1591	0.0029	0.2185
Correlation of sales growth, profits growth	0.4924	0.0148	0.0769
Correlation of sales growth, forecast error	0.0610	0.0066	0.1642
Std. deviation of profits growth	0.4921	0.0075	0.5584
Correlation of profits growth, markup growth	0.1784	0.0150	0.1884
Correlation of profits growth, forecast error	0.1082	0.0090	0.1771
Std. deviation of markup growth	0.0915	0.0028	0.1593
Correlation of markup growth, forecast error	0.0887	0.0074	0.2068
Std. deviation of forecast error	0.5707	0.0091	0.2485
Probability of meeting forecasts	0.7094	0.0028	0.7706
Probability of just meeting forecasts	0.7707	0.0046	0.8294
Mean of markup	1.5540	0.0189	1.6379

Notes: Panel A's SMM parameter estimates use efficient moment weighting. Panel B's data moments use a 2003-2018 Compustat-IBES panel of 1,587 firms for 48,016 firm-quarters. Model moments use a 25-year simulated panel of 3,000 firms. Moment units are proportional (0.01 = 1%). Standard errors are firm clustered.

and raises markup volatility, firms' profits become less correlated with markup growth (top right). Since higher short-termism raises the volatility of markup, the correlation between profit and markup growth decreases (top right). With more short-term costs, managers meet their short-term profit targets more often (bottom left). Bunching around the profit target also increases in short-termism (bottom right). So the estimated manager agency conflict ϕ_e, and hence the extent of short-termism, depends upon both markup and forecast error patterns.

Figure 24 in Appendix D plots the relationship between the other estimated parameters

Figure 4: Identifying agency cost parameter ϕ_e



Notes: Figure plots selected simulated target moments on the agency conflict parameter ϕ_e, varying the value above and below the baseline estimate in Panel A of Table 2.

and selected target moments that hold significant importance for identification. Notably, average markup decreases in the demand elasticity to price, η (top left). Greater persistence in idiosyncratic productivity, ρ_a, leads to increased dispersion in the cost of production, resulting in higher volatility of profit growth (top middle). Similarly, heightened volatility in idiosyncratic productivity, σ_a, yields stronger correlations between profits and sales growth due to more substantial productivity shifts (top right). Observable demand noise, σ_ε, induces more pronounced shifts in current sales and an enhanced probability of meeting forecasts (bottom left). In contrast, forecast error bunching declines as unobservable profit noise, σ_ν, increases, as managers' ability to precisely control realized profits diminishes (bottom middle). Finally, higher accounting manipulation costs, ϕ_a, compels firms to manipulate profits without sales, leading to a reduced sensitivity of profit growth to sales growth (bottom right).

Baseline Estimates. The estimation procedure produces a set of estimated parameters that are consistent with previous studies. The price elasticity of demand, η, is estimated to be 1.727, closely aligned to previous estimates in Foster et al. (2016). The idiosyncratic productivity exhibits a high level of persistence, with ρ_a estimated to be 0.843, while the standard deviation, σ_a, is estimated to be 18%. These estimates are comparable to those found in Gilchrist et al. (2017). The standard deviations of the observed demand and unobserved demand components, σ_e and σ_u, are estimated to be 7.5% and 3.3%, respectively, implying a ratio of roughly 2, consistent with the baseline parameters in Terry (2022). The quadratic manipulation cost, ϕ_m, is estimated to be 1.63, while the degree of private benefit of the manager is estimated to be $\phi_e = 0.029$, in line with previous estimates (Terry, 2022; Terry et al., 2023; Celik and Tian, 2022). Panel A of Table 2 provides a summary of the estimated parameters and their standard errors obtained from the estimation.

Model fit. Panel B of Table 2 presents the data moments, standard errors, and simulated moments. The estimation process, constrained by the overidentified and nonlinear nature of the model, demonstrates an overall good fit. Firstly, the model successfully replicates the signs of all covariances, closely matching the volatility of sales growth, the jump near the zero threshold, the probability of meeting forecasts, and the correlation between profit growth and markup growth. Secondly, in the simulation, we incorporate the assumption that unobserved demand shocks impact revenues, leading to measurement errors in both sales and profit growth. Consequently, the cross-correlation between these two variables is smaller in the model than in the data. Finally, the average markup and the volatility of forecast errors in the model also closely to the corresponding moment in the data.

Table 3: The impact of short-termism

Quantitative Impact	p.p.
A. Micro variable	
Mean markup increase from short-term pressure	8.043
Mean shareholders profit gain from short-term pressure	5.768
B. Macro variable	
Welfare change from short term pressure	[-3.474,-5.959]
Market capitalization change from short-term pressure	-9.178
Average effect	0.770
Distributional effect	-9.948

Notes: The table presents the main results of the baseline model. We estimate the impact of short-termism comparing the average moments in the model with short-term incentives (θ_π^*) to the moments in the model without short-term incentives ($\theta_\pi = 0$). The quantitative impact of short-termism on micro variables is calculated by fixing the distribution of firms from the benchmark model and changing the respective policy functions. The quantitative impact of short-termism on macro variables is calculated based on model moments computed over a 50-quarter simulated panel of 3,000 firms, with a burn-in period of 25 years. Moment units are expressed in percentage points (1 = 1%).

Appendix D.2 shows that the model can reproduce a set of untargeted moments consistent with the data. Figure 25 in Appendix D illustrates that the distribution of forecast errors generated by the model closely aligns with the data estimates, even though we only target the "jump" at the zero forecast error. Additionally, Figure 26 shows that, in the steady state, the model qualitatively replicates the positive relationship between the probability of beating forecaster error and size (left panel) and markup growth (right panel) at the firm level. Lastly, we run the same regression discontinuity design used in the empirical section on simulated data and show that the model replicates both qualitatively and quantitatively the local effect of short-termism on markup growth (see Table 18 in Appendix D).

5.2 The impact of short-termism

Table 3 shows that short-termism has significant effects on firms' pricing behavior and the aggregate economy.[33] Our findings underscore that, while decisions focused on short-term gains enhance firm value within the micro context, they lead to adverse consequences at the aggregate level. This outcome is rooted in the inherent nature of short-term frictions, which aim to address micro-level managerial challenges but inadvertently impede firms from expanding their customer base.

Micro effect of short-termism. The first two rows of Table 3 show that, for a given customer base, short-termism prompts firms to increase their markups, leading to an immediate benefit for shareholders. To quantify this, we fix the distribution of firms in the benchmark model with short-term incentives and calculate the average percentage change in the respective policy functions.[34] According to the baseline model, a firm of average size in the economy raises markups by 8.04% due to short-termism, a significant increase compared to recent evidence on markups and competition (De Loecker et al. (2020) among others).[35] This effect is driven by the corrective mechanism of short-term incentives, designed to influence manager behavior towards meeting short-term financial goals by increasing markups and profits.

Shareholders benefit from higher profits due to these short-term costs, with an average

[33] We compare the average moments computed with short-term incentives (θ_π^*) to those without short-term incentives ($\theta_\pi = 0$) from a simulated panel of 3,000 firms over 50 quarters.

[34] Denote by x the log value of a firm variable of interest in bin q and by s the share of firms within bin q. We calculate the effect of short-termism on micro variable as follows:

$$\Delta x = \sum s^1 \left(x^1 - x^0\right), \quad 1 = \text{Short-term and } 0 = \text{No Short-term.}$$

This resembles the within component in Baily et al. (1992).

[35] Using simulated data, we show that the presence of short-termism increases the HHI index of the overall economy by about 18%, highlighting how corporate governance can impact market concentration, competition and antitrust.

increase of around 5.768%. To put this into perspective, compared to an average of $700 million in annual profits per firm in Compustat, short-termism adds approximately $38 millions in profits per firm.[36] The positive effects that short-term has on shareholders' returns contrast the loss that the same mechanism generates when influencing R&D (Terry, 2022), or when associated to agency frictions (Celik and Tian, 2022).[37][38] This highlights the differences that short-term incentives have on firms via different manager's decisions (pricing vs R&D, for instance), and calls for a comprehensive analysis.

Macro effect of short-termism. Table 3 shows that short-term pressure results in a welfare loss of between 3.4% to 5.9%, calculated in consumption equivalent using the Laspeyres and Paasche indexes.[39] These estimates are in line with the effects that short-termism has on managers' pricing decisions. These magnitudes are quantitatively large and meaningful, lower than the estimated cost of agency frictions on growth around 7% (Celik and Tian, 2022), but higher than the welfare cost of short-term on growth via R&D around 1.1% (Terry, 2022).

Furthermore, Table 3 indicates that short-termism leads to a loss in the total market capitalization of around 9.178%. This potentially counter intuitive outcome is the result of two opposed forces: an average effect and a distributional effect.[40] The average effect

[36] In Compustat, we proxy profits as sales minus cost of good sold and sg&a (*saleq* - *cogs* - *xsgaq*).

[37] Other related frictions like CEO turnover frictions (Taylor, 2010) or manager cash incentive conflicts (Nikolov and Whited, 2014) also generate losses as opposed to short-termism in this case.

[38] Profits excluding accrual manipulation on the other hand increase by an average of 4%.

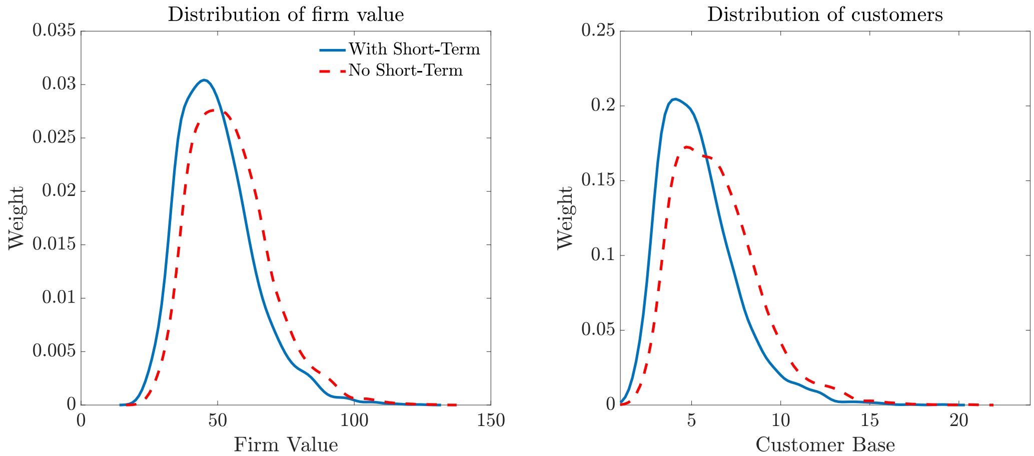
[39] We express the effect of short-termism on welfare using the Laspeyres and Paasche indexes. Let total consumption in each scenario be defined as the sum of total sales, $p^i y^i = \sum p_x^i y_x^i$, with $i = 0, 1$ representing respectively the no-short-term scenario the short-term scenario. We calculate the upper and lower bounds of the welfare loss using simulated data as follow:

$$\text{Welfare Loss} \in \left[\log\left(\frac{p^1 y^0}{p^0 y^0}\right), \log\left(\frac{p^1 y^1}{p^0 y^1}\right)\right], \quad 1 = \text{ST and } 0 = \text{NO}$$

Notice that, given the absence of an optimizing consumer in our model, we use the Laspeyres and Paasche because they represent the upper and lower bounds of most common measures as Compensating and Equivalent Variations.

[40] We decompose the effect of short-termism on market cap into an average effect and distribution effect

Figure 5: Distribution of simulated data



Notes: In red, the kernel density of the policy functions for firm value and customer base with no short-term incentives ($\theta_\pi = 0$), while in blue the kernel density of the policy functions with short-term incentives (θ_π^*). On the left-hand side, the marginal density over firm value. On the right-hand side, the marginal density over customer capital. These policies are based on the model's parameterization reported in Table 2. We average over time before plotting the distributions. All plots are generated from averaging 3000 simulated firms over 50 quarters before plotting.

reflects the positive impact of short-termism on the market value of the firm of average size in the distribution, which increases due to short-term incentives, in line with the markups and profit dynamics described above. The distributional effect is tied to the influence of short-termism on the average size of firms in the economy, shifting the size distribution towards smaller firms. As short-termism reduces manager's private benefit from increasing firm size, firms in a world influenced by short-termism are inclined to remain relatively smaller. This, in turn, results in a decrease in total market capitalization. Table 3 shows

using the following within-between decomposition (Griliches and Regev, 1995). Denote with m the market value of a firm in a bin q, and with s the share of firms within a bin q. We can decompose the effect of short-termism on aggregate market value as:

$$\Delta m = \sum_q \left(\frac{s^1 + s^0}{2}\right)\left(m^1 - m^0\right) + \sum \left(\frac{m^1 + m^0}{2}\right)\left(s^1 - s^0\right), \quad 1 = \text{Short-term and } 0 = \text{No Short-term.}$$

The first term represents the impact of short-termism on the average firm value given customer base, the average effect. The second term reflects the effect of short-termism on the ergodic distribution, the distributional effect. The results are very similar when using the Baily et al. (1992) decomposition.

that the distributional effect (-9.94%) dominates the average effect (0.77%), rationalizing the negative impact that short-term has on total market capitalization. To put these findings into perspective, in the context of the \$34 trillion dollars annual market capitalization in Compustat (2003-2018), short-termism would be responsible for an aggregate loss of approximately \$3.1 trillion dollars. Figure 5 displays the distribution of firms over customer capital and firm value as we transition from an economy with short-termism to one without short-termism in the simulated data.

It is important to stress that these results should be considered the upper bound of the effect of short-term pressure on welfare and prices, as managers can only manipulate markups to meet analysts' forecasts, and all firms in the model are subject to short-term pressure. In the next section, we extend the model to consider different versions that encompass different modeling assumptions or additional mechanisms highlighted in the literature.

5.3 Robustness and extensions

We show that our results are robust to different model specifications and further discuss the relevance of the customer capital accumulation relative to a standard CES demand case.

Model specifications. We consider two different specifications: one includes a private benefit of the manager linked to total sales, and the other with the cost of accruals decreases with firms' size. Appendix D.5 provides additional details.

Table 19 in Appendix D.5 report the results of the model and estimated parameters assuming that the cost of accruals is decreasing in firms' size as follow:

$$\Psi_{j,t} = \phi_m \left(\frac{m_{j,t}}{b_{j,t}} \right)^2 b_{j,t},$$

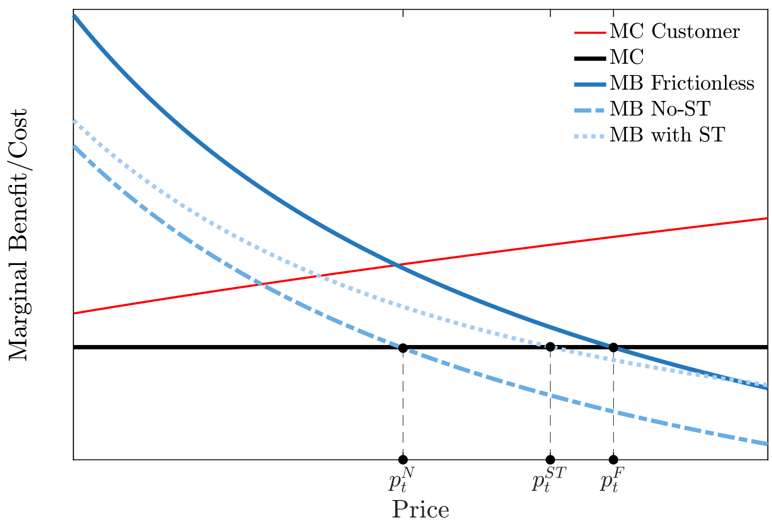
As the costs of accruals decrease with size, larger firms have stronger incentives to use accrual manipulation rather than markup to meet earnings forecasts. Hence, this leads to a lower impact of short-termism on firms' markups. Upon conducting model estimation, short-termism prompts firms to increase their markups of approximately 7%. This adjustment results in a subsequent average increase of 5.5% in firms' profits distributed to shareholders. On the aggregate level, there is an observed welfare loss of approximately 4% and a decrease in market capitalization by 9%, primarily driven by distributional effects. Conversely, at the individual firm level, there is a discernible 0.8% increase in market value, highlighting again the trade-off between firm-level and aggregate interest.

Table 20 in Appendix D.5 reports the results of the model and estimated parameters under the assumption that the private benefit of the manager and the cost imposed by the board of directors are increasing with total sales. In this specification, the private benefit of the manager is now relatively higher than in the benchmark model which requires a higher short-term cost imposed to correct managers' behavior.[41] Upon model estimation, the effects of short-termism are considerably larger than the benchmark model. The influence of short-termism compels firms to enact an approximate 12% markup increase, culminating in an average uptick of 13% in firms' profits distributed to shareholders. On the aggregate level, our estimations reveal a welfare loss of about 6% and a reduction in market capitalization by 14%, attributed to a diminished accumulation of customers over time. All the results are in line with the results in the benchmark model.

Customer Accumulation vs CES We contrast our model specification with a standard static CES framework that does not incorporate customer capital, eliminating the investment motive within the framework. While the absence of any investment motive may seem

[41] After estimating the model, the private benefit of the manager is estimated to be around 10%, necessitating a high value of short-term cost to control managers' decisions.

Figure 6: Optimal pricing decisions - CES case



Notes: The diagram illustrates the relationship between marginal cost in the CES line (depicted by the black line) and marginal benefit (represented by the blue lines) concerning price adjustments in different scenarios. These scenarios include the absence of agency conflict (dark blue line), the lack of managers' short-termism pressure (medium blue line), and the presence of manager short-term pressure (light blue line), all as functions of current prices. The vertical lines pinpoint the optimal price levels where marginal benefit equals marginal cost for each scenario. Notably, p_t^F signifies the price maximizing firm value without agency conflict; p_t^N stands for the price established by the manager, incorporating private benefits and devoid of short-term costs; and p_t^{ST} represents the price optimizing manager value while facing short-termism costs. It's important to highlight that θ_π is not optimally depicted in the diagram. In comparison, the red line showcases the outcome in presence of customer capital, when there is a positive marginal cost associated with changing the price, potentially leading to the loss of customer capital in the future. The intersection point between marginal cost (with customer capital) and marginal benefit underscores the tendency toward lower prices across all three settings.

inconsistent with the definition of short-termism itself, it is worth noting that short-termism may produce the same qualitative effects on pricing and markup in the presence of a CES demand without dynamic demand accumulation.

To grasp the intuition behind this alternative scenario, we examine Equation 10 in the context of our simplified two-period model by setting $\theta = 0$. This makes the demand independent of the customer capital stock, removing any forward-looking component in the pricing decision.

$$\left(1-\eta\frac{p_t-c}{p_t}\right)-\frac{\eta}{p_t}\phi_e+\left[\theta_\pi\mathbb{P}\Big(\Pi_t<\Pi_t^f\Big)+\theta_\pi f_\nu\frac{\partial\Pi_t}{\partial p_t}\right]=0, \tag{21}$$

where the right hand side is now equal to zero as in any standard static pricing problem, meaning that the cost of raising prices today is only the lower current demand. Importantly, even though the investing motifs has disappeared, Figure 6 shows that the effect of short-termism is qualitatively the same: managers' private benefits decrease markup below the firm's optimal level and short-termism represents again a correction mechanism used by the board to correct the agency conflict.[42] Hence, quantifying the impact of short-termism on average markup and aggregates in the CES scenario is informative on the role of customer accumulation and its interaction with short-termism.

Table 21 in Appendix D.5 reports the results of the model and estimated parameters under the CES assumption.[43] In this specification, distributional effects are absent, and short-termism affects aggregates solely through its micro-level effect. Upon model estimation, the effects of short-termism at micro-level are smaller than in the benchmark model. The influence of short-termism compels firms to increase markups by an approximate 2.1%, resulting in an average uptick of 0.11% in firms' profits. At the aggregate level, we estimate a 1.7% welfare loss for consumers due to higher average prices. Differently from the benchmark case, short-termism triggers a 0.12% increase in total market capitalization, attributed to the average market value increase and the absence of distributional effects on long-term customers.

Lastly, while the results qualitatively align with our benchmark model, incorporating

[42] Graphically, the marginal cost curve is now flat and lies below the upward sloped marginal cost curve that arises in the presence of customer capital accumulation.

[43] To introduce asymmetric information between managers and analysts and dispersion in analysts' forecasts, we assume that analysts observe current productivity but not firms' idiosyncratic demand.

customer capital accumulation within our framework improves the quantitative performance, particularly in terms of key moment matching. In particular, in the CES model the estimated mean markup increases to 1.78, compared to the observed 1.55 in the data, which is higher than what previous literature suggests. This connects with a substantial body of recent empirical literature exploring the relationship between markups, customer capital, and firm dynamic (Foster et al., 2016) and, supports the relevance that customer capital has in quantifying the impact of short-termism on micro and macro variables.

6 Conclusions

The model of corporate governance adapted by firms can have a significant impact on the aggregate economy. This paper examines how the emphasis on short-term goals, typical of the Anglo-Saxon model of governance, impacts firms' investment decisions on customer capital, pricing and, ultimately aggregate welfare.

Firm performance is routinely scrutinized and compared to analysts' forecasts, generating pressure on managers to meet short-term profit targets. Using micro-level data from Compustat-IBES, we provide evidence that short-term behavior may results in opportunistic markup manipulation to meet analysts' forecast. Managers may have incentives to raise their markups to meet short-term profit targets and outperform analysts' expectations at the expenses of investment in future customers.

We quantify the impact of short-termism on markups using a model with short-term frictions and endogenous markups due to customer accumulation. Our study reveals that short-termism causes firms to increase their markups by around 8%, which translates into approximately $38 millions of additional annual profits for each firm in the period 2003-2018.

Additional, we estimate a consumption-equivalent welfare loss between 3.4% and 6% due to higher prices. Lastly, short-termism leads to an aggregate loss of 9.17% in the total market capitalization, amounting to a loss of approximately $3.1 trillion based on Compustat firms, primarily driven by the distributional effect on firms' size.

Overall, our results suggest that models of corporate governance implying strong emphasis on short-term goals, while closely associated to highly liquid and transparent capital markets, come at the cost of non-negligible welfare losses that might be relevant to regulators and policy makers.

Chapter II

Strategic Investors and Exchange Rate Dynamics

1 Introduction

Two well-known puzzles in international economics are the limited explanatory power of macroeconomic fundamentals in accounting for exchange rate fluctuations (known as the exchange rate determination puzzle) and the excessive volatility of exchange rates relative to fundamentals (known as the excess volatility puzzle) (Meese and Rogoff, 1983; Obstfeld and Rogoff, 2000).[44] Recent evidence from the microstructure approach to exchange rates suggests that investor heterogeneity plays a crucial role in understanding exchange rate dynamics and determination. For example, both puzzles can be explained by the rational confusion arising from information heterogeneity (Bacchetta and Van Wincoop, 2006). Similarly, exchange rate behavior is linked to order flow, which, in turn, is associated with the heterogeneity among investors (Lyons et al., 2001; Evans and Lyons, 2006).

This paper investigates how the exchange rate dynamics are influenced by the presence of heterogeneous investors with varying degrees of price impact. We use data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions to document that currency markets are highly concentrated, meaning that a relatively small number of entities have a substantial presence in the foreign exchange markets. Moreover, we document the presence of heterogeneity in price impact: trading activities in the foreign

[44] Meese and Rogoff (1983) show that macroeconomic models have lower predictive power compared to a random walk model. Similarly, Obstfeld and Rogoff (2000) show that exchange rates exhibit significantly more fluctuations than their underlying fundamentals.

exchange rate market impact exchange rate prices, and these effects are stronger when markets are more concentrated. Existing models of exchange rate determination typically assume that investors perceive the equilibrium price as given, overlooking the influence of a small group of large investors who recognize the price impact of their decisions and have the ability to exert pressure on market prices.[45]

We embed the heterogeneity in price impact into a two-country, dynamic monetary model of exchange rate determination. Investors face an international portfolio choice model with noise shocks. Departing from the conventional assumption of price-taking investors, we introduce a continuum of investors who exhibit varying degrees of price impact. A fraction of investors are atomistic and competitive, operating as price takers. Conversely, the remaining fraction consists of a finite number of strategic investors with a non-zero mass, who act oligopolistically and internalize the effects of their trading decisions on equilibrium prices.

Our theory of exchange rate determination with heterogeneity in price impact highlights market structure as a crucial factor influencing exchange rate dynamics. According to our theory, the exchange rate is determined as a weighted average of fundamental factors, such as interest rate differentials, and noise components. Strategic investors, who recognize their price impact, adjust their trading behavior by trading less on any given information. Therefore, the presence of strategic investors amplifies the impact of noise shocks on the exchange rate while dampening the influence of fundamental shocks.

Heterogeneity in price impact contributes to understanding the exchange rate disconnect

[45] Evidence of manipulation in the exchange rate market further support the assumption of non-zero price impact. In June 2013, Bloomberg News reported that "*traders at some of the world's biggest banks colluded to manipulate the benchmark foreign-exchange rates used to set the value of trillions of dollars of investments in Pensions Funds and money managers globally*". Subsequently, extensive investigations were conducted, resulting in banks pleading guilty and paying fines totaling more than $10 billion. Despite significant institutional reforms implemented in 2015, there are indications that market manipulation may not have completely ceased (Osler, 2014; Osler et al., 2016; Cochrane, 2015).

and the excess volatility puzzles. Firstly, the presence of strategic investors leads to a reduction in the information loading factor of the exchange rate (reduced informativeness), meaning that the exchange rate provides less information about underlying fundamentals. Consequently, strategic behavior helps accounting for the limited explanatory power of macroeconomic variables in predicting exchange rates. Secondly, as fundamental factors exhibit lower volatility compared to noise shocks, the strategic behavior of investors helps to rationalize the excess volatility observed in exchange rates relative to fundamentals. By increasing the relevance of the noise component in exchange rate dynamics, strategic behavior contributes to the heightened volatility of exchange rates relative to the underlying fundamentals factors.

We use a panel of 10 currencies spanning from 2006 to 2016 to empirically validate the main predictions of our model. We combine daily exchange rate data with currency-level concentration data obtained from U.S. Commodity Futures Trading Commission (CFTC). In line with the theoretical predictions, a currency traded in a market with a 10% higher market share of strategic investors exhibits an 18% lower predictive power compared to the average predictive power in the data. Similarly, a currency traded in a market with a 10% higher market share of strategic investors exhibits an excess volatility ratio that is 12% higher compared to the average ratio.

Lastly, we assess the impact of strategic behavior on exchange rate dynamics and compare it to the influence of another dimension of investors' heterogeneity previously explored in existing literature, specifically information heterogeneity (Bacchetta and Van Wincoop, 2006; Candian and De Leo, 2022; Stavrakeva and Tang, 2020). Information heterogeneity also contributes to the disconnect of exchange rates from fundamentals and the excess volatility of exchange rate. Due to rational confusion, investors are uncertain whether changes in the exchange rate stem from noise shocks or fundamental shocks. As a result, this leads to the amplification of the effects of noise shocks and the dampening of the effects of fundamental shocks.

We extend our theoretical framework to include information heterogeneity in the spirit of Nimark (2017) and Bacchetta and Van Wincoop (2006). We use the ECB Professional Forecasters survey data on analysts' forecasts for future exchange rates from 2002 to 2020 to calibrate information dispersion. We solve the dynamic infinite regress problem using the recursive algorithm developed by Nimark (2017). By filtering the underlying states, we construct counterfactual exchange rates by removing one dimension of heterogeneity and examining the resulting dynamics.

In our benchmark calibration, investors' heterogeneity significantly influences the dynamics of exchange rates, increasing the exchange rate disconnect by 24% and the excess volatility by 13%. Moreover, each dimension of heterogeneity is quantitatively relevant, with the heterogeneity in price impact accounting for 62% of the additional volatility and 35% of the additional disconnect attributed to investors' heterogeneity. Thus, heterogeneity in price impact appears to be more relevant in explaining exchange rate excess volatility, underscoring the importance of jointly considering both dimension in the analysis of exchange rate markets. Furthermore, the two dimensions of heterogeneity reinforce each other: as strategic investors trade less, strategic behavior reduces the informativeness of the exchange rate, making prices more dispersed for any level of information heterogeneity. Our decomposition analysis underscores the importance of incorporating investors' heterogeneity, particularly highlighting a crucial aspect of the exchange rate markets that has been overlooked until now.

1.1 Related literature

Our work contributes to the microstructure approach to exchange rates by focusing on the heterogeneity of investors' price impact. Recent evidence from this literature highlight the importance of investor heterogeneity in understanding exchange rate dynamics and determination. For instance, the exchange rate determination puzzle, the excess predictability puzzle and the excess volatility puzzle can be explained by the rational confusion resulting from information heterogeneity among investors (Bacchetta and Van Wincoop, 2006; Candian and De Leo, 2022; Stavrakeva and Tang, 2020). Furthermore, exchange rate behavior is linked to order flow, which, in turn, is associated with the heterogeneity among investors (Lyons et al., 2001; Evans and Lyons, 2006). However, despite extensive evidence that foreign exchange rate markets are highly concentrated and atomistic price-taking investors are hardly realistic, the literature has ignored the potential heterogeneity in price impact (Osler, 2014; Osler et al., 2016; Cochrane, 2015). A notable exception is the work in Corsetti et al. (2004) and Corsetti et al. (2002), which theoretically studies the role that large investors have in speculative attacks in the foreign exchange markets. Differently to them, we focus on exchange rate determination and puzzles by incorporating heterogeneity in price impact, drawing on the modeling approach of Kyle (1989) and Kacperczyk et al. (2018), which has not been previously applied in the context of exchange rate markets.

This paper contributes to the rich literature on the determination and dynamics of exchange rates in the presence of frictions. Prior work explores various types of frictions, including informational frictions (Evans and Lyons, 2002; Bacchetta and Van Wincoop, 2006), infrequent portfolio adjustment (Bacchetta and Van Wincoop, 2010, 2019), imperfect and frictional markets (Gabaix and Maggiori, 2015; He and Krishnamurthy, 2013). To the best of our knowledge, our work is the first to specifically focus on this aspect of the market structure – the presence of strategic investors and heterogeneity in price impact – for the determination of the exchange rate.

This paper also relates to the vast literature attempting to explain major puzzles in international economics, both theoretically and empirically. We contribute by providing a new rationale, based on strategic behavior and price impact, for the failure of macroeconomic fundamentals to predict exchange rates and the large volatility of the exchange rate relative to fundamentals (Meese and Rogoff, 1983; Obstfeld and Rogoff, 2000; Engel and Zhu, 2019).[46] Moreover, we empirically study cross-currency differences in exchange rate puzzles and dynamics, which have been relatively unexplored, and find that different levels of price impact can explain cross-currency differences in a panel of 10 currencies.

The rest of the paper is organized as follows. Section 2 documents a set of facts that are consistent with the presence of strategic behavior in currency market. Section 3 introduces the theoretical framework and explains the fundamental mechanism of strategic behavior. In Section 4, we discuss the main implications for the dynamics of the exchange rate and provide empirical evidence that supports the theoretical predictions. Section 5 expands the basic framework to incorporate information heterogeneity and quantifies the respective contributions of each mechanism. Finally, Section 6 presents the conclusion. Any proofs, derivations, and robustness analyses that were omitted can be found in the Appendices.

2 Motivating Facts

As a first step, we use data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions to show that currency markets are highly concentrated, and investors' price impact decreases in more competitive markets. The U.S. Commodity

[46] We also show that the presence of strategic behavior and excess predictability interact (Fama, 1984). Although we do not propose novel explanations for UIP deviations, the presence of strategic investors can account for currency level differences in UIP deviations.

Futures Trading Commission (CFTC) data provides detailed information on currency futures positions held by asset managers, institutional investors, and leveraged funds in the currency futures market. The dataset encompasses 11 currency pairs, including both major and non-major USD currency pairs traded in the market. Data is reported on a weekly basis and spans the years 2006 to 2016.

Our first fact show that a relatively small number of entities have a substantial presence in the foreign exchange markets. Figure 7 reports the average concentration ratios by currency groups (major and non-major currencies), computed as the share of net open interest positions held by the largest four and eight entities operating the foreign exchange market.[47] [48] Two noteworthy observations emerge. Firstly, the eight (four) largest entities collectively held approximately 50% to 70% (40% to 60%) of the open interest positions in the market, revealing a significant level of market concentration. Secondly, concentration is highly heterogeneous across currency pairs, with Non-Major USD currency pairs exhibiting a 20% higher degree of concentration compared to major currency pairs.[49] Figure 29 in Appendix A shows qualitatively similar patterns when concentration is measured using the number of entities trading each currency (on average, 10 to 25 entities actively trade, with more traders being active in major currency markets).[50] The high concentration in

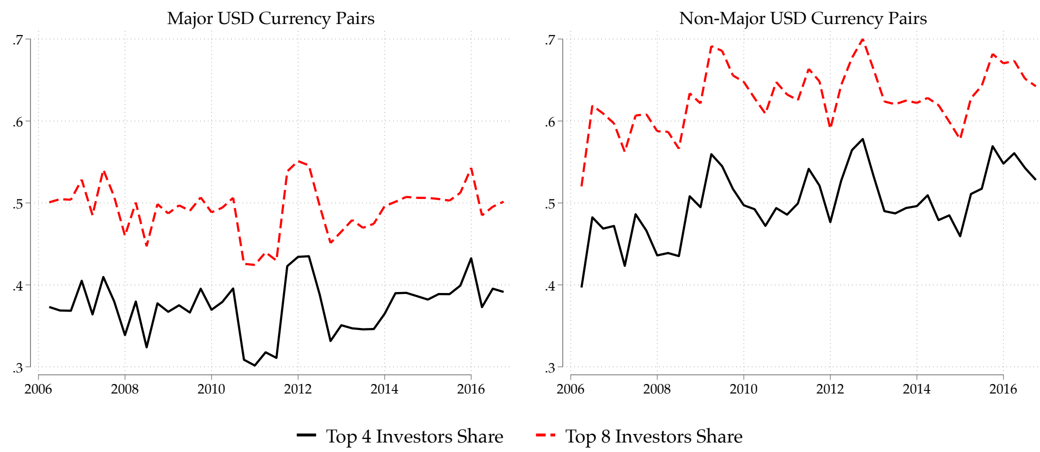
[47] Net positions are calculated by offsetting each trader's long and short positions. As a result, an entity with relatively large, balanced long and short positions in a single market may be counted among the four and eight largest traders in both the gross long and gross short categories, but it is unlikely to be counted among the four and eight largest traders on a net basis.

[48] As standard in this literature, we refer to Euro, Yen, Pound, and Swiss Franc as major currencies, while non-major currencies include Brazilian Real, Russian Rublo, Mexican Peso, Australian Dollar, New Zealand Dollar, and Canadian Dollar

[49] Figure 28 in Appendix A shows the concentration ratios for all individual currencies from 2006 to 2016. The Brazilian Real, Russian Rublo, and New Zealand Dollar are the currency pairs with the highest concentration, while the Euro and and Canadian Dollar exhibit the lowest.

[50] The high concentration measured in here aligns with other pieces of evidence, such as the BIS Triennial Survey of Foreign Exchange Markets or the NY FED OTC Foreign Exchange Market Survey. However, these surveys are limited in their scope, frequency of observation or coverage. The leading foreign exchange rate market survey, conducted by Euromoney and covering global markets, reveals that around 25 entities transact 70% of the total turnover. Additional information can be found here: https://www.euromoney.com/article/b1lp5n97k4v6j0/fx-survey-2020-press-release.

Figure 7: Market Concentration – U.S. CFTC



Notes: The figure shows the average concentration ratio of net open interest positions help by asset managers, institutional investors, and leveraged funds across currencies, divided between major and non-major currency groups. We consider the share held by the eight and the four largest entities in each market. Concentration ratios are computed on 'Net Position', meaning that are calculated after offsetting each trader's long and short positions. Major currency pairs consist of the United States Dollar paired with the Euro, British Pound, Japanese Yen, and Swiss Franc. Non-Major currency pairs include the United States Dollar paired with the Australian Dollar, Canadian Dollar, New Zealand Dollar, Mexican Peso, Brazilian Real, and Russian Ruble. The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016, with quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

the foreign exchange markets raises the question whether leading traders can significantly influence market dynamics.

Our second fact shows that trading activities in the foreign exchange rate market impact exchange rates, and the effects are stronger when markets are more concentrated. We aim to estimate how the trading activities of market participants influence exchange rate movements. To this end, we follow Evans and Lyons (2002) and Ready and Ready (2022) and regress the changes in exchange rates on the investors' net imbalances reported in our data, as follows:

$$\Delta s_{i,t} = \alpha_i + \gamma_t + \beta \text{ Imbalance}_{i,t} + \eta(i_t - i_t^\star) + \varepsilon_{i,t} \tag{22}$$

where $\Delta s_{i,t}$ represents the one-month percentage change in exchange rates, defined as domestic currency over foreign currency (i.e., an increase in exchange rate represents a depreciation of the foreign currency); α_i and γ_t are currency and time fixed effects, respectively, which controls for currency-specific characteristics and common temporal variations; $(i_t - i_t^\star)$ captures the one-month interest rate differential between US and the foreign country, common determinant in standard exchange rate models (Evans and Lyons, 2002). Lastly, $\text{Imbalance}_{i,t}$ represents the sum of net open interests positions of asset managers, institutional investors, and leveraged funds in a specific currency i within the month.[51] A value of β_1 different from zero suggests the presence of a price impact of traders' flow in the foreign exchange rate market. We then augment the baseline regression in Equation (27) by interacting $\text{Imbalance}_{i,t}$ with a proxy for the degree of concentration in the currency market. We measure concentration in each currency market using the market concentration measure as in Figure 7, the numbers of active traders (Figure 29 in Appendix A), or by distinguishing between major and non-major currencies. The coefficient of the interaction term is informative on how investors' price impact changes depending on the degree of market competition.

Table 4 reports the results of the estimates. Columns (1) and (2) indicate that increased trading flow within the future FX market exerts a downward pressure on foreign-to-domestic exchange rates (Evans and Lyons, 2002).[52] Specifically, a one-million-dollar increase in

[51] The CFTC distinguishes the market participants into the 'sell side' and 'buy side.' Sell-side participants include financial intermediaries that usually act as dealers in the market, while asset managers, institutional investors, and leveraged funds represent buy-side participants. We exclusively focus on buy-side participants as our primary focus is on active traders. Figure 27 in Appendix A presents the net open interest positions by market participants for each currency in our dataset.

[52] Episodes of market manipulation provide additional evidence of non-zero price impact in the exchange rate market. In June 2013, Bloomberg News reported that "*traders at some of the world's biggest banks colluded to manipulate the benchmark foreign-exchange rates used to set the value of trillions of dollars of investments in Pensions Funds and money managers globally*". Subsequently, extensive investigations were conducted, resulting in banks pleading guilty and paying fines totalling more than $10 billion. Despite significant institutional reforms implemented in 2015, there are indications that market manipulation may not have completely ceased (Osler, 2014; Osler et al., 2016; Cochrane, 2015).

Table 4: Price Impact Regressions

Dep. Variable: Δ Exchange Rate (%)	Average		Heterogeneity		
	(1)	(2)	(3)	(4)	(5)
Imbalances (Mil $)	-0.0118***	-0.0129***	0.0198	-0.0105***	-0.0288***
	(0.0020)	(0.0020)	(0.0142)	(0.0019)	(0.0069)
Interest Differential		2.2537*	2.2332*	2.2778*	2.2319*
		(1.1561)	(1.1330)	(1.1659)	(1.1556)
Imbalances (Mil $) × Conc. (Avg)			-0.0642**		
			(0.0278)		
Imbalances (Mil $) × Non-Major Pairs				-0.0080**	
				(0.0031)	
Imbalances (Mil $) × Number (in tens)					0.0044**
					(0.0019)
Time FE	Yes	Yes	Yes	Yes	Yes
Currency FE	Yes	Yes	Yes	Yes	Yes
Cluster SE	Currency	Currency	Currency	Currency	Currency
Observations	1,160	1,160	1,160	1,160	1,160
Mean of Dep. Variable	0.2004	0.2004	0.2004	0.2004	0.2004

Notes: The table displays the results of a pooled regression in which the dependent variable is the monthly exchange rate change, and the independent variable is the contemporaneous one-month net trade imbalance. The net imbalance is the sum of net imbalances among asset managers, institutional investors, and leveraged funds. Exchange rate change is measured in percentages, and net imbalance is measured in millions of dollars (i.e., a coefficient of 0.01 represents a weekly exchange rate change of 0.01% per million dollars of trading imbalance). Interest differential measures the difference between the one-month US interest rate and the one-month foreign interest rate. Columns (1)-(2) present the results with currency and time fix effects, and controlling for the lagged one-month interest rate differential, respectively. Column (3)-(5) report the heterogeneous effect due to market concentration. Concentration is measured using the market share of the top eight entities (Column (4)), distinguishing between major and non-major currencies (Column (5)), and the number of active traders (Column (6)). Standard errors are clustered at the currency pair level and are displayed in parentheses. The sample period covers June 2006 through December 2016, except for the Brazilian Real-USD pair, which starts in May 2011. Additional information about the data used is provided in Appendix A

trading imbalances towards a foreign currency leads to approximately a 0.01% appreciation of the foreign currency. These effects are both statistically and economically significant, accounting for roughly 5% of the average monthly exchange rate variation.

The impact of tradings on the exchange rate is more pronounced in markets that are more concentrated. Columns (3)-(5) examine the relationship between net imbalances and exchange rates, depending on different measures of market concentration. In Column (3), an increase in trading imbalances has a more significant negative impact on exchange rates when the share of open interests held by the top 8 traders is larger. This result remains robust when measuring concentration by currency pairs group or by the number of active traders, as shown in Column (4) and Column (5), respectively.

Taken together, the two facts highlight that market concentration is a salient feature of the exchange rate markets, with key implications on investors' price impact and its heterogeneity across currencies. In the next section, we demonstrate the importance of incorporating strategic behavior into models of exchange rate determination to gain a deeper understanding exchange rate dynamics and puzzles.

3 A Monetary Model with Strategic Investors

We propose a framework that incorporates strategic behavior in the spirit of Kyle (1989) and Kacperczyk et al. (2018) into a standard two-country, discrete time, general equilibrium monetary model of exchange rate determination (Mussa, 1982; Jeanne and Rose, 2002). To provide the key insight on the main mechanism, we initially present a version of the model that assumes agents have rational expectations about the dynamics of the exchange rate. In Section 5, we extend the model to include dispersed information, following Bacchetta and Van Wincoop (2006), and conduct our quantitative decomposition.

3.1 Basic Set-up

There are two economies, Home and Foreign, both producing the same good. Variables referring to Foreign are indicated with a star. We assume that purchasing power parity holds, so that:

$$p_t = p_t^\star + s_t,$$

where s_t is the log nominal exchange rate, p_t ($p_t^\star$) the log price level in the Home (Foreign) country. The exchange rate is defined as the value of the foreign currency in term of domestic currency, and an increase in the exchange rate reflects an appreciation of the foreign currency. There are three assets: one-period nominal bonds issued by both Home and Foreign with interest rates i_t and $i_t^\star$, respectively, and a risk-free technology with fixed real return r. The latter is infinitely supplied while bonds are in fixed supply in their respective currency. We follow Bacchetta and Van Wincoop (2010) and assume asymmetric monetary rules between the two countries. The Home central bank commits to a constant price level, $p_t = 0$, which implies that the domestic interest rate is equal to the risk free technology, $i_t = r$. On the other hand, the monetary policy in Foreign is stochastic, $i_t^\star = -u_t$ where

$$u_t = \rho_u u_{t-1} + \sigma_u \epsilon_t^u \qquad \epsilon_t^u \sim N(0,1) \tag{23}$$

is the Foreign monetary policy shock. Thus, the interest rate differential is defined as

$$i_t - i_t^\star = u_t + r,$$

implying that the dynamics of the exchange rate are solely influenced by the monetary policy of the Foreign country.[53] In our model, we refer to a shock in the Foreign monetary policy as a fundamental shock.

There is a continuum of investors of mass one. We assume there are overlapping generations of investors that live for two periods and make only one investment decision. We abstract away from saving decisions by assuming that investors derive utility only from their end-of-life wealth (Bacchetta and Van Wincoop, 2006, 2010). Investors in both countries

[53] Bacchetta and Van Wincoop (2010) specify a simplified Wicksellian rule of the form $i_t^\star = \psi(p_t^\star - \bar{p^\star}) - u_t$ where ψ is set equal to zero, consistent with the low estimates of ψ reported by Engel and West (2005). Bacchetta and Van Wincoop (2010) show that an exogenous interest rate rule, as in our case, does not compromise the existence of a unique stochastic steady state for the exchange rate.

are born with an exogenous endowment, ω, and have the possibility to invest in nominal bonds and the risk free technology. We assume that Foreign country is infinitesimally small, implying that the market equilibrium is determined by the investors located in the Home country. There are two type of investors: strategic (S) and competitive (C). A mass $1-\lambda$ of investors consists of standard atomistic price-takers investors. The remaining segment, with size λ, consists of a finite number N of strategic investors. Each strategic investors has a positive mass, λ_i, with $\sum_i^N \lambda_i = \lambda$. Notably, strategic investors internalize their effect on asset prices, operating as an oligopoly.

Investor j maximizes mean-variance preferences over next period wealth, w_{t+1}^j, by allocating their initial endowment between domestic and foreign bonds:

$$\max_{b_t^j} \quad E_t^j(w_{t+1}^j|\Omega_t^j) - \frac{\rho}{2} Var_t^j(w_{t+1}^j|\Omega_t^j) \tag{24}$$

$$\text{s.t. } w_{t+1}^j = (\omega - b_t^j)i_t + (i_t^\star + s_{t+1} - s_t)b_t^j, \tag{25}$$

where b_t^j represents the foreign bond holdings, ρ the rate of risk aversion and Ω_t^j the information set of investor j at time t. i_t and $i_t^\star + s_{t+1} - s_t$ are the log-linearized returns of domestic and foreign bonds, respectively. Under PPP and the monetary policy assumptions above, we have that $p_t^\star = -s_t$, implying that both returns are expressed in real terms. The only difference between the two assets is that the return on foreign bonds is stochastic.[54] We assume that agents have symmetric rational expectations about the dynamics of the exchange rate, $\Omega_t^j = \Omega_t$, postponing dispersed information to Section 5.

Investors' demand schedule and portfolio allocation vary depending on their type. Strategic investors internalize the effects that their demand has on equilibrium prices (more precisely, on the equilibrium exchange rate), while competitive investors do not. In

[54] $p_t = 0$ implies $i_t = r$. Similarly, $p_t^\star = -s_t$ implies that the return on foreign bonds, $i_t^\star + s_{t+1} - s_t$, is expressed in real terms as well.

Appendix B, we show that the optimal demand for foreign bonds by investor j is as follows:

$$b_t^j = \begin{cases} \dfrac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho\sigma_t^2}, & \text{for } j = C \\ \dfrac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho\sigma_t^2 + \frac{\partial s_t}{\partial b_t^S}}, & \text{for } j = S \end{cases} \tag{26}$$

where σ_t^2 is the variance of the exchange rate change, $Var_t(s_{t+1} - s_t)$. We focus on a stochastic steady state where the variance σ_t^2 is time-invariant.

Investors' demand for foreign bonds depends positively on the expected excess return, $q_{t+1} \equiv E_t(s_{t+1}) - s_t + i_t^\star - i_t$. On the other hand, it depends negatively on the variance of the exchange rate, σ_t^2, and on investors' risk aversion, ρ. Note that strategic behavior, captured by investors' own price impact $\frac{\partial s_t}{\partial b_t^S}$, reduces investors' demand of foreign bonds for every level of excess return. Given a total supply of foreign bond B, the price impact of a strategic investor i is

$$\frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i \rho\sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)} > 0, \tag{27}$$

which is positive, increasing in the mass of the investor, λ_i, and decreasing in the fraction of atomistic investors $1 - \lambda$. The individual price impact becomes $\frac{1}{N}\frac{\lambda\rho\sigma_t^2}{B\rho\sigma_t^2+(1-\lambda)}$ in the case strategic investors are symmetric and have the same mass, $\lambda_i = \frac{\sum_i \lambda_i}{N} = \frac{\lambda}{N}$.[55] The structure of the market determines the magnitude of the price impact and, consequently, the relevance of strategic behavior: the magnitude of the individual price impact is negatively affected by the number of strategic traders, N, and positively related to the size of the strategic segment, λ. Therefore, the price impact is larger in more concentrated markets

[55] In our analysis, we focus on the case of symmetric strategic investors due to the unavailability of comprehensive investor-level market share data. The U.S. CFTC data, used in Section 2 and in the rest of the paper analysis, provides information only on the aggregate market share of the top four or eight investors or the number of investors in total. Importantly, all qualitative predictions are not altered by the symmetry assumption. See Appendix B for the derivation of the analytic expression of the price impact.

characterized by a lower N and/or higher λ.[56] Importantly, Table 4 in Section 2 provides empirical evidence on how the degree of market competition affects investors' price impact that are in line with the theoretical implications of Equation (27).

In addition to strategic and competitive investors, we introduce another group of investors referred to as noise traders. As is standard, their presence allows to match key empirical moments of exchange rates, such as exchange rate volatility, disconnect and deviations from UIP (Kyle, 1989; Bacchetta and Van Wincoop, 2006, 2010). Following Bacchetta and Van Wincoop (2010), we assume that the demand of noise traders for foreign bonds is exogenous and given by:

$$X_t = (\bar{x} + x_t)\bar{W},$$

where $\bar{W}$ is the steady state aggregate financial wealth in the Home economy, $\bar{x}$ is a constant and x_t follows the following exogenous process:

$$x_t = \rho_x x_{t-1} + \sigma_x \epsilon_t^x \qquad \epsilon_t^x \sim N(0,1).$$

In the stochastic steady state, the demand for foreign assets absorbed by noise traders is equal to $\bar{x}\bar{W}$. Deviations from this steady state are driven by x_t, which is interpreted as a noise shock and is orthogonal to the fundamental shock u_t in Equation (23). Positive shocks to x_t increase the desire for foreign assets, leading the foreign currency to appreciate without movements in the interest rate differential.

[56] In our international portfolio model, strategic investors have a lower price impact on the equilibrium price of an asset compared to a closed-economy version. This is due to the presence of valuation effects on the supply of assets once denominated in domestic currency. By internalizing the effect that their demand has on the exchange rate, strategic investors also take into account how the value of the supply of foreign assets denominated in domestic currency varies when the exchange rate changes. This is reflected by the presence of B, the total supply of foreign assets, at the denominator of Equation (27). See Appendix B for additional details.

Equilibrium and Basic Mechanism We derive an expression for the equilibrium exchange rate by combining the demand schedules of investors and the market clearing condition of the foreign bond market. The market clearing condition is given by:[57]

$$(1-\lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i} + X_t = Be^{s_t}, \tag{28}$$

where the left hand side represents the total demand of foreign bonds from competitive investors, strategic investors and noise traders, and the right hand side represents the (constant) supply of foreign bonds, B, denominated in domestic currency.

We define the concept of equilibrium in our model as follow: for a history of fundamental and noise shocks $\{\varepsilon_t^{\Delta i}, \varepsilon_t^x\}_{t=0}^{-\infty}$, an equilibrium path is a sequence of portfolio allocations, $\{b_t^C, \{b_t^{S,i}\}_{i=1}^N\}$, and foreign bond price (exchange rate), $\{s_t\}$, such that investors optimally choose their portfolio allocation and the market clearing condition holds.

The model allows us to derive an explicit solution for the exchange rate s_t from the market clearing condition in Equation (28):

$$s_t = \underbrace{(1-\mu)\left(\frac{\bar{x}}{b} - 1\right)}_{\text{constant}} + \underbrace{\mu(E_t s_{t+1} + i_t^\star - i_t)}_{\text{fundamental}} + \underbrace{(1-\mu)\frac{1}{b}x_t}_{\text{noise}}, \tag{29}$$

where $b = \frac{B}{W}$ and $\mu = \frac{1}{1+\Phi(\lambda,N)}$ with $\Phi(\lambda, N) = \frac{B\rho \operatorname{Var}_t(s_{t+1})\left(1+B\rho \operatorname{Var}_t(s_{t+1})-\lambda \frac{N-1}{N}\right)}{\left(1+B\rho \operatorname{Var}_t(s_{t+1})-\lambda\frac{N-1}{N}\right)-\frac{\lambda^2}{N}}$. The exchange rate follows a forward looking auto-regressive process with drift, where the constant term depends on a set of parameters and the stochastic component depends on future fundamental and noise shocks. By further manipulating Equation (29), it can be shown

[57] The market clearing for the domestic bond is not explicitly considered because domestic bonds are perfectly substitutable with the risk free technology, which is infinitely supplied. Furthermore, in a monetary model, a market clearing condition for the money market would also be required. Bacchetta and Van Wincoop (2006) and Bacchetta and Van Wincoop (2010) assume that investors generate a money demand (independent of their portfolio decision) and that money supply accommodates it under the exogenous rule for interest rates. We do not explicitly model the money market in order to limit notation, leaving it in the background.

that the exchange rate s_t can be written as follows:

$$s_t = \mu \sum_{k=0}^{\infty} \mu^k (i^\star_{t+k} - i_{t+k}) + \frac{1-\mu}{b} \sum_{k=0}^{\infty} \mu^k (x_{t+k}). \tag{30}$$

The exchange rate is a weighted average of current and future fundamental shocks $(i^\star_{t+k} - i_{t+k})$ and noise shocks (x_{t+k}). The weight μ quantifies the amount of information about the fundamental conveyed by the exchange rate. Notably, the informativeness of the exchange rate decreases when strategic investors operate in the foreign bond market (higher λ or lower N imply higher Φ and, thus, lower μ). When there is a higher proportion of strategic investors (higher λ) or a lower number of strategic traders (lower N), investors' demand declines because of the stronger price impact. Therefore, the demand from noise traders becomes relatively more important in determining the exchange rate.[58] [59]

We calibrate and simulate the basic model to illustrate the mechanism discussed above. We use data on 18 exchange rates, all defined against the USD, from 1993 to 2019 at a monthly frequency.[60] Without loss of generality, we set $\bar{r} = 0$, so that the $i_t - i^\star_t = u_t$. Assuming covered interest rate parity holds, we compute the one-month interest rate differential as the difference between the one-month forward and the spot exchange rate. We assume that the fundamental, u_t, follows an AR(1) process. We estimate the volatility and the persistence of the fundamental process for each currency using interest rate differentials, and calibrate σ_u and ρ_u to match the average volatility and persistence across currencies.

[58] When traders recognize that the residual supply curve is upward-sloped, quantities are restricted and less elastic. Therefore, prices become less informative. This aligns with the key intuition from Kyle (1989).

[59] The informativeness parameter, μ, relates to the magnification factor in Bacchetta and Van Wincoop (2006). In their work, information dispersion among investors reduces the information content of exchange rates by amplifying the impact of noise traders. As in their work, the behavior of the parameter μ plays a crucial role in the amplification mechanism examined here.

[60] We consider the following currencies: Euro, Japanese Yen, Argentinian Peso, Brazilian Real, Canadian Dollar, Swiss Franc, Australian Dollar, Chilean Peso, Indian Rupee, Mexican Peso, British Pound, South African Rand, Russian Ruble, Swedish Krona, Turkish Lira, New Zeland Dollar, Singapore Dollar, Norwegian Krone. See Appendix A for additional details on data.

Table 5: Benchmark Parametrization

Parameters	Value	Target
λ	0.6	Net concentration ratio (Top 8) – U.S. CFTC
N	8	Number of traders related to λ – U.S. CFTC
ρ_u	0.85	Average persistence AR(1) Δi_t
σ_u	0.005	Average StD innovation AR(1) Δi_t
σ_x	0.131	σ_t (StD ER change)
σ_t	0.028	Average StD ER change
ρ_x	0.9	ER Random Walk/Average Disconnect
b	0.333	Home Bias
ρ	50	Bacchetta and Van Wincoop (2019)

Notes: The table summarizes the parametrization used in the basic framework. For each parameters, we report the value used in the model, the corresponding moment and data used to calibrate, and, if applicable, the target moment used to estimate it. Appendix A provides additional information on the data used.

This yields $\sigma_u = 0.005$ and $\rho_u = 0.85$. The variance of the exchange rate change, σ_t, is assumed to be constant over time and calibrated to match the average standard deviation of the one-period exchange rate change across currencies, which is 0.028.

As standard in this literature, the process governing the demand of noise traders, x_t, is calibrated to match exchange rate dynamics. The persistence of the noise shock, ρ_x, is set high enough to ensure the exchange rate behavior is sufficiently close to a random walk. The volatility of the process is chosen to match the volatility of the one-period change in exchange rate. However, Equation (30) shows that exchange rate dynamics depend on the underlying market structure. Therefore, we first calibrate the parameters controlling the magnitude of the strategic behavior, λ and N, and then σ_x and ρ_x.[61] We use data from the U.S. Commodity Futures Trading Commission, and set $N = 8$ and $\lambda = 0.6$, which is the average concentration ratio of the top eight traders in the currency market (Figure 7).

[61] $\bar{x}$ is calibrated such that the value of the exchange rate in the stochastic steady state is zero, excluding any trend in the dynamics of exchange rate. This assumption does not affect the results of our model.

Given the benchmark values for λ and N, we set $\sigma_x = 0.131$ and $\rho_x = 0.9$.[62]

Lastly, we set b, the inverse home bias measure, equal to 0.33, indicating that foreign assets account for one third of the total domestic financial wealth. This value is an approximate average obtained from the IMF IIPS dataset (Bacchetta and Van Wincoop, 2019).[63] Moreover, we follow Bacchetta and Van Wincoop (2019) and set the rate of relative risk aversion, ρ, to 50.[64] The parametrization, summarized in Table 5, uses values in line with previous literature.

The main implication of heterogeneity in price impact is that the response of the exchange rate to fundamental and noise shocks depends on the presence of strategic behavior. Specifically, compared to a "competitive" exchange rate market without strategic investors ($\lambda = 0$ or $N \to \infty$), the presence of strategic investors amplifies the exchange rate's response to noise shocks and dampens its response to fundamental shocks. Appendix B shows that the result is independent of the parameterization of the model.

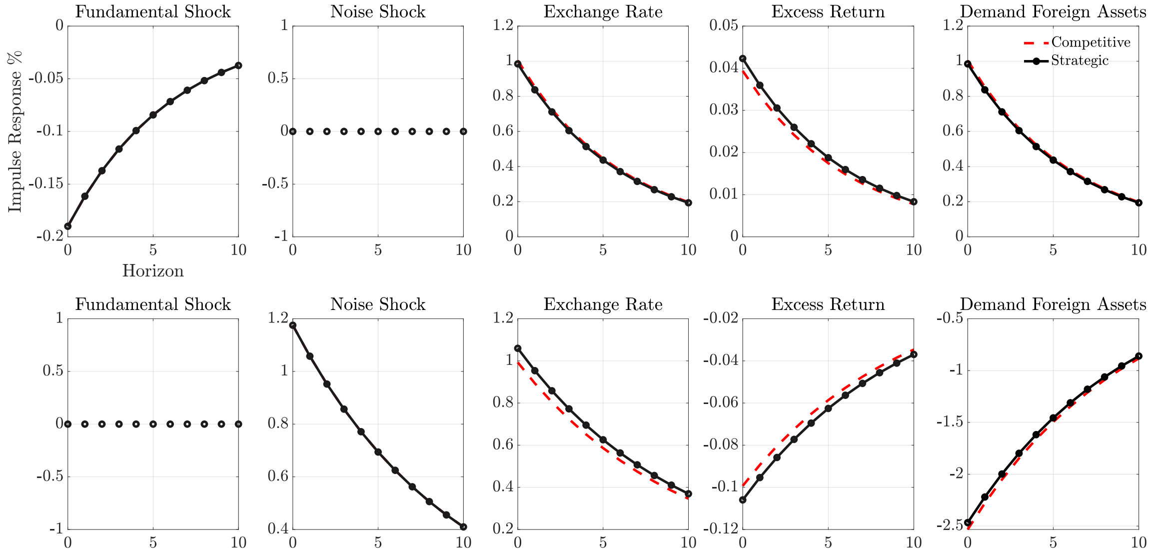
The bottom row of Figure 8 plots the impulse response functions to a noise shock in the presence of strategic investors compared to a scenario without strategic investors ("competitive" market). A positive noise shock, which can be interpreted either as a positive demand shock or a negative supply shock of foreign assets. Either way, the residual demand

[62] Taking into account the presence of strategic investors in the underlying market structure has the effect of reducing the implied volatility of noise traders required to match exchange rate dynamics. This is because strategic investors amplify the effects of noise traders. Figure 32 in Appendix D shows that there exists a negative relationship between the level of strategic behavior (N and λ) and σ_x, given a target value for the exchange rate volatility. In a competitive market, the volatility of the noise shock should be $\sigma_x = 0.14$ in order to match the same volatility of the exchange rate, which is almost 20% higher than in our benchmark calibration. This highlights the importance of considering the underlying market structure. Moreover, this represents a positive results for the determination of the exchange rate, as it suggests that noise traders are not as noisy as previously believed.

[63] Without loss of generality, the supply of foreign assets, B, is normalized to one. In order to ensure model consistency, we set ω, the initial endowment of each investor, equal to 3. This choice is derived from the relationship $b = \frac{B}{\bar{W}}$. By calibrating b and normalizing B, we determine that $\bar{W} = 3$. Total financial wealth in equilibrium is equal to the initial endowment.

[64] In the model, currency premia arise solely from investors' risk aversion, which would be relatively small for typical levels of risk aversion. However, our results are qualitatively robust when considering different levels of risk aversion.

Figure 8: Impulse Response to Exogenous Shocks



Notes: The top panel (bottom) shows the response to a fundamental (noise) shock. The size of the shocks is calibrated to produce a 1pp change in the exchange rate at impact in the competitive model. The first and second columns show the dynamics of the exogenous shocks in fundamentals and noise, respectively. The third column shows the dynamics of the exchange rate. Column four shows the response of the realized excess return, defined as $q_{t+1} = s_{t+1} - s_t + i_t^{\star} - i_t$. The last column shows the response of the total demand of foreign assets, defined as $(1-\lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i}$, where b_t^C and $b_t^{S,i}$ are defined according to Equation 26. The solid black line shows the response in the benchmark parametrization with strategic investors, $\lambda = 0.6$. The red dashed line shows the response in a competitive economy without strategic investors, $\lambda = 0$. Remaining parameters are common across scenarios, see Table 5.

of foreign assets decreases, increasing the price of the foreign assets and the exchange rate without any change in fundamentals. As the exchange rate increases, the excess return falls below its steady state. The lower excess return prompts investors to purchase fewer foreign assets, rebalancing their portfolios in favor of domestic assets.

The presence of strategic investors amplifies the response of the exchange rate to a noise shock due to the lower sensitivity of the demand of foreign bonds. Strategic investors internalize the negative impact of their trades on prices. Therefore, in a world where investors are strategic (solid line), the decline in the demand for foreign assets is less pronounced compared to a competitive market scenario (dashed red line), making the total demand for foreign assets less sensitive to the noise shock. In order for the market to clear, the response of the excess return is dampened relative to a competitive market. In other words, the smaller decline in investors' demand due to strategic behavior exerts additional upward pressure on the price of the foreign bonds and the exchange rate, thereby amplifying the effect of noise shocks on the exchange rate.

The top row of Figure 8 shows the exchange rate's response to a fundamental shock and its dampening in the presence of strategic investors compared to a "competitive" market. A contraction in monetary policy in the foreign country leads to a drop in the interest differential, increasing the excess return, and thus, investors' demand for foreign assets. This results in the appreciation of the foreign currency. In a world where investors are strategic (solid black line), their holdings of foreign assets increase relatively less due to their price impact, which makes their demand less sensitive. As a consequence, the price of foreign assets increases relatively less compared to a competitive market, hereby dampening the effect of the fundamental shock on the exchange rate.

4 Implications for Exchange Rate Dynamics

We use the calibrated model to illustrate and discuss the implications of strategic behavior for exchange rate dynamics, focusing on exchange rate volatility and exchange rate disconnect. Specifically, we demonstrate that the presence of strategic investors amplifies the volatility of the exchange rate and contributes to an increased disconnect between the exchange rate and underlying fundamentals.[65]

[65] Appendix B demonstrates that the presence of strategic behavior also has implications for deviations from uncovered interest rate parity (UIP). Although strategic behavior does not inherently generate excess predictability, it does contribute to larger UIP deviations.

Exchange Rate Disconnect One of the most robust empirical pieces of evidence on exchange rate dynamics is the disconnect between exchange rates and fundamentals (Meese and Rogoff, 1983; Cheung et al., 2005; Rossi, 2013). We show that heterogeneity in price impact and the presence of strategic behavior help explaining the limited explanatory power of standard theories of exchange rate determination.

As is standard, we measure the disconnect of exchange rates by assessing the explanatory power of the following regression equation:

$$s_{t+1} - s_t = \alpha + \beta(i_t - i_t^\star) + \varepsilon_{t+1}, \tag{31}$$

where $i_t - i_t^\star$ represents the fundamental driver of the one-period exchange rate change $s_{t+1} - s_t$. We simulate the model, estimate Equation (31), and observe how the explanatory power – measured using the R^2 – of the disconnect regression changes as the economy becomes increasingly populated by strategic investors.[66]

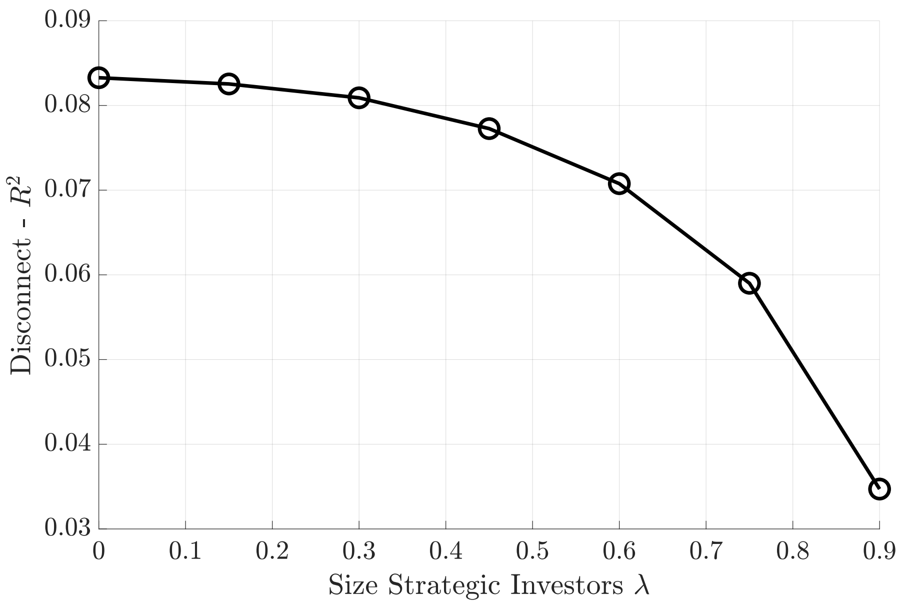
Figure 9 illustrates the R^2 of the disconnect regression for different degrees of strategic behavior, represented by different levels of λ. On average, the R^2 is low, consistent with the notion that exchange rates are disconnected from fundamentals.[67] Importantly, the disconnect increases in the presence of strategic investors, with the R^2 in our benchmark calibration ($\lambda \approx 0.6$) being about 15% lower compared to a competitive market.[68] This can be explained by the behavior of the informativeness of the exchange rate μ. Less competitive markets reduce the information content of exchange rate, amplifying its response to noise shocks and increasing the share of total variance in the exchange rate explained by noise.

[66] We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in.

[67] The R^2 from simulated data is close to the average R^2 estimated from the data used for the calibration, approximately 0.07.

[68] Figure 33 in Appendix D shows that the same qualitative implications hold when the disconnect is measured using alternative measures used in the literature, such as the RMSE.

Figure 9: Exchange Rate Disconnect



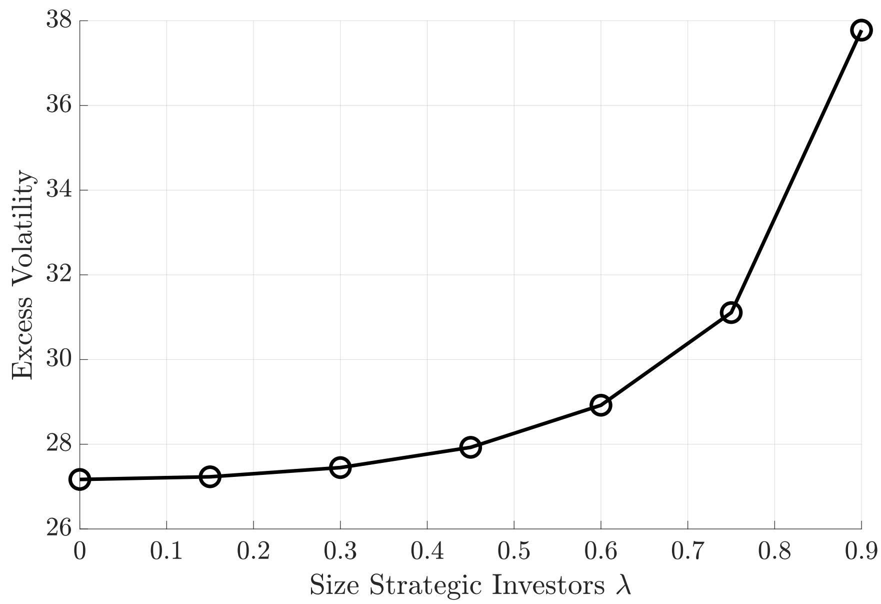
Notes: The figure shows the estimated R^2 of the disconnect regression in Equation 31 using simulated data. We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 5.

Exchange Rate Excess Volatility There is extensive evidence demonstrating that exchange rates exhibit higher volatility compared to fundamentals, which is commonly referred to as the "excess volatility puzzle" (Obstfeld and Rogoff, 2000; Engel and Zhu, 2019). We show how the presence of strategic behavior contributes to this excess volatility of the exchange rate relative to fundamentals by intensifying the influence of noise traders.

By manipulating Equation (30), we can derive an expression of the unconditional variance of the exchange rate as a combination of the variances of both fundamental and noise shocks:

$$\mathrm{Var}(s) = \frac{\mu^2}{(1-\mu\rho_u)^2}\left[\frac{1}{1-\mu^2} + \frac{\rho_u^2}{1-\rho_u^2}\right]\sigma_u^2 + \frac{(1-\mu)^2}{(1-\mu\rho_x)^2 b^2}\left[\frac{1}{1-\mu^2} + \frac{\rho_x^2}{1-\rho_x^2}\right]\sigma_x^2. \tag{32}$$

Figure 10: Excess Volatility



Notes: The figure shows the excess volatility ratio computed using simulated data from our model. We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. The excess volatility ratio is computed using the ratio between the volatility of the exchange rate in Equation (32) and the volatility of the fundamental, $\frac{\sigma_u}{\sqrt{1-\rho_u^2}}$. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 5.

The presence of strategic investors diminishes the informativeness of the exchange rate, placing relatively more emphasis on the noise component. Since the noise component is more volatile than the fundamental component, this contributes to the increasing the volatility observed in the exchange rate.[69]

Figure 10 shows that the excess volatility of the exchange rate is increasing in the presence of strategic behavior, due to the higher volatility of the exchange rate induced by strategic behavior (Equation (32)). We compute the excess volatility of the exchange rate

[69] Appendix B shows that the effect of strategic behavior is not necessarily monotonic from a theoretical perspective. However, it is important to note that under standard parameterizations, monotonicity is satisfied. On this regard, our calibration is very conservative, meaning that higher values of ρ_x and lower values ρ_u or b would all strengthen presence of monotonicity. Further details are available in Appendix B.

as the ratio between the volatility of the exchange rate in Equation (32) and the volatility of the fundamental, $\frac{\sigma_u}{\sqrt{1-\rho_u^2}}$ (Engel and Zhu, 2019). Using simulated data from our model, we show that the excess volatility rises with the presence of strategic investors, with the excess volatility ratio in our benchmark calibration ($\lambda \approx 0.6$) being around 8% higher compared to a competitive market.[70]

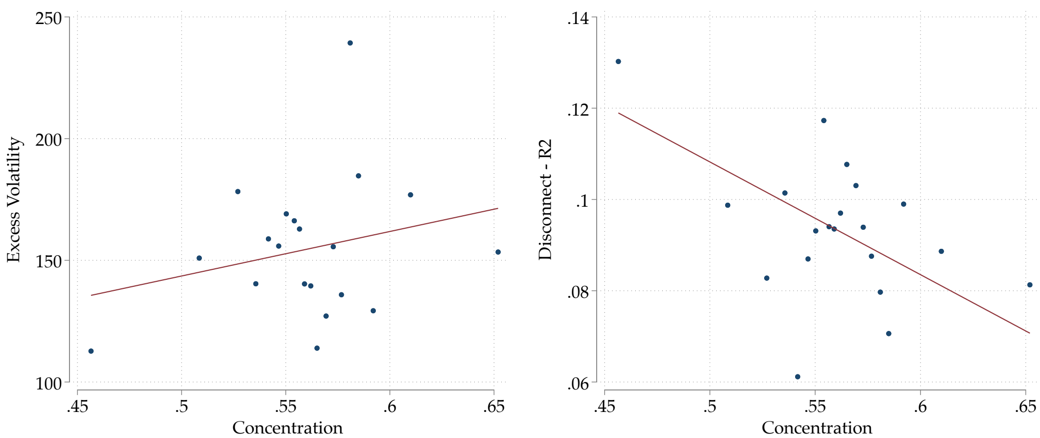
Testing predictions We leverage the heterogeneity in market concentration across currencies to test the implications provided by our theory. The model delivers two distinct testable relationships between exchange rate dynamics and the level of strategic behavior: (i) the disconnect of the exchange rate from fundamental increases in the level of strategic behavior (ii) higher the level of strategic behavior results in higher excess volatility of the exchange rate. We test our predictions using a set of 10 currencies merged with the U.S. CFTC transaction data, available since June 2006 to December 2016.[71]

We use the concentration ratio of the top eight investors, as reported by the U.S. CFTC, as our proxy of strategic behavior in the foreign exchange market (λ). We correlate this information with time-varying metrics of exchange rate disconnect and excess volatility. We utilize a 2-year rolling window with monthly exchange rate data to create time-varying indexes for exchange rate disconnect and excess volatility. We measure the exchange rate disconnect using the R^2 of the regression in Equation (31), while excess volatility is calculated as the ratio between the volatility of the exchange rate in Equation (32) and the volatility of the interest rate differential. The panel nature of our dataset enable us to incorporate currency and year fixed effects, mitigating potential concerns regarding spurious

[70] Figure 34 in Appendix D shows that the same qualitative result holds when measuring the excess volatility of the exchange rate using the ratio between the volatility of the exchange rate change and the volatility of changes in the fundamental, $\frac{\text{Var}(\Delta s)}{\text{Var}(\Delta u_t)}$.

[71] We exclude the South African Rand from our analysis due to a limited number of time observations in the CFTC dataset. To reduce noise in weekly transactions, we aggregate the data to a monthly level.

Figure 11: Testing Model Predictions



Notes: The figure plots the positive relationship between the level of strategic behavior and the excess volatility (left panel) and the disconnect (right panel) of the exchange rate in the actual data. Concentration is the share of open interest held by the top eight traders in the future FX market. Data is from the U.S. CFTC spanning from 2006 to 2016. The exchange rate disconnect is measured using the R^2 from the regression in Equation (31), while excess volatility is calculated as the ratio of exchange rate volatility from Equation (32) to the volatility of the interest rate differential. To measure excess volatility and disconnect, we use a 2-years rolling window regression with average monthly exchange rate data. The resulting data are demeaned at the currency and year level, and values of the excess volatility ratio and disconnect are winsorized at 1%. We exclude the South African Rand from the set of 11 currencies. Table 24 in Appendix D reports the estimated coefficients. Appendix A provides additional information on the data used.

correlation and strengthening the validity of the empirical evidence.[72]

Figure 11 provides evidence that are consistent with the predictions of our theoretical framework. The left panel documents a strong, positive, and statistically significant relationship between our measure of strategic behavior in the exchange rate markets and the excess volatility of the exchange rate. Likewise, the right panel reveals that as the presence of strategic investors in the market increases, currencies become more disconnected to fundamentals, as evidenced by the decreasing estimated R^2.

Table 24 in Appendix D reports the estimated coefficients along with the corresponding

[72] The results remain unchanged when we increase the rolling window size to 3 and 4 years, and using different proxies for strategic behavior, such as the number of active traders.

standard errors clustered at the country level. We find that a currency traded in a market with a 10% higher concentration ratio exhibits an excess volatility ratio that is about 12% higher compared to the average excess volatility observed in the sample. Similarly, a currency traded in a market with a 10% higher concentration ratio exhibits an 18% lower predictive power compared to the average R^2 in the sample.

5 Strategic Behavior vs Dispersed Information: A Quantitative Assessment

We now compare the effects that heterogeneity in price impact have on excess volatility and disconnect to the effect of investors' information heterogeneity. Dispersed information arising from heterogeneous information sets leads to higher exchange rate disconnect and excess volatility (Bacchetta and Van Wincoop, 2006; Evans and Lyons, 2002), representing a competing mechanism with heterogeneity in price impact. To assess the relevance of these two competing dimensions of heterogeneity, we extend the basic framework presented in Section 3 by relaxing the full information assumption and including information heterogeneity based on Nimark (2017). Through the lens of our model, we quantitatively evaluate the relative importance of strategic behavior and information heterogeneity in driving the dynamics of exchange rates.

5.1 Relaxing the Full Information Assumption

The model incorporates all standard elements of an exchange rate monetary model, along with the strategic behavior described in Section 3. However, in contrast to the basic framework, we assume that investors possess imperfect knowledge of the shocks affecting the economy, resulting in dispersed information. The remaining structure of the economy remains the same.

The main implication of information heterogeneity is that the optimal demand for foreign bonds by investor j at time t now depends on their individual information set, $\Omega_t(j)$:

$$b_t^j = \begin{cases} \dfrac{E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t}{\rho\sigma_t^2} & \text{if } j = C \\ \dfrac{E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t}{\rho\sigma_t^2 + \frac{\partial s_t}{\partial b_t^S}} & \text{if } j = S \end{cases} \tag{33}$$

where the excess return, $q_{t+1} = E_t(s_{t+1}|\Omega_t(j)) - s_t + i_t^\star - i_t$, and the variance of the exchange rate change, σ_t^2, are now conditional to the information set at time t, $\Omega_t(j)$. In contrast to the basic framework, we assume that σ_t^2 is endogenous but common to all investors, implicitly assuming that investors have the same capacity to process information. Despite the presence of information heterogeneity, the main implication of strategic behavior still holds true. Specifically, the own price impact reduces the demand of strategic investors for any given level of excess return.

Information Structure The information structure in our model follows Nimark (2017), and generalize the case in Singleton (1987) and Bacchetta and Van Wincoop (2006). Investors form expectation regarding the future price of the foreign bond (exchange rate) by observing their private signal about the fundamental, as well as the history of the exchange rate. Formally, investors' information set is given by:

$$\Omega_t(j) = \{f_{t-T}(j), s_{t-T} : T \geq 0\},$$

where

$$f_t(j) = \Delta i_t + \eta_t(j) \text{ where } \eta_t(j) \sim N\left(0, \sigma_\eta^2\right)$$

represents the private signal about fundamentals. Therefore, investors have imperfect knowledge about the history of shocks that affect the economy because they observe an unbiased signal $f_t(j)$ regarding Δi_t, with an idiosyncratic measurement error $\eta_t(j)$. Investors are unable to perfectly observe the path of the foreign interest rate, and cannot deduce the fundamental component from observing the exchange rate due to the presence of unobserved transitory noise shock x_t (Admati, 1985). The private signal, $\eta_t(j)$, implies that investors have different expectations about foreign Central Bank's operating procedures. Consequently, the need to 'forecast the forecasts of others' (infinite regress problem) arises due to information dispersion.[73]

Equilibrium and Solution. We extend the definition of equilibrium of the basic framework discussed in Section 3 to incorporate the presence of dispersed information. In the extended framework, an equilibrium path is defined as a sequence of quantities $\{b_t(j)\}$ and foreign currency (asset) price $\{s_t\}$ that satisfy the following conditions: given an history of shocks $\{\varepsilon_t^x\}_{t=0}^{-\infty}$ and signals about fundamentals $\{f_t(j)\}_{t=0}^{-\infty}$, investors optimally choose their portfolios, and the market clearing condition is upheld.

The effect of strategic behavior on the exchange rate, as well as its mechanism, extends to the model with dispersed information as in the basic framework. Combining the market clearing condition with investors' demand schedules, we can derive the following expression for the exchange rate:

$$s_t = (1-\mu)\left(\frac{\bar{x}}{b} - 1\right) + \mu\left(\int E[s_{t+1} \mid \Omega_t(j)]dj\right) - \mu(i_t - i_t^\star) + (1-\mu)\frac{1}{b}x_t, \qquad (34)$$

[73] The key distinction with Singleton (1987) and Bacchetta and Van Wincoop (2006) lies in the nature of private signals, which are not short-lived. In other words, innovations to the fundamental process are not perfectly and publicly observed after a finite number of periods. Short-lived private information allows to derive a finite dimensional state representation, overcoming the infinite regress problem. The solution method proposed by Nimark (2017)and used here enables us to solve our model while relaxing the assumption made by Singleton (1987).

where μ and Φ are defined as in the basic framework, with the former decreasing in the presence of strategic investors (decreasing in λ and increasing in N).

In the presence of dispersed information, a closed-form solution for the exchange rate is not available since it depends on higher-order expectations regarding the fundamental:

$$s_t = \mu \sum_{k=0}^{\infty} \mu^k \big[i_{t+k} - i^{\star}_{t+k}\big]^{(k)}_t + \frac{1-\mu}{b} x_t, \tag{35}$$

where $\Big[i_{t+k} - i^{\star}_{t+k}\Big]^{(k)}_t$ denotes the average expectation in period t of the average expectation in period t+1, and so on, of the average expectation in period t+k-1 of k period ahead fundamentals, that is, $\Big[i_{t+k} - i^{\star}_{t+k}\Big]^{(k)}_t = \underbrace{\int \mathbb{E}_t \ldots \Big[\int \mathbb{E}_{t+k-1}}_{k}\Big(i_{t+k} - i^{\star}_{t+k}\Big)dj\Big] \ldots dj$ for any integer k > 0. In the case of dispersed information, the informativeness parameter μ represents the weight assigned to higher-order expectations regarding future fundamentals in influencing exchange rate dynamics.

We solve the model using the methodology outlined in Nimark (2017). To account for higher order expectations, we assume that agents have rational expectations about how other agents form their own expectations, and that this information is common knowledge. Using this assumption, we compute the dynamics of the exchange rate while accounting for expectations of arbitrarily high orders. Denoting the hierarchy of expectations about fundamentals with $\Delta i^{(0:k)}_t$, which is the vector of average expectations on Δi_t of any order from zero to k, we show in Appendix C that the exchange rate s_t can be expressed as:[74]

$$s_t = v_0 \Delta i^{(0:k)}_t + \frac{1-\mu}{b} x_t \tag{36}$$

[74] There exist other approaches that rely on the fact that average first-order expectations about the endogenous variables can be computed given the guessed laws of motion of the endogenous variables by using the assumption of rational expectations. We find the approach in Nimark (2017) more reliable and fast to implement.

where v_0 is a vector of k weights associated to higher order expectations. In contrast to the baseline model, an aggregate shock in this model affects the exchange rate not only directly, but also through higher order expectations $\Delta i_t^{(1:k)}$.

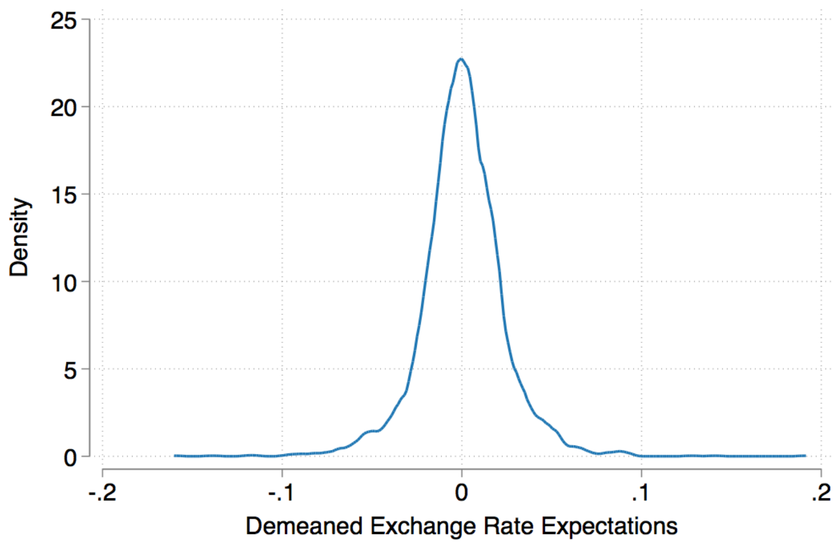
Parametrization and Mechanism. We extend the parametrization of the basic framework in Table 5 to account for the presence of dispersed information. We leverage the data on exchange rate expectations from the ECB Professional Forecasters survey to calibrate the volatility of the private signal, σ_η. The survey runs at quarterly frequency since 2002 and contains information on professional forecasters' expectations for the euro-dollar exchange rate at various horizons. The distribution of the demeaned, same-quarter exchange rate expectations in Figure 12 exhibits a significant dispersion, with a standard deviation of approximately 0.02, indicating the presence of information heterogeneity among investors.[75] To calibrate the precision of the private signal (σ_η) and the volatility of the noise component (σ_x), we use Simulated Method of Moments. We simulate the model for 8,000 periods with a burn-in of 3,000 periods, repeating it 25 times with different random number generators. We match the volatility of the exchange rate change and the median dispersion in the same-quarter exchange rate forecasts across quarters. This yields $\sigma_x = 0.024$ and $\sigma_\eta = 0.006$. Table 25 in Appendix D summarizes the parametrization.[76]

Similarly to the presence of strategic behavior in our basic framework, the presence of dispersed information also amplifies the effects of noise shocks on the exchange rate while dampening the effects of fundamental shocks. Information heterogeneity leads to rational confusion, which means that investors always revise their expectations whenever

[75] In the data, we consider the log of the expected exchange rate to be consistent with the log-linearized exchange rate s_t in our model. Table 23 in Appendix A provides additional measures of the dispersion of exchange rate expectation across horizon and time periods.

[76] Note that the dispersion in the exchange rate expectations generated by the model falls short relative to the target moment. One possible explanation is that the expectation data from the ECB Professional Forecasters survey are reported at the quarterly level, while our model is calibrated at a monthly horizon. Unfortunately, data on exchange rate expectations at higher frequencies are not available.

Figure 12: Distribution Exchange Rate Expectations



Notes: The figure shows the distribution of the same-quarter EUR/USD exchange rate expectations from the ECB Professional Forecasters survey. Data covers the period from 2002Q1 to 2020Q4 and is collected at a quarterly frequency Expectations are in log and demeaned at the quarterly frequency. Table 23 in Appendix A provides additional measures of the dispersion of exchange rate expectation across horizon and time periods.

the exchange rate changes, independently of the underlying shock. This confusion arises because investors are uncertain whether the fluctuations in the exchange rate are driven by noise shocks or fundamental shocks. Consistent with previous literature (Bacchetta and Van Wincoop, 2006), Figure 36 in Appendix D shows that, after a negative fundamental shock, investors' expectation do not fully react because part of the response of exchange rates is attributed to the noise component. As a result, the response of exchange rate to a fundamental shock is dampened. Similarly, the response to a positive noise shock is amplified because the upward movements in the exchange rate are mistakenly confused with a negative change in fundamentals. This rational confusion adds further upward pressure on the exchange rate.[77] This indicates that these two dimension of heterogeneity have similar

[77] As standard in this class of models, the model produces endogenous persistence due to the time it takes

qualitative implications for the dynamics of the exchange rate, albeit through different mechanisms. Strategic behavior reduces the sensitivity of investors' demand for foreign assets, while Information heterogeneity leads to rational confusion.

5.2 Quantitative Analysis

We leverage the model that incorporates the two dimensions of heterogeneity, and study whether investor heterogeneity matters for exchange rate puzzle and which dimension of heterogeneity is relatively more important.

We assume that the model embedding both strategic behavior and dispersed information represents the actual data, and decompose the contributions of both elements to the dynamics of the exchange rate. Using our calibrated model, we filter the underlying states and conduct three different counterfactual scenarios:[78] Given our calibration, we use the model to filter the underlying states and perform three different counterfactuals: i) a competitive, full-information rational expectation benchmark economy without strategic investors and dispersed information ($\lambda = \sigma_\eta = 0$); ii) an economy where investors have dispersed information but are not strategic ($\lambda = 0$ and $\sigma_\eta > 0$); iii) an economy where investors are strategic and have full-information ($\lambda > 0$ and $\sigma_\eta = 0$). We perform the decomposition for different initial level of strategic behavior ($\lambda \in \{0, 0.2, 0.4, 0.6, 0.8\}$), given the measurement noise in our proxy for strategic behavior. We focus on the exchange rate disconnect, which is measured by the RMSE of the disconnect regression in Equation (31), and the exchange rate excess volatility, which is measured by the volatility of the exchange rate.[79]

for rational confusion to be resolved. This means that average and higher-order expectations gradually converge to the rational expectation benchmark based on full information over time.

[78] See Appendix C for additional details on the filtering algorithm.

[79] To measure excess volatility, we directly examine the volatility of the exchange rate. This is without loss of generality because the denominator of the excess volatility ratio – the volatility of the fundamental – remains constant across all counterfactual scenarios.

Table 6 shows that investors' heterogeneity can have significant impact on exchange rate dynamics, and the relative importance of each dimension of heterogeneity greatly depends on the degree of strategic behavior in the market. Investors' heterogeneity increases exchange rate disconnect by 16% to 38% and volatility by 6% to 29%, playing a quantitatively significant role in shaping exchange rate dynamics, as highlighted in previous studies (Evans and Lyons, 2002; Bacchetta and Van Wincoop, 2006, 2010, 2019).[80]

By comparing the competitive rational expectation model to an economy with only one dimension of heterogeneity, we show that the specific contributions of each individual dimension to exchange rate dynamics depends on the degree of strategic behavior. As λ increases, the contribution of strategic behavior rises from 3% to 66% for disconnect and from 9% to 86% for excess volatility. It's worth noting that the marginal effect of λ on the additional disconnect is lower than on additional volatility, suggesting that dispersed information appears to be more relevant in explaining exchange rate disconnect, regardless of the size of strategic investors in the market. Meanwhile, heterogeneity in price impact has a relatively more pronounced effect on excess volatility dynamics. These results underscore the importance of considering both dimensions in the analysis of exchange rate markets.

The final column in Table 6 shows that the response of the exchange rate in a model that incorporates both dispersed information and strategic behavior is not simply the sum of the individual mechanisms. Instead, there is a non-linear interaction between the two. For each value of λ, this non-linear interaction, accounting for approximately 0.1% to 2.5% of the overall effect, demonstrates that the two mechanisms reinforce each other. The

[80] The economic relevance of the contribution of investors' heterogeneity extends beyond the changes in predictive power or in volatility, which may be relatively small in absolute terms. By influencing exchange rate dynamics, investors' heterogeneity has far-reaching implications fir carry trade return, invoicing choices, relative international prices, trade patterns, and other aggregate macro variables (Boz et al., 2020; Itskhoki and Mukhin, 2021; Lustig et al., 2019). Quantifying the macroeconomic effects resulting from investors' heterogeneity, alongside more granular documentation of this heterogeneity, offers promising venues for future work.

Table 6: Disconnect and Volatility Decomposition

Mass Strategic Investors (%)	Extra Disconnect (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
0.00	16.76	0.00	100.00	0.00
20.00	17.18	2.97	96.88	0.15
40.00	18.91	13.74	85.59	0.67
60.00	23.57	34.65	63.79	1.56
80.00	37.67	65.42	32.14	2.44

Mass Strategic Investors (%)	Extra Volatility (%)	% Share Strategic Behavior	% Share Dispersed Information	Non linearity
0.00	5.18	0.00	100.00	0.00
20.00	5.66	8.90	91.00	0.11
40.00	7.62	33.70	65.92	0.39
60.00	12.87	62.81	36.57	0.62
80.00	28.61	85.72	13.74	0.53

Notes: The table reports the contribution of strategic behavior and dispersed information to the exchange rate disconnect (top panel) and the excess volatility (bottom panel) for different value of λ (first column). Exchange rate disconnect is measured using the RMSE of a standard, one-period disconnect pooled regression, Equation (31). Excess volatility is measured using the standard deviation of the exchange rate. The second column reports the extra disconnect and volatility of the full model relative to a benchmark economy that abstract away from both dispersed information and strategic behavior ($\lambda = 0$ and $\sigma_\eta = 0$). The third and fourth columns report the share of the extra disconnect and volatility due to dispersed information and strategic behavior, respectively. The former (latter) is computed comparing RMSE/volatility in the benchmark economy to the RMSE/volatility from an economy without strategic behavior, $\lambda = 0$ and $\sigma_\eta > 0$ (without dispersed information, $\lambda > 0$ and $\sigma_\eta = 0$). The last column reports the discrepancy due to the non-linear interaction between dispersed information and strategic behavior. We exclude the Argentinian Peso from calculation. Appendix A provides additional information on the data. Appendix C provides additional information on the estimation and filtering procedure.

idea is that strategic behavior leads to greater price dispersion regardless of the quality of the signal, σ_η. This, in turn, reduces the weight that investors assign to their signals and amplifies the impact of noise shocks while dampening the impact of fundamental shocks.[81]

[81] In Figure 35 in Appendix D, we show the simulated price dispersion for different levels of strategic behavior and signal quality. Note that when the quality of the signal is sufficiently low (high σ_η), the volatility of the exchange rate may no longer increase. As the signal quality deteriorates, less importance is given to the fundamental component. This leads to a situation where the exchange rate becomes less informative, resulting in a reduction in the amplification of the noise component (Bacchetta and Van Wincoop, 2006).

6 Conclusion

The heterogeneity in price impact and concentration in the foreign exchange rate markets may play a key role in understanding exchange rate dynamics. In this paper, we explore the implication of strategic behavior within a simple monetary model of exchange rate determination. We show that strategic behavior reduces the informativeness of the exchange rate by amplifying the response to non-fundamental shocks while dampening the response to fundamental shocks. As a result, heterogeneity in price impact helps to explain the weak empirical link between fundamentals and exchange rates, as well as the excess volatility observed in exchange rate movements.

Although our model is stylized to derive fundamental insights and analytic results, we provide empirical evidence supporting the theoretical predictions using a panel of 10 currencies. Furthermore, we extend the theoretical framework by including a competing dimension of investors' heterogeneity, namely information dispersion. We demonstrate that strategic behavior has a quantitative impact on influencing exchange rate dynamics similar to information dispersion.

This paper represents a step forward in incorporating microstructure institutions in the analysis of exchange rate dynamics. Our framework is tractable and can be integrated into macro models of exchange rate determination. As shown in previous literature, the introduction of investor heterogeneity qualitatively and quantitatively alters conclusions regarding optimal monetary and exchange rate policies. It also calls for additional efforts in documenting and studying investors' heterogeneity in foreign exchange rate markets.

Chapter III

Firms' Investment and Central Bank Communication: The Role of Financial Heterogeneity

1 Introduction

Financial frictions and firm heterogeneity play an important role in understanding the investment channel of monetary policy. Their profound impact, particularly evident during the Global Financial Crisis, has prompted numerous studies examining how firms with varying financial characteristics respond to unexpected monetary policy interventions. Research has investigated how firms' investment sensitivity to monetary policy relates to various balance sheet characteristics. For example, heightened default risk has been shown to undermine the effectiveness of monetary policy (Ottonello and Winberry, 2018). Studies on liquidity suggest that firms with ample cash reserves are less vulnerable to unexpected monetary hikes (Jeenas, 2018b). Additionally, monetary policy hikes tend to impact younger and smaller firms more aggressively (Cloyne et al., 2018; Gertler and Gilchrist, 1994). This paper offers novel insights into this literature by showing that firms' investment responses to monetary policy depend on the information content of Federal Reserve policy shocks.

Monetary policy has undergone a significant evolution since the era of traditional Keynesian theory. In the classical Keynesian framework, central banks influence firms' capital investment through changes in interest rates and the money supply, the *pure monetary channel*. However, recent evidence highlights the growing role of beliefs and expectations in influencing firms' investment and aggregate demand, the *information channel* (Romer and Romer, 2000; Nakamura and Steinsson, 2018)[82]. This channel utilizes non-monetary communication tools such as public statements, speeches, and press conferences to influence firms' and investors' perceptions of the economic future. A notable example is ECB Governor Mario Draghi's 2012 commitment to do "*whatever it takes to preserve the euro*," which significantly enhanced market confidence and stabilized the European economy[83]. Given the increasing importance of both channels, understanding how financial heterogeneity influences the effectiveness of monetary communication policies is crucial for policymakers.

I show that the investment responses to monetary policy shocks among firms with varying financial positions differ depending on the specific channel. To begin, I separate Federal Reserve policy communication shocks into two components, following the identification strategy proposed by Jarociński and Karadi (2020). I leverage the fact that during the Federal Open Market Committee (FOMC) announcements, the Federal Reserve discloses information about current and future changes in policy rates, as well as non-monetary information about the economic outlook. Using high-frequency data on interest rate expectations and stock market prices, I decompose interest rate surprises into two components: those that negatively correlate with stock market prices and mainly affect the economy through an interest rate channel, the *pure monetary shocks*, and those that positively correlate with stock market prices and mainly affect investment through an information channel, the *Fed information shocks*. With this separation, I then explore how firms with varying financial characteristics respond to these two types of monetary policy shocks using firm-level data from Compustat.

[82] The size of these additional shocks is not negligible in the data. Jarociński and Karadi (2020) shows that the Fed information components explains about 30% of the effects of monetary policy innovations in the U.S. and up to 45% in Europe.

[83] Draghi's statement proved powerful enough to shield Europe from a potential economic collapse, illustrating the profound impact of central bank communication on market perceptions and economic stability.

I show that firms with a high level of debt are, on average, more responsive to pure monetary shocks but less sensitive to Fed information shocks. I use Jordà (2005)'s Local Projection with Instrumental Variable approach to estimate the dynamic heterogeneous response of capital accumulation to the two types of monetary shocks across firms, differentiated by their past leverage. I use the average Tobin's Q as the instrumental variable to normalize the size of the shocks relative to the endogenous variable[84]. I show that, in response to a pure monetary policy shock that increases the average Tobin's Q by 1 percent, a firm with 10 percentage points more leverage prior to the shock accumulates approximately 0.20% more capital stock after 2 years. Conversely, following a Fed information shock that similarly raises the average Q by 1 percent in a quarter, a firm with 10 percentage points more leverage before the shock accumulates about 0.25% less capital eight quarters after the shock. These results are primarily driven by the heterogeneous sensitivity of firms at the extreme end of the leverage distribution. Additionally, relating to the previous literature, the findings are robust across different identification strategies, measures of financial positions, and time periods.

Motivated by such evidence, I investigate the aggregate implications of those findings. To this end, I develop a New-Keynesian dynamic general equilibrium heterogeneous firm model with idiosyncratic productivity and financial frictions to quantify the aggregate implication for monetary policy. The model features a well-defined distribution of investment firms that are heterogeneous by idiosyncratic productivity. These firms produce a homogeneous wholesale good using a decreasing returns to scale technology, hire labor in a competitive labor market at the equilibrium wage and invest in new capital facing adjustment costs. Firms finance investment with internal and external funding, corporate bonds, and equity. Corporate bonds are issued at discount and priced by financial intermediaries. I introduce

[84] This approach ensures that both types of shocks have an expansionary effect on the average firm's investment response.

financial frictions by assuming the presence of quadratic equity issuance costs (Altınkılıç and Hansen, 2000). The monetary authority determines the nominal interest rate following a Taylor rule, and engages in non-monetary communication which affects investors sentiment within the financial markets.

The model helps to rationalize the empirical findings in the paper. A pure monetary shock increases the nominal interest rate and reduces the marginal benefit of capital through the stochastic discount factor. Because the return on future investment falls, firms find it optimal to reduce their capital stock over time. Firms with high levels of leverage are the most adversely affected by a pure monetary shock, as it increases their reliance on more expensive external financing sources. Consequently, highly leveraged firms are induced to invest relatively less as a result of an increase in their marginal cost of capital. Instead, a Fed information shock affects investment through the financial market by increasing the price of corporate bonds due to positive market sentiment. This leads to higher investment by firms, on average, as the improved future economic outlook enhances the marginal returns on capital. However, firms with high leverage are less responsive to these shocks as they have already reached their borrowing limits and have limited capacity to further increase investment.

Finally, I use the model to revisit the state dependent effects of monetary policy depending on a market response to a Fed communication. Previous literature focuses on studying the effect of monetary policy in a recession compared to normal times. In the model, a market pessimistic reaction to a Fed announcement increases the cost of debt making external financing more expensive. This in turn, reduces the effectiveness of conventional monetary policy interventions in a period of recession. Because of real and financial frictions, monetary policy interventions are state-dependent in the model. A TFP-induced recession produces two effects on the economy that may affect the potency of monetary policy. First, it increases the share of financially constrained firms that are more sensitive to Taylor rule shocks. Second, it increases the relative cost of capital financing due to the presence of fixed adjustment costs on investment, discouraging firms from investing in response to a positive shock. Using my calibrated model, I find that an expansionary Taylor rule shock without a negative market reaction is 12% more effective than in normal times. A negative market reaction to the same shock dampens the effectiveness of monetary policy by more than 20 percent compared to the case where there is no market response.

Literature. This paper contributes to several strands of the literature. First, it contributes to the literature that studies how the effect of monetary policy varies across firms with different balance sheet characteristics. This literature has investigated the excess sensitivity to a monetary policy innovation by looking at different metrics of the firms' performance and proxies for financial frictions. An earlier paper by Gertler and Gilchrist (1994) finds evidence that small firms are more sensitive than large firms to an interest rate tightening with respect to sales and inventories. Bahaj et al. (2019) study the role of financial frictions in the transmission of monetary policy to employment and found that younger, more-levered firms are most sensitive. Closer to my paper, two recent papers, Ottonello and Winberry (2018) and Jeenas (2018a), study the role of leverage in the transmission of monetary policy with respect to investment using Compustat data with contrasting results. Ottonello and Winberry (2018) find that firms with low default risk or low leverage accumulate relatively more capital after an interest rate cut. Jeenas (2018a) instead, find the opposite. High leverage firms display excess sensitivity to monetary policy interventions, but the result disappears once one controls for cash holdings. In light of this debate Cloyne et al. (2018) suggest measuring financial frictions by looking at dividend policy over the firm's life cycle and find that younger corporations paying no dividends are more responsive to monetary policy with respect to investment and borrowing decisions.[85] My paper contributes to this literature by showing that the role of financial frictions for monetary policy depends on the channel.[86]

Second, it contributes to the growing literature that studies the effect of the effect of Fed information on the economy. The idea that Fed announcements can convey information about the future path of output and inflation beyond current and future monetary policy stance was put forth by Romer and Romer (2000) and formally developed in a model by Ellingsen and Söderström (2001). Campbell et al. (2012), Nakamura and Steinsson (2018), Jarociński and Karadi (2020) and Andrade and Ferroni (2021) shows that the presence of information effects can contaminate traditional estimates of monetary policy shocks that rely oh high-frequency identification and, it can change our conclusions of the effectiveness of monetary policy interventions.[87] My contribution to this literature is twofold. First, I show that pure monetary policy surprises have a significant effects on firm-level decisions and that, financial frictions, proxy by leverage amplifies the investment response. Second, I show that Fed information shocks affecting investors' beliefs are non-fundamental, and are consistent with the idea that central bank non-monetary information affects the level of sentiment in the economy.

Finally, it contributes to the theoretical literature that studies the role of credit market frictions in amplifying monetary policy disturbances. In a seminal paper, Bernanke et al.

[85] I discuss the differences between the results of those papers in the empirical analysis.

[86] Other papers in this literature study more generally the implication of heterogeneity in firm or industry behavior in response to monetary policy shocks Gaiotti and Generale (2002), Ehrmann and Fratzscher (2004), Peersman and Smets (2005).

[87] Jarociński and Karadi (2020), Andrade and Ferroni (2021) and Miranda-Agrippino and Ricco (2018) use market-based measures of interest rate expectations and economic fundamentals, combined with a sign-restriction approach to separate interest rate surprises. Other papers have proposed different identification strategies. Doh et al. (2020), Handlan (2020) and Acosta (2021) use machine-learning and text-based techniques applied to the Fed's alternative policy statements to identify interest rate surprises due to Fed information. Cai et al. (2021) and Lakdawala (2019) remove information effects from the Fed statement by controlling for the difference between the Fed's and the public's information.

(1999) embed the financial accelerator in a representative firm New Keynesian model with financial frictions and show that pro-cyclical firms' net worth amplifies monetary policy interventions. Ottonello and Winberry (2018) confirm the exact mechanism in a model with firms' heterogeneity and default risk. I contribute to this literature quantifying the distributional effects of monetary policy intervention allowing for the presence of a Fed information shock in an addition to a standard Taylor rule shock.

2 Empirical analysis

In this section, I show that the role of financial frictions on monetary policy transmission depends on the channel through which investment is affected by monetary policy. I begin by disentangling monetary policy innovations into two structural shocks, namely pure monetary shocks and Fed information shocks. Then, I discuss the dataset and measurement of financial frictions and investment in the data. Finally, I show that firms with high levels of financial frictions respond differently to monetary policy intervention, accumulating relatively more or less capital depending on the underlined shock.

2.1 Disentangling monetary policy shocks

I decompose monetary policy innovations into two structural shocks using the methodology proposed by Jarociński and Karadi (2020). I use high-frequency data and a set of sign restrictions on stock prices and interest rate expectations to disentangle market-based variations around Federal Open Market Committee (FOMC) announcements into two sets of shocks.[88] I leverage the fact that during the FOMC announcements, the Fed revels both information about the actual and future policy actions (i.e., monetary policy

[88] Assuming that investors do not learn any additional information during this window, variations in financial market variables that arise around the FOMC policy announcements within a short time frame provide an exogenous proxy for the effect of monetary policy.

communication), as well as additional information about the state of the economy (i.e., non-monetary policy communication), Romer and Romer (2000), Nakamura and Steinsson (2018) and Campbell et al. (2012). Since financial market variables respond to both pure monetary policy communication and non-monetary policy communication, market-based variations surrounding FOMC statement provide a valid set of events to distinguish between the variations caused by the former and the variations caused by the latter.[89]

The empirical separation comes from identifying a shock that increases both stock market prices p_t and interest rate expectations Δi_t^e simultaneously, versus a shock that decreases p_t while increasing Δi_t^e in a 15-minutes window around an FOMC statement.[90] The first is a monetary policy shock that affects the economy through the interest rate, the *pure monetary shock* ε_t^{mps}; the second is a monetary policy shock that affects the economy by changing the investors' beliefs about the future economic outlook, the *Fed information shock* $\varepsilon_t^{\text{info}}$.[91]

$$\begin{pmatrix} \Delta i_t^e \\ \Delta p_t \end{pmatrix} = \begin{pmatrix} + & + \\ - & + \end{pmatrix} \times \begin{pmatrix} \varepsilon_t^{\text{mps}} \\ \varepsilon_t^{\text{info}} \end{pmatrix}$$

Sign restrictions are justified by economic theory. When the Fed announces a tightening of monetary policy, investors expect future policy rates to increase. This leads to a drop in stock market prices, as expected earnings decrease and the discount factor at which dividends are capitalized declines. Therefore, pure monetary communication typically results in a negative response of stock market prices and interest rate expectations. However, if stock prices increase in response to a positive interest rate surprise during the FOMC

[89] Standard high-frequency identification approach is used in Ottonello and Winberry (2018), Jeenas (2018a), Cloyne et al. (2018) among others to identify monetary policy shocks.

[90] I measure interest rate expectations as the 3-month federal funds rate future as standard in the literature. If agents are risk-neutral, federal funds rate futures perfectly reflect the conditional expectations about future interest rates.

[91] Other approaches used in the literature to identify the two shocks and that are based on similar identifying assumptions are Miranda-Agrippino and Ricco (2018), and Acosta (2021).

window, it indicates the presence of another component - non-monetary information - that is responsible for the positive correlation between stock prices and federal funds rate futures.

In my baseline specification, I employ a Bayesian structural VAR model with aggregate macroeconomic variables and monthly high-frequency financial variables to separate the two structural shocks.[92] Figure 38 in Appendix E illustrates the two series of monetary policy shocks identified using a sign restriction and a BVAR model.

2.2 Data and measurement

For the empirical analysis, I use firm-level data from the quarterly Compustat database which provides a reliable source of information on firms' financial statements and has been extensively used in previous research to study the effects of monetary policy on capital investment decisions.[93] I combine firm-level data with the pure and the Fed information shocks identified in the previous section and other aggregate variables. I sum the shocks at a quarterly level as in Cloyne et al. (2018). This results in a panel of 10,259 firms with quarterly financial information, spanning from 1990-Q1 to 2018-Q4.[94]

I study the heterogeneous response to monetary policy of capital stock accumulation instead of capital expenditure. Following the methodology of Ottonello and Winberry (2018), I use the perpetual inventory method to calculate the capital stock $k_{i,t}$ for each firm i at the end of the quarter t. Analyzing the dynamics of firms' capital stocks rather than investment expenditure is preferred due to measurement error issues, which make it difficult to precisely detect systematic responses in investment rates in the cross-section at

[92] I use the co-movement between the high-frequency variations in the 3-month federal funds rate future and stock market prices in a 15-minutes window surrounding scheduled FOMC announcements summed up at monthly level.

[93] Around 50% of aggregate business investment in the US is accounted for by firm-level investment data from Compustat.

[94] Ottonello and Winberry (2018) aggregate the shocks at the quarterly level by taking a weighted average of the shocks calculated at the monthly level, and they find similar results.

the quarterly level Doms and Dunne (1998).

I use leverage $\text{lev}_{i,t}$ to proxy the level of financial frictions of a firm in a given quarter. I construct the variable leverage as the ratio between total debt and shareholders' equity. I choose this variable to measure the level of firms' financial frictions in the data because of two reasons. First, in a standard theoretical model with financial frictions, leverage can be interpreted as an inverse measure of firms' net worth.[95] Second, firms' leverage is 60% correlated with measures of default risk, and leads to similar conclusions when studying the dynamic heterogeneous response to monetary policy shocks, Ottonello and Winberry (2018).

To test the robustness of my results, I consider alternative measures of financial frictions such as cash liquidity, size, age, distance to default and credit ratings. Appendix E provides further details on the construction of the variables and the cleaning.

2.3 Heterogeneity of investment response

I estimate the dynamic heterogeneous response of investment to the two identified shocks separately using Jordà (2005)'s Local Projection with Instrumental Variable (LP-IV) as in Cloyne et al. (2018).[96] I prefer to use LP-IV instead of standard local projection for two reasons. First, it imposes a unit effect of normalization of the shocks in terms of a 1 unit change in the endogenous variable as explained in Stock and Watson (2018). Second, it is more efficient than the standard LP-OLS regression as it does not soffer of the generated regressor problem, Pagan (1984).

I use the one-quarter percentage change in the aggregate Tobin's Q, Δq_t, as the

[95] In a firm investment model with firm heterogeneity and financial frictions due to default risk or external equity financing, conditional to firms' size, higher level of debt predicts an higher marginal cost of capital.

[96] Others papers, Ottonello and Winberry (2018), Ferrando et al. (2020), Jeenas (2018a) directly estimate the effect of the interact between the exogenous series of the shocks with the firm-level variable leverage on capital accumulation in a 1-stage regression. I checked that the results do not change qualitatively.

endogenous policy variable which is the log-difference of the average Q calculated across firms for each quarter. By choosing Δq_t as the endogenous variable, I normalize the two shocks to have an expansionary effect on capital investment, irrespective of their sign. This allows me to compare the results of the heterogeneous regression across multiple shocks, without estimating the average response of firms' capital investment.[97]

In the baseline specification, I regress the capital change h-period ahead $\Delta_h \log(k_{i,t+h}) = \log(k_{i,t+h}) - \log(k_{i,t-1})$ on the interaction between the average change in Q, Δq_t, and the variable leverage (in log), $\text{lev}_{i,t-4}$, lagged by four quarters:

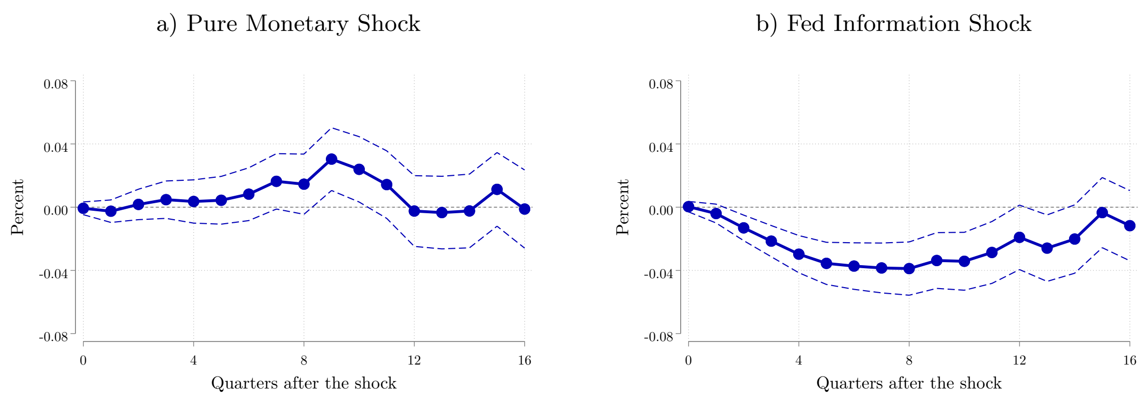
$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t\times j,h} + (\beta_h^s \Delta q_t + \delta_h)\,\text{lev}_{i,t-4} + \Gamma_h' W_{i,t-1} + u_{i,t+h} \tag{37}$$

where h indexes the forecast horizon. I instrument the endogenous variable $\Delta q_t \cdot \text{lev}_{i,t-4}$ with the interaction between $\text{lev}_{i,t-4}$ and the exogenous disturbances ε_t^{mps} and $\varepsilon_t^{\text{info}}$ separately. I include firm fixed effects α_i to capture time-invariant differences in investment behavior across firms, sector-by-quarter fixed effects at the SIC-1 digit level $\alpha_{j\times t}$ to control for differences in how sectors respond to aggregate fluctuations, and firm size as a control variable, measured as the logarithm of past total assets. Finally, I include an interaction between firm size and the two shocks to capture heterogeneity in investment responsiveness due to differences in collateralizable assets.

The coefficients $\beta_h^s = \{\beta_h^{\text{mps}}, \beta_h^{\text{info}}\}$ measure how the cumulative response of investment h periods ahead to a pure monetary and a Fed information shock at time t depends on the firms' financial positions lev_{t-4} in quarter $t-4$. In particular, β_h^s is an estimate of the cumulative differential response of investment h periods ahead between two firms with a 1%

[97] Cloyne et al. (2018) uses the change in 1-year Treasury rate as endogenous policy variable following Gertler and Karadi (2015). However, since a pure monetary shock and a Fed information shock have opposite effects on investment given an increase in interest rates, using the interest rate as the endogenous variable complicates the interpretation of the results.

Figure 13: Heterogeneous response of investment



Notes: The figure illustrates the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in past leverage. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation 37 using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructued following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

difference in past leverage.[98] Hence, a positive value of β_h^s implies that high-leverage firms invest relatively more in response to an exogenous policy shock than low-leverage firms, suggesting that financial frictions may be amplify the effects of monetary policy. Conversely, if β_h^s is negative, it suggests that high-leverage firms invest relatively less than low-leverage firms in response to a policy shock, indicating that financial frictions dampen the response of investment to a policy intervention.

Results. Figure (13) shows that sensitivity to monetary policy and hence, the role of financial frictions depends on the channel of transmission of monetary policy. In response to a pure monetary policy shock that increases the average Q by 1 pp, a firm with 10 pp more leverage before the shock accumulate around 0.03% more capital stock after 2 years.

[98] Due to the linearity assumption in the interaction term, the heterogeneous effect of the shocks is independent of the level of past leverage.

Conversely, in response to a Fed information shock that equally increases the average Q by 1 pp in a quarter, a firm with 10 pp more leverage before the shock accumulates around 0.03% less capital around 8 quarters after the shock occurred. Hence, financial frictions amplify the effects of pure monetary shocks on investment while dampening the effects of Fed information shocks.

Figure 40 in Appendix F shows that the heterogeneous sensitivity to the two shocks is primarily influenced by firms located at the tail end of the leverage distribution. I split firm-level observations into three leverage percentile bins: low, medium, and high. A firm is classified as low leverage if it falls within the 40th percentile of past year leverage, medium if it falls between the 40th and 80th percentile, and high if it is above the 80th percentile. I estimate the heterogeneous firm-level response to the two shocks relative to that of a low leverage firm. In response to a pure monetary shock, high leverage firms exhibit a significantly stronger sensitivity compared to medium leverage firms, accumulating 1.2 pp more capital than low leverage firms after 8 quarters from the shock, while medium leverage firms accumulate 0.9 pp more capital than low leverage firms. The opposite happens in response to a Fed information shock. Relative to low leverage firms, medium leverage firms do not display a statistically significant difference in their capital response. However, high leverage firms exhibit a significant decrease of around 1.6 pp in their capital relative to low leverage firms.[99]

Finally, Figure 41 in Appendix F quantifies the heterogeneous sensitivity of the non-linearity effects over the leverage distribution. I construct the average dynamic response of investment for each leverage group by combining the average response of capital for low-leverage firms with the differential response for medium and high-leverage firms. I then

[99] These results are consistent with previous literature highlighting that firms within the first 40th percentile of the distribution and between the 40th and 80th percentile do not display significantly different riskiness profiles and balance sheet characteristics and thus, they respond similarly to aggregate shocks.

compare the average responses across the different groups. In the case of a pure monetary shock, a firm in the top 20% of the leverage distribution exhibits a 50% higher sensitivity compared to a firm in the bottom 40%. However, the same firm is 60% less sensitive than a firm in the bottom 40% when it comes to another factor.

Robustness. I undertake a series of robustness checks to ensure the consistency and robustness of the results shown in Figure 13. Specifically, I show that my results are robust to different time periods, alternative shock identification approaches, and various model specifications. I defer the discussion of my results regarding different measures of financial frictions in relation to the prior literature to the subsequent section.

Figure 42 and 43 in Appendix F provide evidence of the robustness of the results to different time periods. To ensure the consistency of the findings, I re-estimate the main specification presented in Equation 37 using two distinct time periods. Firstly, I focus on the period from 1990 to 2008, excluding the period characterized by the zero lower bound and the financial crisis (Ottonello and Winberry, 2018). Secondly, I consider the interval from 1994 to 2018, excluding the period when the Federal Reserve did not provide additional information during the FOMC meetings, apart from changes in the policy rule.[100] Importantly, the results obtained from both alternative time periods are qualitatively and quantitatively consistent with the estimates presented in Figure 13.

Figure 44 in Appendix F presents the robustness of the results to different model specifications. Specifically, I estimate the heterogeneous response of capital to the monetary policy shocks without incorporating additional time or sector-time fixed effects (Cloyne et al., 2018). This enables an interpretation of the estimated coefficients that accounts for

[100] This exclusion is important for valid identification since the release of additional information around the FOMC announcement relies on the presence of other informational sources, such as the FOMC statement. As from 1990 to 1994 the Fed did not provide any communication during the FOMC meeting, it may impact the identification from high-frequency variables.

potential general equilibrium effects. Notably, the results remain consistent and unaffected by this alternative specification, further bolstering the robustness of the findings.

Finally, Figure 45 in Appendix F shows the robustness of the results to different shock identification procedures. Specifically, I differentiate between two types of monetary policy shocks by examining the co-movement between 3-month federal funds rate futures and stock market prices. I categorize shocks based on whether a positive interest rate surprise during the 30-minute FOMC window is accompanied by a decrease or increase in stock prices. A positive interest rate surprise accompanied by a decline in stock prices is classified as a pure monetary shock, whereas a positive surprise accompanied by an increase in stock prices is considered a Fed information shock.[101] I find that by using these series of shocks, the results align qualitatively with the ones in Figure 13.

2.4 Relating to prior literature

My study complements the existing literature by highlighting the importance of differentiating between channels when examining the role of financial frictions in investment and monetary transmission. Previous studies, such as Ottonello and Winberry (2018), Cloyne et al. (2018) and Jeenas (2018a) among others, have explored the heterogeneous effects of monetary policy on investment but without explicitly separating the two channels. These studies have discussed the role of firms' financial frictions in the transmission of pure monetary shocks, employing various proxies for financial frictions and different model specifications.

Figure 50, and 51 in the Appendix G connect my results to the findings of Ottonello and Winberry (2018). Ottonello and Winberry (2018) find that firms with higher default risk or leverage, compared to their long-term average, are less responsiveness to monetary

[101] This is what Jarociński and Karadi (2020) labels as the "Poorman" identification strategy.

policy surprises, which they use as a proxy for pure monetary shocks. They argue that when financial variables, such as leverage or other proxies for financial frictions, are demeaned at the firm level, it can alter the predictions regarding heterogeneous sensitivity.[102] Figure 50 in the Appendix G shows that firms with a higher proximity to default are relatively more sensitive to exogenous pure monetary shocks, while displaying lower sensitivity to Fed information shocks, consistent with my findings. Figure 51 show that once, we split monetary policy surprises in two channels, the heterogeneous response to monetary policy are robust to demeaning leverage at the firm level.[103]

Figure 46, and 47 in Appendix G show that my results are also closely tightened to Jeenas (2018a). His findings are twofold. First, cash holdings are a more effective proxy for financial frictions compared to leverage. They show that after controlling for cash liquidity, the significance of past leverage diminishes in explaining the differential sensitivity to monetary policy shocks.[104] This suggests that cash liquidity serves as a comprehensive measure of financial frictions. Second, he shows that firms that have more cash display less responsiveness to monetary policy surprises. Figure 46 in Appendix G shows that once we split the channels of monetary policy, firms with lower cash liquidity are relatively less sensitive to exogenous pure monetary shocks, while they are relatively more sensitive to Fed information shocks, in line with the results of Jeenas (2018a) and the findings in Figure 37. Figure 47 shows that my results survive when controlling for an interaction between the shocks and cash liquidity.

Figure 48 in Appendix G connects to findings of Gertler and Gilchrist (1994). In their

[102] The argument is that demeaning the right-hand side of the specification in equation (37) would allow controlling for permanent differences across firms that would otherwise be left in the error term and potentially bias the results.

[103] After demeaning leverage at the firm level, the heterogeneous response to Fed information shock is attenuated, indicating that the long-term component of leverage plays a crucial role in driving the observed heterogeneity.

[104] In this sense, cash liquidity is a sufficient statistic to measure the level of financial frictions.

seminal paper, Gertler and Gilchrist (1994) and more recently Crouzet and Mehrotra (2020) investigate the heterogeneous response of investment to monetary policy shocks based on past sales growth. They find that small firms tend to be more sensitive to monetary policy shocks due to higher levels of financial frictions. To examine this further, I construct the size variable following the methodology of Gertler and Gilchrist (1994) using Compustat data. I then estimate the heterogeneous response of investment between small and large firms to the two shocks as in equation 37. Figure 48 in Appendix G shows that small firms are more responsive to pure monetary policy shocks and less sensitive to Fed information shocks.

Finally, Figure 52 in Appendix G connects with the findings of Whited (1992). Whited (1992) suggests using credit ratings as a measure of the level of financial frictions faced by firms. Credit ratings capture the likelihood of default more accurately than leverage and exhibit less volatility over time. In Figure 52, I present robust results by dividing the sample of firms into three groups based on their Standard & Poor's credit rating from Compustat. Firms with lower credit ratings, on average, display higher sensitivity to pure monetary shocks and lower sensitivity to Fed information shocks. This supports the hypothesis that credit ratings can serve as a reliable indicator of the impact of financial frictions on firms' response to different monetary policy channels.

3 Equity market misvaluation and Fed information

In this section, I show that the primary transmission channel of Fed information to firms' capital investment is primary non-fundamental. Previous studies have established that non-monetary communication from central banks influences real investment by shaping investors' beliefs about the state of the economy. However, there is limited research exploring whether this influence is related or unrelated to future fundamentals.[105]

The fundamental narrative is consistent with the idea that non-monetary communication from the central bank plays a vital role in providing new information about the fundamental state of the economy. This information is assimilated by market participants and the general public, who incorporate it into their existing beliefs and adjust their expectations accordingly. For example, if the central bank communicates positive information about aggregate productivity or labor market conditions, it can shape expectations and influence economic behavior, Romer and Romer (2000), Nakamura and Steinsson (2018). This can have implications for firms' capital investment decisions, as they may adjust their expenditures based on their revised outlook for future economic conditions.[106]

Instead, the non-fundamental narrative is in line with the idea that non-monetary communication from the central bank influences investor sentiment and the level of optmism in the economy. Investors do not learn any new information about the fundamental state of the economy from the FOMC announcements.[107] According to this perspective, when the central bank communicates a positive outlook for the future, it can foster increased optimism in the financial markets and improve the financial conditions of firms. Consequently, firms may respond by expanding their investment expenditures due to the improved borrowing capacity facilitated by positive investor sentiment.[108]

Q-Test for Fed information. I propose a test based on the marginal value of capital (or Tobin's Q) to differentiate between the fundamental and non-fundamental narratives of

[105] The distinction between the fundamental and non-fundamental narratives is crucial for understanding the factors driving fluctuations in firms' capital investment in response to Fed information.

[106] The fundamental narrative emphasizes the role of non-monetary communication as a source of fundamental news that impacts economic expectations and behavior.

[107] This is line with the macroeconomic of narratives of Flynn and Sastry (2022).

[108] The non-fundamental narrative highlights the significance of non-monetary communication in shaping investor sentiment and influencing firms' investment decisions through the enhancement of their financial environment (Alimov and Mikkelson (2012), Arif and Lee (2014), Li et al. (2022)).

Fed information. The Tobin's Q serves as a comprehensive measure of a firm's investment profitability, and it depends on the ability of a firm to generate dividends for its shareholders, as well as by aggregate and firms' idiosyncratic financial conditions. Thus, by analyzing how the Tobin's Q responds to a Fed information shock $\varepsilon_t^{\text{info}}$, I can gain valuable insights into the underlying transmission mechanism.[109]

I test the hypothesis that variations in investor sentiment in the financial markets account for the majority of the effects of Fed information on firms' investment profitability. To show this, I study the relationship between the Fed information shock $\varepsilon_t^{\text{info}}$ and the firms' Q conditional to common measures of aggregate market sentiment. If the Fed information shock $\varepsilon_t^{\text{info}}$ influences investors' beliefs and is related to future fundamentals, conditioning the analysis on investor sentiment would result in the $\text{cov}\left(\varepsilon_t^{\text{info}}, Q_{j,t}\right)$ that is closer to the unconditional one. If $\varepsilon_t^{\text{info}}$ affects investors' beliefs while being unrelated to future fundamentals, conditioning to investor sentiment would lead the $\text{cov}\left(\varepsilon_t^{\text{info}}, Q_{j,t}\right)$ to be closer to zero.

To implement the test, I regress the one-period change in the firm-level Q on the Fed information shock $\varepsilon_t^{\text{info}}$, controlling for common measures of market sentiment in the financial market, λ_t:

$$\Delta \log Q_{i,t} = \alpha_i + \beta_0 \varepsilon_t^{\text{info}} + \beta_1 \lambda_t + \Gamma Z_{i,t-1} + u_{i,t} \tag{38}$$

where α_i controls for firm-fixed effects, $Z_{i,t-1}$ controls for firms' size and firms' time trend. I use the change in the Volatility Index (VIX) as my baseline measure of investor sentiment.

Table (7) provides evidence supporting the non-fundamental narrative of Fed information.

[109] Regardless of the narrative, the Fed information shock $\varepsilon_t^{\text{info}}$ is expected to be positively related with the firm' marginal value $Q_{i,t}$. In the case of news, the positive correlation between $\varepsilon_t^{\text{info}}$ and $Q_{i,t}$ arises primarily due to higher expected future dividends, whereas in the case of the non-fundamental, this correlation is primarily due to an improvement in investor sentiment.

Table 7: Results of the Q-test for Fed information

	Baseline	Controlling for VIX
	(1)	(2)
Fed Information Shock	1.413***	0.258
	(0.483)	(0.331)
Pure Monetary Shock	-1.344***	-0.963**
	(0.480)	(0.382)
Fixed Effects	Firm	Firm
Controls	Size, Trend	Size, Trend
Period	1990-2018	1990-2018
Observations	344115	341385

Notes: The table reports panel OLS estimates of the coefficients of a regression of the change in the Tobin's Q on the monetary policy shocks. Average Tobin's Q is the ratio of total assets, the market value of equity from CRSP, minus the book value of equity and deferred taxes to total assets. Pure and Fed information shocks are identified using Jarociński and Karadi (2020) approach. Variations in investor sentiment are proxy by the change in volatility index (VIX). The dataset runs from 1990-Q1 to 2018-Q4. Standard errors, clustered two-way at the firm and quarter level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

Column (1) shows that Fed information shocks positively predict an increase in the firms' marginal value when not controlling for aggregate measure of sentiment.[110] Column (2) shows that, after accounting for market sentiment, the Fed information shock ($\varepsilon_t^{\text{info}}$) does not show any significant effect in on firm investment profitability. The effect of $\varepsilon_t^{\text{info}}$ on $Q_{i,t}$ becomes statistically insignificant, confirming the hypothesis that Fed information influencing investors' beliefs is non-fundamental.

Table 26 and 27 in Appendix H provide additional robustness checks to validate the results. Table 26 shows that the results are robust to alternative measures of market sentiment: the excess bond premium (EBP) from Gilchrist and Zakrajšek (2012), which captures the risk premium in the bond market; the 1-year horizon macro uncertainty index proposed by Jurado et al. (2015); and the global risk aversion index from Bekaert et al.

[110] In contrast, tightening pure monetary shocks negatively affect firms' profitability, in line with the standard monetary policy theory.

(2022), used as a proxy for the price of risk on households. Table 27 shows that the results remain consistent even after including additional controls in the regression specified in Equation 38.[111]

Finally, Appendix H provides additional evidences in favor of the non-fundamental hypothesis of Fed information.

4 Model

In order to interpret these empirical results and quantify the aggregate implication for monetary policy, I develop a general equilibrium New-Keynesian model with heterogeneous firms, idiosyncratic productivity, and real and financial frictions. The presence of idiosyncratic productivity allows me to study the distributional effects of firms' characteristics more precisely by capturing the rich heterogeneity we observe in the firm-level data. Because those effects tend to be highly non-linear, standard macroeconomic models that do not incorporate this heterogeneity would fail to capture the distributional effects of leverage.[112]

The theoretical part of this paper is organized into three sections. In section 3, I describe the main elements of the model and the estimation of the parameters. The key actors in the model are a set of firms that make investments and are heterogeneous because of idiosyncratic productivity. They finance investment with internal and external source of funds, corporate bond, and equity issuance (Gomes, 2001).[113] Real frictions arise from adjustment costs in capital accumulation, while financial frictions are introduced through

[111] These additional controls account for the fact that the average Q is used as a proxy for the marginal value of capital. Typical controls utilized in the literature include leverage, cash liquidity (to capture the presence of financial frictions), past sales growth, and the sales-to-capital ratio.

[112] However, modeling firms' heterogeneity increases computational complexity. That entails the disadvantage of modeling Fed information shocks in a reduced form to keep the model computationally tractable.

[113] This is different from Ottonello and Winberry (2018), who assume that firms can endogenously default in equilibrium and exit from the market.

an equity financing premium and leverage-dependent interest rates on bonds. Both types of frictions are important for matching the data.

Section 4 of the paper comprises the calibration of the model and the validation of its predictions on the data. Given the parametrization of the model, I show that on simulated data, the average and heterogeneous dynamic response of investment to the represented policy shocks in the model are consistent with the empirical findings and provide an intuition of the mechanism. Finally in section 5, I present the aggregate implications of the heterogeneity for monetary policy. I show that the aggregate effects of monetary policy may depend on the distribution of leverage, which varies over the business cycle, and the effect that Fed communication has on market sentiment.

4.1 Heterogeneous firms

Time is discrete and the horizon is infinite. In each period there is a unit mass of firms indexed by j with a well-defined distribution $\Gamma_t = \Gamma(\varepsilon_{j,t}, K_{j,t}, B_{j,t})$ over idiosyncratic productivity $\varepsilon_{j,t}$, capital $K_{j,t}$ and debt $B_{j,t}$. Firms are owned by a representative household. Firms produce an homogeneous wholesale good $Y_{j,t}$ in the economy which is purchased by retailers at the equilibrium price p_t^w. After producing, paying taxes and investing in new capital, firms decide either to distribute dividends to the household or to issue equity paying a premium.

Production and investment. Firms produce an homogeneous wholesale good $Y_{j,t}$ using capital $K_{j,t}$ and labor $N_{j,t}$ with a decreasing return to scale technology: $Y_{j,t} = \varepsilon_{j,t} K_{j,t}^{\alpha} N_{j,t}^{\nu}$ where $\alpha + \nu \leq 1$ is the degree of return to scale. The decreasing return to scale assumption guarantees the existence of an optimal firm size. Firms' technology is subject to a firm specific shock $\varepsilon_{j,t} \in \mathcal{E} \equiv \{\varepsilon_1, \varepsilon_2, ..., \varepsilon_N\}$ which follows a discrete time first-order stationary Markov chain with $P(\varepsilon_{j,t+1} = \varepsilon_s | \varepsilon_{j,t} = \varepsilon_i) \equiv \pi_{is} \geq 0,$ and $\sum_s^N \pi_{is} = 1, \forall i.$

Each period, firms hire labor in a competitive labor market at the equilibrium wage w_t, invest in new capital $K_{j,t+1}$ and issue one period debt $B_{j,t+1}$. Because firms do not face any frictions in adjusting labor, the optimal labor policy $N^*_{j,t}$ solves the static problem:

$$N^*_{j,t} = \underset{N_{j,t} \geq 0}{\arg\max} \left\{ p^w_t \varepsilon_{j,t} K^{\alpha}_{j,t} N^{\nu}_{j,t} - w_t N_{j,t} \right\} = \left(\frac{\nu p^w_t \varepsilon_{j,t}}{w_t} \right)^{\frac{1}{1-\nu}} K^{\frac{\alpha}{1-\nu}}_{j,t}$$

After hiring labor and producing, firms decide the investment policy in physical capital, given that the existing capital stock depreciates at the rate δ. In equilibrium, capital accumulation follows the standard law motion for capital $K_{j,t+1} = (1-\delta)K_{j,t} + I_{j,t}$, where $I_{j,t}$ is the amount of new investment in capital stock. I assume that the price of investment is fixed and it is normalized to 1. To generate a more realistic firm size distribution I assume that firms face adjustment costs whenever they invest or divest in new capital:

$$\mathcal{G}(K_{j,t+1}, K_{j,t}) = c_0 \left(\frac{K_{j,t+1} - (1-\delta)K_{j,t}}{K_{j,t}} \right)^2 K_{j,t} + c_1 Y_{j,t} \mathbb{1}_{I_{j,t} \neq 0}, \tag{39}$$

where $\mathbb{1}_{\mathrm{I}_{j,t} \neq 0}$ is an indicator that equals one if firm investment is different from zero and c_0 and c_1 are two parameters controlling the strength of the adjustment costs. The functional form $\mathcal{G}$ is made up of two terms. The first term is a quadratic adjustment cost which generates slow convergence to the optimal firm size implied by the decreasing returns to scale assumption and idiosyncratic productivity. The second term adds a non-convex adjustment cost component which introduces periods of inaction in the firms' investment choices, Doms and Dunne (1998).

The presence of adjustment costs brings two advantages to the model. First, allow imperfect correlation between firm size and idiosyncratic shocks by introducing the desire to smooth firms' investment in the model. In a world without adjustment cost, the optimal choice of capital would only depend on the conditional expectations of firms' future productivity, making firms continuously adjust capital every period, at odds with the firms' behavior in the data. Second, it introduces a forward-looking component in investment choice by creating a positive correlation between investment and expected marginal-Q, which is missing in the absence of real frictions.

Financial frictions. Each firm jointly decides the capital to buy for the next period and its financing policy. As a means of financing investment, firms rely on both internal and external funds, which are represented by corporate bonds $B_{j,t}$ offered at a discount and new equity issuance. Firms prefer debt over equity financing because of a tax advantage[114]. The corporate tax rate is denoted by τ. Internal financing is represented by the cash flows generated from production net of debt repayment and tax saving and, it is the preferred source of firms' financing in the model because of the absence of transaction costs. The total source of internal financing available to a firm after production, debt repayment and taxes at the beginning of every period is:

$$\Pi = (1-\tau) \max_{N_{j,t} \geq 0} \left\{ p_t^w Z_t \varepsilon_{j,t} K_{j,t}^{\alpha} N_{j,t}^{\nu} - w_t N_{j,t} \right\} - \eta - B_{j,t} + \tau(\delta K_{j,t} + i_t B_{j,t}) \tag{40}$$

The first term is the after taxes operating profits gross of the cost of debt; the second term is the amount that firms have to repay to the bondholders at the beginning of every period t; the last term is the tax rebate from issuing debt and depreciating capital. The parameter η is a fixed cost of production introduced in the model to match the cross-sectional moments in the data.

Beyond internal funds, firms have access to the bond market. Firms can finance investments by issuing one-period corporate bonds at discount. The price of debt is $\mathcal{Q}$ and

[114] Because of tax advantage, Modigliani-Miller's theorem does not hold and firms choose to finance investment by issuing debt over equity.

it is firm-specific and determined in equilibrium by a financial intermediary.[115] Because debt is risk-free, bondholders require firms to be able to repay their debt in every state of the world, Hennessy and Whited (2007). This is guaranteed by introducing a ceiling on the maximum amount of resources that firms can collect on the bond market for financing investment. I follow Jeenas (2018b) and Buera and Moll (2015), I assume that debt is constrained to be less than a fixed fraction of the future capital stock.[116]

$$\mathrm{B}_{j,t+1} \leq \theta_k \mathrm{K}_{j,t+1} \tag{41}$$

This linearity in the ceiling on debt introduces two elements. First, it directly limits the maximum leverage that a firm can achieve next period at value θ_k. Second, as explained in DeAngelo et al. (2011), the presence of a forward-looking variable in the ceiling constraint adds value to the financial flexibility in the future. This effect will affect the firms' optimal decision for capital and debt in the model.

Finally, firms can raise funds by issuing new equity shares. Equity issuance is more expensive than debt financing and arises just when current investment opportunities justify the additional cost. To introduce that, I first define dividends in the model. The amount of dividends paid to the shareholders after issuing debt and investing in new capital is:

$$\mathcal{D} = \Pi(\varepsilon_{j,t}, K_{j,t}, B_{j,t}) - \mathcal{G}(K_{j,t+1}, K_{j,t}) - I_{j,t} + \mathcal{Q}B_{j,t+1} \tag{42}$$

If $\mathcal{D}$ is positive it means that firm distributes positive dividends to the shareholders while if it is negative, it means that firm is collecting external resources from the household by

[115] Since I do not restrict debt to be positive, $\mathrm{B}_{j,t}$ can take both positive or negative values, with a positive value denoting debt and a negative value denoting cash.

[116] In Hennessy and Whited (2007) debt is collateralized by the following period operating profits to guarantee that firms always can repay their debt. In contrast, in Khan and Thomas (2013) the maximum debt is constrained to a fraction of the value of current capital, which resembles the idea that smaller firms can borrow less today.

issuing new equity. However, to ensure that equity issuance is infrequent in the model, I assume firms incur additional costs when raising new equity funds. I assume that the firm pays a quadratic cost to raise external equity funds, which is as follows:

$$\mathcal{H}(\mathcal{D}) = \Big(a_0 + a_1 \mathcal{D}_{j,t}^2\Big) \mathbb{1}_{\mathcal{D}_{j,t}<0} \tag{43}$$

The cost of external finance is zero if a firm decides to distribute dividends. At the same time, it is positive, and it marginally increases in the amount of new issuance if a firm is receiving injections of funds from the shareholders, consistent with the empirical findings in Altınkılıç and Hansen (2000). The parameters a_0 and a_1 control the degree of financial friction[117]. The equity payout left to the shareholders is equal to the dividends net of equity issuance cost.

4.2 Financial intermediary

The household owns a representative, perfectly competitive financial intermediary. The financial intermediary transfers household deposits to firms in the form of zero-coupon bonds. To introduce a premium on the corporate bond, I assume that the intermediary charges a premium Φ above the safe-interest rate on the cost of borrowing $\mathcal{R}_t^b$ which is $\mathcal{R}_t^b = (1 + i_t)\Phi$. The premium Φ is subject to an exogenous shock $\varepsilon_t^{\text{sent}}$ that captures an exogenous change in the investors' sentiment in the financial markets. A positive shock to $\varepsilon_t^{\text{sent}}$ improves investors' sentiment which decreases the premium on holding bond assents pushing firms to increase borrowing (Li et al., 2022).

Additionally, I introduce the assumption that the shock has heterogeneous effects on the price of debt among firms. Specifically, when a positive shock $\varepsilon_t^{\text{sent}}$ occurs, the premium

[117] In the literature, it is common to introduce also a fixed cost of equity issuance as in Hennessy and Whited (2007). In the calibration, I set the fixed cost of equity issuance to zero to avoid a jump in the value function.

charged by intermediaries decreases in proportion to firms' leverage. This assumption aims to capture the notion that as market sentiment improves, highly leveraged firms derive less benefit from it due to their limited borrowing capacity being already utilized (Whited, 1992). I specify a functional form for Φ in the calibration section and estimate its' parameters to match the heterogeneous response of investment observed in the data.

4.3 The New-Keynesian block

Retailers. There is a unit continuum of retailers indexed by i. Retailers purchase the homogeneous good $Y_{j,t}$ produced by the wholesale heterogeneous firms at price p_t^w and transform it into a differentiated good $\tilde{Y}_{i,t}$ using a linear technology $\tilde{Y}_{i,t} = Y_{j,t}$. Retailers are subject to Rotemberg quadratic adjustment costs and set the prices $p_{i,t}$ for the differentiated good $\tilde{Y}_{i,t}$ in a monopolistic competitive market.

Final good producers. There is a unit mass of perfectly competitive final good producers. Final good producers buy a basket of differentiated goods $\tilde{Y}_{i,t}$ from the retailers at price $p_{i,t}$ and aggregate into a final consumption good using a standard CES aggregator production function. The retailers and the final good producers aggregate to derive the standard New Keynesian Phillips curve

$$\log \Pi_t = \frac{\theta - 1}{\phi_p} \log \frac{p_t^w}{p} + \beta \mathbb{E}_t \log \Pi_{t+1} \tag{44}$$

which links gross inflation today Π_t to the expected future path of the retailer marginal cost p_t^w. A complete derivation of the equation (44) is in the Appendix.

4.4 Monetary authority

To introduce a role for the monetary authority, I assume that the central bank sets the nominal interest rate i_t following a standard Taylor rule, that is:

$$\log(1+i_t) = \log(1+\bar{i}) + \phi_\pi \log\left(\frac{1+\pi_t}{1+\bar{\pi}}\right) + \varepsilon_t^{\text{mps}} \tag{45}$$

where, $\bar{i}$ is the stationary value for the interest rate, and $\bar{\pi}$ is the inflation target. The parameter ϕ_π measures the response of monetary policy to deviations in inflation from its targeted values. Under this assumption, a change in the nominal rate can occur endogenously, if the central bank sees inflation increasing, or exogenously if the central bank deviates temporarily from the systematic Taylor rule.

To map the model to the data I assume that a shock to the Taylor rule $\varepsilon_t^{\text{mps}}$ proxies a pure monetary shock while, a shock to the investor sentiment $\varepsilon_t^{\text{sent}}$ proxies a Fed information shock. proxies a Fed information shock. This captures the idea that, as the monetary authority engages in non-monetary communication, it affects firms' investment primary through the willingness to take risks and the price of debt in the bond market.

4.5 Household and government

Household. There is a representative household that owns all the firms in the economy. The representative household supplies labor in the market N_t, consumes the output produced C_t, and saves in one-period deposits D_t. Household maximizes the discounted sum of the future utility, taking the wage w_t and the interest rate i_t as given. The household utility function is additive and separable in consumption and labor. The household problem is as follows:

$$\max_{\{C_t,N_t,B_t\}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left\{ \frac{C_t^{1-\gamma}-1}{1-\gamma} - \chi N_t \right\} \tag{46}$$

such that

$$C_t + D_t = w_t N_t + \frac{1 + i_{t-1}}{1 + \pi_t} D_{t-1} + \mathcal{D}_t + \mathcal{D}_t^R + \mathcal{D}_t^F + G_t \tag{47}$$

where $\mathcal{D}_t$, $\mathcal{D}_t^R$ and $\mathcal{D}_t^F$ are respectively the dividends payed by the wholesale heterogeneous firms, retailers and final good producers and G_t is the government transfer from firms taxes. The first order conditions of the household problem pin down the Euler equation for consumption, the labor supply and the stochastic discount factor $\Lambda_{t,t+1} = \beta \mathbb{E}_t \Big[\frac{C_t}{C_{t+1}} \Big]$.

Government. I close the model by assuming that there is a government that run a balanced budget constraint every period. For simplicity, I assume that the collected taxes from the firms are rebated to the household in a lump-sum fashion

$$G_t = \int \tau(p_t^w Y_{j,t} - w_t N_{j,t}) - \tau(\delta K_{j,t} + i_t B_{j,t}) d\Gamma \tag{48}$$

Ricardian equivalence holds in the model, so the precise financing path of the given stream of government expenditure is irrelevant.

4.6 Calibration and estimation

I calibrate the model parameters following the literature. A set of parameters are calibrated based on previous works. In contrast, I estimate the parameters governing real and financial frictions to match the cross-sectional moments of the model's stationary equilibrium to the averages observed in the data. I calculate the average moments to target in the data at the quarterly level as in Jeenas (2018a).

Calibrated parameters. I set the household discount factor $\beta = 0.98$ which implies a roughly 2% nominal interest rate in the stationary equilibrium consistent with the long-term average of the 1-year Treasury yield used in the empirical analysis. I set the depreciation rate $\delta = 0.01$ to match the cross-sectional average of the firms' investment rate in the data at quarterly frequency.[118] I calibrate the firms' production function and the idiosyncratic technological process parameters following Gilchrist et al. (2014) and Jeenas (2018b). I set the capital share $\alpha = 0.255$ and the labor share $\nu = 0.595$ which imply a decreasing returns to scale of 0.85 as commonly used in the literature.

I assume that the idiosyncratic productivity ε follows an AR(1) log-normal process $\log \varepsilon_{i,t} = \rho_\varepsilon \log \varepsilon_{i,t-1} + u_{i,t}$, with $u_{i,t} \sim N(0, \sigma_\varepsilon^2)$. I discretize the stochastic process for the logarithm of idiosyncratic productivity using the Tauchen (1986) method. I set the auto-correlation parameter $\rho_\varepsilon = 0.785$ and the standard deviation $\sigma_\varepsilon = 0.125$ which are close to the parameters estimates in Gilchrist et al. (2014) on Compustat firms. I follow Bordalo et al. (2021) to calibrate the corporate tax rate $\tau = 0.2$.[119] The maximum leverage parameter θ_k instead is set to guarantee that the next period cash on hand is sufficient to repay the financial intermediaries given the amount of debt chosen. I also use the parameter θ_k as the upper bound of the variable leverage when discretizing the leverage choice.

I set the CRRA parameter σ in the representative household utility function to 1 to have a logarithm in consumption. I calibrate the parameters governing the New-Keynesian block following Ottonello and Winberry (2018) instead. I calibrate the elasticity of goods θ to 10, and the price adjustment coefficient cost $\phi_p = 90$, which implies a mark-up in the steady-state equal to 11%. I set ϕ_π, the coefficient on the inflation gap, at 1.25, values in line with those used in the New Keynesian literature. I fix the disutility of labor parameter k to 1.5 to have a value of hours worked in the steady-state close to 0.6. For the quantitative exercise, I set the function $\Phi^{-1} = 1 + \varepsilon_t^{\text{risk}} e^{-\theta_l \frac{\mathrm{B}'}{\mathrm{K}'}}$ so that in the steady state the price of debt is the same across firms. I estimate the parameter θ_l to 1.5 to produce a differential

[118] Other papers calibrate $\delta = 0.025$ based on the quarterly measure of capital depreciation from the U.S national income and product accounts (NIPA).

[119] They estimate the corporate tax rate based on the (CBO) (2017) data. Other papers in the literatue have calibrated τ in an interval between 0.15 and 0.35, Graham (2000), Begenau and Salomao (2019).

Table 8: Summary of the parameters in the model

Parameters	Description	Value	Target
A. Calibrated			
β	Discount factor	0.98	2% risk-free rate
δ	Depreciation rate	0.01	Average investment rate
α	Capital share	0.255	Jeenas (2018)
ν	Labor share	0.595	Jeenas (2018)
τ	Corporate tax	0.2	Bordalo et al. (2021)
χ	Labor disutility	1.5	SS Labor ≈ 0.6
σ	CRRA coefficient	1	Log Utility Consumption
ρ_ε	Productivity persistence	0.785	Gilchrist et al. (2014)
σ_ε	Productivity dispersion	0.125	Gilchrist et al. (2014)
θ	Goods substitutability	10	Ottonello, Winberry (2018)
ϕ_p	Price adjustment cost	90	Ottonello, Winberry (2018)
ϕ_π	Taylor rule inflation coefficient	1.25	Ottonello, Winberry (2018)
B. Estimated			
η	Fix cost of production	0.054	Average leverage
c_0	Non-convex adjustment cost	0.125	Average dividends/total assets
c_1	Quadratic adjustment cost	4.9	Inaction rate
a_0	Fix issuance cost	0	
a_1	Quadratic issuance cost	12.54	Frequency equity issuance
θ_k	Max leverage	0.988	Maximum leverage

Notes: I report the calibrated and the estimated parameters of the model in panel A and panel B. The values of the targeted moments are calculated at quarterly frequency from Compustat data.

response of firm-level investment to a Fed information shock of approximately 1% consistent with figure (13).[120] Finally, I calibrate the parameters of the aggregate shocks to match the persistence and the effect of the dynamic response observed in the data. A summary of the calibrated parameters used in the model is in the table (8.A).

Estimated parameters. The parameters $(\eta, c_0, c_1, a_0, a_1)$ governing the fixed cost of production, the real and the degree of financial frictions are estimated using simulated method of moments to match a set of empirical moments drawn from Compustat. I choose

[120] Alternatively, one could estimate θ_l in the model to match the heterogeneous response observed in the data after simulation. I avoid this procedure as it is intensive computationally.

the moments to target based on the previous works in the literature and perform a sensitivity analysis before estimation to ensure that the target moments are informative about the structural parameters.

I target the average leverage, as defined earlier in the empirical analysis, the average return on capital[121] at the quarterly frequency as in Hennessy and Whited (2007) which are informative about the fixed cost of production and the degree of quadratic adjustment cost. I also target the inaction rate of investment, defined as the percentage of the firms with an investment rate lower, in absolute value, than one-tenth of the average investment rate in the data as in Khan and Thomas (2013). The rate of inaction is informative about the real friction parameters and, in particular, about the fixed cost component of investment, and it is a common target in the investment literature. Finally, I target the percentage of firms that issue equity in the data which is the share of firms that report having raised funds from the issuance of common and preferred stock in Compustat as in Hennessy and Whited (2007) and Begenau and Salomao (2019). This moment is informative to pin down the structural parameters governing the degree of financial frictions in the model. Intuitively, an increase in the equity issuance component a_1 raises the firms' cost of equity financing, and therefore, it reduces the share of financially constrained firms in the model[122].

The estimation procedure returns the following estimated parameters: the quadratic adjustment cost parameter $c_0 = 4.9$, the non-convex adjustment cost parameter $c_1 = 0.125$, the fix cost of production $\eta = 0.054$ and the quadratic issuance cost $a_1 = 12.54$. These estimates are in line with other papers in the literature. The table (8.B) reports a summary of the parameters that are estimated and the target moments.

[121] I calculate the average return on capital in Compustat as the ratio of total dividends, cash dividends plus equity repurchases, and total assets.

[122] Hennessy and Whited (2007) target this moment along with the first and second moments of the ratio of equity issuance to assets, the frequency of negative debt, and the co-variance between equity issuance and investment to pin down the level, the slope and the curvature of equity issuance costs in a similar model to mine.

5 Mechanism and validation

This section validates the mechanisms at play in the model. Section 4.1 discusses the mechanism and the role of financial frictions within the model. Section 4.2 presents the aggregate impulse response function to various monetary policy surprises in the model. Section 4.3 tests the model's heterogeneous sensitivity and provides an explanation of the underlying mechanism.

5.1 Firms' problem and financial frictions

In the model, firms make two substantial choices. They choose the amount of capital to buy for the next period K' and the amount of debt B' to issue for financing investment. I denote with $\{\varepsilon, S\}$ the set of state variables $\{\varepsilon, K, B\}$ for a firm j and with a $'$ a variable tomorrow. At the beginning of every period t, each firm solves the following dynamic profit maximization problem subject to a set of constraints:

$$V(\varepsilon, S) = \max_{K',B'} \left\{ \mathcal{D}(\varepsilon, S, S') - (a_0 + \frac{a_1}{2}\mathcal{D}^2)\mathbb{1}_{\mathcal{D}<0} + \Lambda_{t,t+1} \sum_{\varepsilon'} \pi(\varepsilon'|\varepsilon) V'(\varepsilon', S'|\varepsilon) \right\} \tag{49}$$

subject to:

$$\mathcal{D}(\varepsilon, S, S') = \Pi(\varepsilon, S) - c_0 \left(\frac{K'}{K} - 1 + \delta \right)^2 K + c_1 Y \mathbb{1}_{I \neq 0} - K' + (1-\delta)K + \mathcal{Q}B' \tag{50}$$

$$\Pi(\varepsilon, S) = \max_{N \geq 0} \, (1-\tau)(p_t^w Y - w_t N - \eta) - B + \tau(\delta K + i_t B) \tag{51}$$

$$B' \leq \theta_k K' \qquad (\lambda') \tag{52}$$

$$\mathcal{Q}(S') = \frac{1 + \varepsilon_t^{\text{risk}} e^{-\theta_l \frac{B'}{K'}}}{1 + i_t} \tag{53}$$

where $V(\varepsilon, S)$ is the value of a firm at the beginning of the period, $\Pi(\varepsilon, S)$ is the cash on hand available to finance investment, $\mathcal{D}(\varepsilon, S, S')$ are the dividends to the shareholders, and

λ' is the multiplier associate to the non-binding constraint on debt.

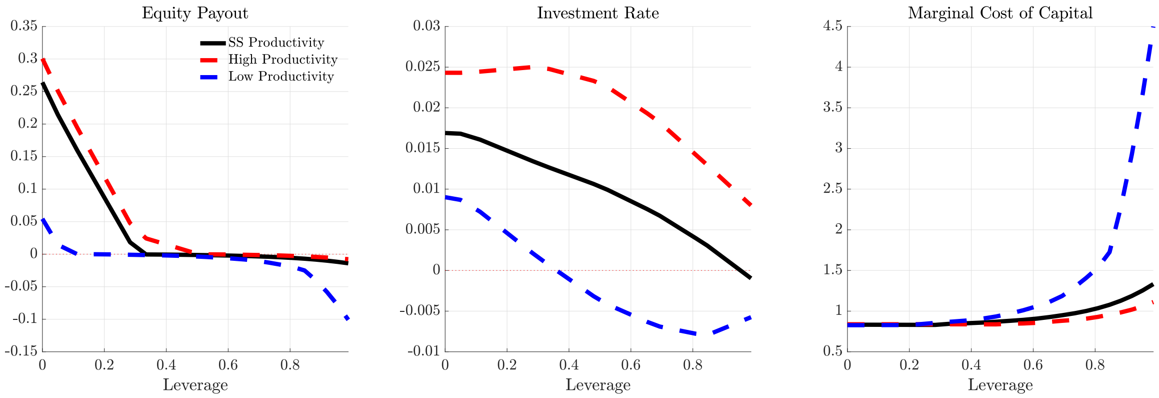
The presence of equity issuance cost is the main source of financial frictions in the model. I define the level of financial friction faced by a firm based on their dividend policy.[123] At the beginning of every period, firms are distinct by the internal funds available to finance investment. I define a firm as *financially unconstrained* (or, with low level of financial friction) if it has accumulated enough internal resources to finance new investment through only cash on hand and new debt issuance. Unconstrained firms never issue equity since it is costly and find it optimal to pay dividends to the shareholders by raising debt. I define a firm as *financially constrained* (or, with high level of financial friction) instead if at the optimum it does not have accumulated enough resources to buy capital K' through debt and cash, and they find optimal to issue equity to forego investment. Constrained firms never distribute dividends to the shareholders and pay an external premium to raise funds through equity.[124]

The steady-state policy functions for capital and equity issuance along the leverage dimension shows a linkage between firms' leverage, and financial frictions in the model. Figure 14 shows two main facts. First, given a fixed amount of capital, high leverage firms are more likely to be financially constrained (first column). In the stationary equilibrium, low leverage firms are more likely to pay dividends to the shareholders while high leverage firms are more likely to issue equity to finance investment. The intuition is that firms with a high level of debt are not generating enough resources via debt and internal resources, and so they find optimal financing investment by issuing equity. Whereas firms with a low level of debt can sustain their optimal investment policy without relying on equity issuance and thus, distribute dividends to the shareholders. Second, firms' financing decisions and investment

[123] This distinction is the same as in Rojas (2018) which defines the financing gap of a firm as the difference between resources needed to operate and invest minus the resources available to do so.

[124] This definition is similar to the one of Ottonello and Winberry (2018) and Jeenas (2018a)

Figure 14: Dividend policy and the marginal cost of capital in the steady state.



Notes: I plot the average shareholder payout, investment rate (in percentage points) and the cost of capital (marginal cost of capital divided by capital) function in the stationary equilibrium along the leverage dimension. The idiosyncratic productivity is fixed at the steady state level and, for all three plots, I average the policy functions across firms that weight in the population distribution for more then 1% of total capital. For each subplot, I add a linear fitted line (red line).

choices are intimately connected (second column). Investment rates are decreasing in the amount of leverage, given a fixed amount of capital. This is because, as firms with a high level of debt are more likely to raise funds through equity, high leverage firms would find raising one additional unit of capital more costly (third column) and thus, they optimally reduce their size in equilibrium.

Figure 56 in Appendix J shows that model steady-state policy predictions are consistent with the equivalent in the data. I construct actual steady-state policy in the data computing the long-term averages of leverage, equity issuance, dividends payout and investment rates for each firm in my dataset from 1990 to 2018. I plot the cross-sectional correlation between firms' leverage and dividends payout, equity issuance, and investment rates. The data shows a very strong relationship between firms' leverage, payout policy and equity issuance in the long run. Specifically, firms with high leverage tend to exhibit lower dividend payouts to shareholders, lower investment rates, and a higher likelihood of issuing equity to finance their activities. These findings align with prior studies in Fazzari et al. (1987), which emphasize the importance of leverage in determining firms' financial decisions and investment behavior.

5.2 Aggregate impulse response in the model

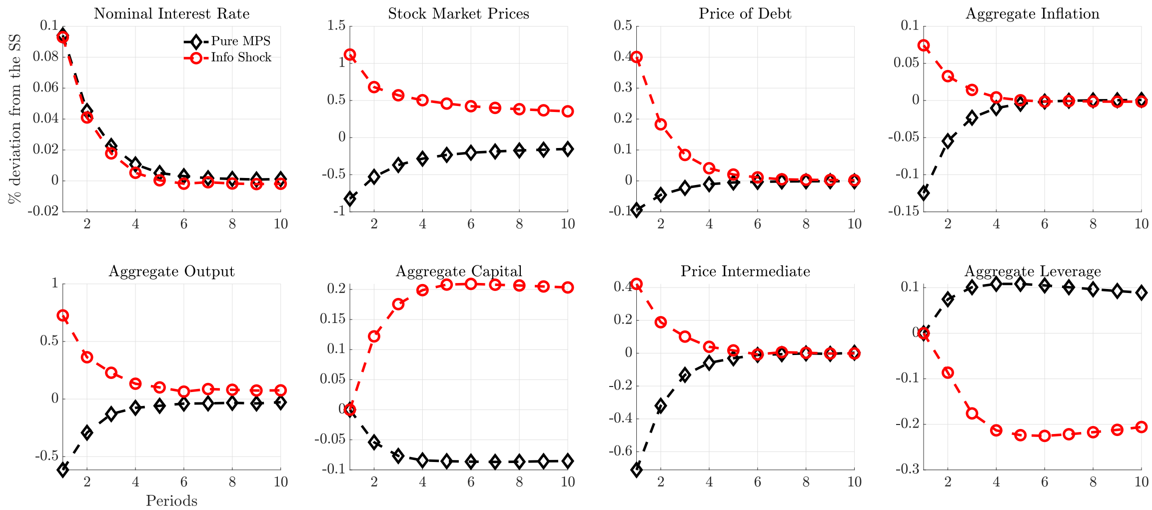
The model can qualitatively match the aggregate impulse responses observed in the data. To do that, I study the aggregate effects of different interest rate surprises along the perfect foresight transition path back to the steady-state. At time t a policy shock arises and the economy temporary departs from its steady state and slowly comes back to equilibrium as in Jeenas (2018a) and Ottonello and Winberry (2018). The impulse response function are obtained simulating a transition path back to the steady state after 100 periods.[125] In order to have comparable results across simulations, I calibrate the standard deviation and the persistence parameters of the two exogenous components to increase the nominal interest rate at impact by roughly 0.1% and to induce a temporary fluctuations for around eight quarters in the model.[126] I plot the impulse responses to the two shocks in figure 15.

In the event that the monetary authority unexpectedly raises the nominal interest rate (i.e., pure monetary shock), a monetary shock leads to the contraction of output, consumption, and labor in the model. Because prices are sticky, they are slow to adjust, inflation and the price of the intermediate output falls, decreasing incentives to invest in new capital. Firms divest since the marginal benefit of capital decreases as the discounted return on future capital and the expected output decline. Furthermore, in response to a Taylor rule shock the cost of raising funds on the bond market increases, and firms that were hit by the shock experience a decline in their cash on hand. In turn, a decline in the amount of internal resources leads firms to raise more funds externally, i.e., via debt and equity issues. It follows that the distribution of firms over leverage shift towards the right

[125] More details of the algorithm are in the Appendix.

[126] Ottonello and Winberry (2018) calibrates the persistence of the monetary shock to be 0.5.

Figure 15: The baseline IRFs in the model



Notes: The impulse response function to different monetary policy shocks in the model. The black line shows the response of the aggregate variables to a pure monetary shock. The red line represents the aggregate response to a Fed information shock. All responses are in percentage deviation for the steady state. The impulse response function are obtained simulating a transition path back to the steady state after 100 periods using a backward-forward algorithm.

hand-side.

A Fed information shock (red line) instead, leads the economy on a pattern similar to an expansionary demand shock and it operates mainly through the cost of borrowing. A Fed information shock increases investors' sentiment in the financial market thus, increasing the price of corporate bonds. Higher price of bonds increases the marginal benefit of debt and decrease in the marginal cost of capital. Differently from a pure monetary shock, labor and output increase and prices slowly adjust upward, producing a period of inflation. As a result of higher inflation, the Fed reacts by increasing the nominal interest rate. Firms increase investment because the shock increases firms operating profits and lower the marginal cost of financing new capital at debt. Since firms in expectations increases the capacity to generate profits and dividends, stock market price increases along the transition path. Both shocks produce a response in the economy consistent with the aggregate impulse responses obtained in figure 39 in the Appendix.

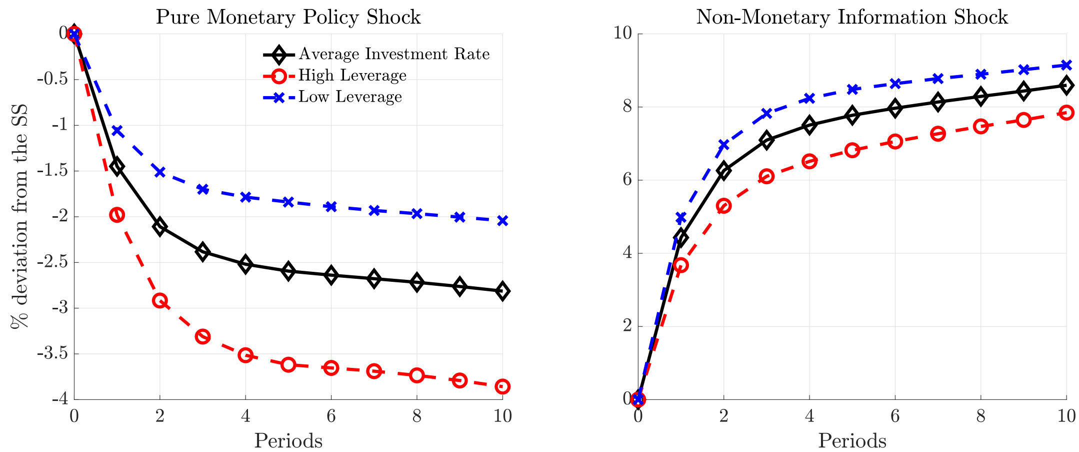
5.3 Heterogeneous response of investment

In this section, I show that the model also accounts for the heterogeneous responses to the two shocks at the firm level. To see this, I examine the response of investment at the firm level to the two shocks. I group the firm-level responses based on past leverage into two bins. I consider firms to be low leverage if their leverage is lower than 50 percent and high if their leverage exceeds 50 percent. In order to obtain an average estimate of the sensitivity of firms to the shock, I average the response of investment across firms within the same category (i.e., high or low leverage).[127] I plot the average responses to the two shocks in figure 16.

Figure 16 illustrates that firms with different leverage respond differently to the shocks in the model, consistent with the empirical findings documented in this paper. In particular, in response to a one standard deviation pure monetary policy shock (first graph), firm investment rate drops by around 0.8pp at impact (black line). Firms with different levels of leverage respond differently to the shock. Low leverage firms reduce their investment rates by almost 10 percent less than the average (blue dotted line). Viceversa, firms with high levels of leverage reduce investment rates by 20pp more than low leverage firms at the time of the impact (red dotted line). In response to a Fed information shock instead, firm investment rates increase by around 1.5 percent points at impact (black line). In the cross-sections, firms with low levels of leverage prior the shock increase their investment rates by 10 percent more than the average (blue dotted line), while firms with high levels of leverage increase their investment rates by 10 percent less than the average (red dotted). These results are consistent with previous results in the empirical part of the paper.

[127] I only consider firms that constitute more than 1 per cent of the total number of firms in the stationary distribution.

Figure 16: Heterogeneous firm-level response in the model



Notes: The average cumulative impulse response function for investment rate across firms. The black line represents the average firm-level response of the investment rate respectively to a pure monetary shock (first graph) and Fed information shock (second graph). The blue line shows the average firm-level response of the investment rate for firms that have less than 50% of leverage (i.e., low leverage). The red line illustrates the average response of the investment rate at the firm level for firms with more than 50% leverage (i.e., high leverage). The averages are calculated by equally weighting firms that constitute more than 1 percent of the total firms.

Pure monetary shock. The mechanism underlying the diverse investment responses observed in Figure 16 to a pure monetary shock exhibits similarities to the framework presented in Ottonello and Winberry (2018). When a Taylor rule shock occurs, resulting in an exogenous rise in the nominal interest rate, the economy enters a recessionary phase. As the real interest rate increases, the stochastic discount factor decreases, leading to reduced marginal profits of capital and a decline in the marginal value of expanding capital investment. Consequently, firms exhibit a tendency to decrease their investment levels, irrespective of their leverage levels.

High leverage firms are more sensitive to the shock if its impact on their cash reserves is strong enough to counterbalance their higher marginal cost of capital. In a partial equilibrium context, highly leveraged or financially constrained firms are less adversely affected by a shock compared to low leverage firms, as they face a steeper marginal cost of capital curve and are more likely to rely on equity issuance. However, a pure monetary shock reduces operating profits for all firms due to a decline in labor and output, as well as higher borrowing costs. This prompts firms to increasingly depend on external financing for new investments. Low leverage firms, with ample cash reserves, are relatively unaffected by the decline in operating profits. In contrast, high leverage firms, already dependent on external financing, respond by increasing equity issuance, which further raises their marginal cost of capital and dampens investment by more.[128]

Figure 59 in Appendix J plots the responses for the key financial variables, cash on hand, equity and debt across firms with different levels of leverage after a pure monetary shock consistent with the explained mechanism.

Fed information shock. The mechanism behind the investment responses in Figure 16 to a Fed information shock is novel instead. A positive Fed information shock has two primary effects on firms' optimal decisions. Firstly, on average, firms increase their debt levels as rising bond prices enhance the attractiveness of debt, enabling them to issue more debt and raise additional funds. Secondly, firms engage in greater capital accumulation as the expected future profits rise, leading to an increase in the expected marginal benefit of capital. This anticipation of improved future economic conditions prompts firms to invest more in capital.

High leverage firms are less sensitive to a Fed information shock because they take less advantage from an improvement in their financial conditions. Firms with low leverage can increase their leverage position without increasing the likelihood of future equity issuance (i.e., if a firm expects to issue equity next period the marginal cost of debt is higher). Firms

[128] This mechanism is analogous to the one observed in Ottonello and Winberry (2018)'s model with risky debt, where high leverage firms exhibit greater sensitivity to a policy hike if changes in the nominal interest rate substantially affect their default probabilities and debt prices. In a risk-free model, the heterogeneity mechanism is more general, as it only requires a shift towards more expensive external financing sources for firms.

with high leverage do not find it desirable to increase their leverage positions instead. There are two reasons for this. First, raising debt will increase the likelihood that they will breach the debt ceiling tomorrow and incur in an additional cost. Second, adding an extra dollar of debt today will result in debt repayment tomorrow and therefore an increased likelihood of requiring external equity financing tomorrow, Strebulaev et al. (2012). It follows that in equilibrium, high-leverage firms find it optimal to reduce their leverage positions, whereas low-leverage firms increase them. Consequently, by expanding their leverage positions, low leverage firms experience a decrease in their marginal cost of capital, which encourages them to invest more.

Figure 59 in Appendix J plots the responses for the response of cash on hand, equity and debt across firms with different levels of leverage after a Fed information shock consistent with the explained mechanism.

6 Quantitative implications

This section studies aggregate implications and provide an explanation of the findings in the empirical part of this paper. Section 4.1 and 4.2 revisits the distributional effects of monetary policy depending on the market sentiment. Section 4.3 explore the heterogeneous responses of bond prices to a Fed information shock and provide a set of counter-factual experiments.

6.1 State dependency of non-monetary communication

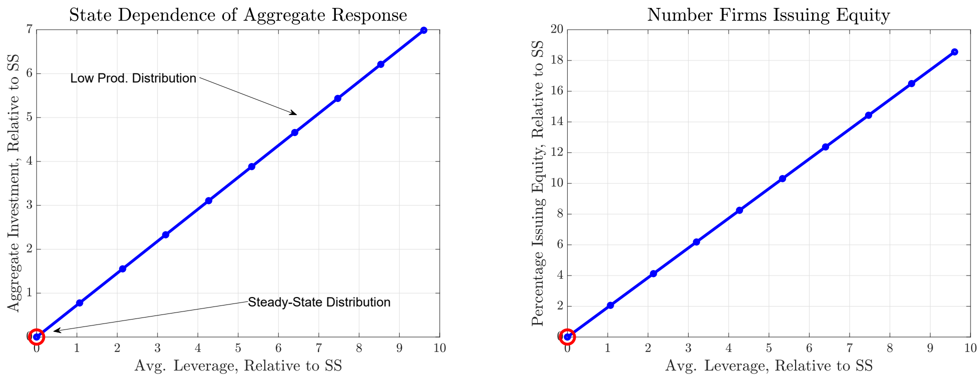
I study the response of aggregate investment to a monetary policy announcement in a recession and compare them in normal times. In order to quantify the state dependence of non-monetary communication, I fix firms' investment response across state space with respect to a Fed information shock as a function of firms' state variables and vary the initial distribution of firms. I vary the initial distribution of firms $\Gamma(z, K, B)$ by taking the weighted average of two reference distributions. The first reference distribution is the steady-state distribution $\Gamma_{\text{ss}}(z, K, B)$. The second reference distribution $\Gamma_{\text{bad}}(z, K, B)$ assumes that the conditional distribution of capital and debt for every level of productivity is equal to the distribution of capital and debt conditional on a low realization of productivity in steady state. I then compute the initial distribution as a weighted average of these two reference distributions, $\omega \cdot \Gamma_{\text{bad}} + (1 - \omega) \cdot \Gamma_{\text{ss}}$.[129]

Figure 17 shows the aggregate response of investment to a Fed information shock as function of the weight ω.Based on the calibration of the model, the effectiveness of a non-monetary policy announcement that increases the interest rate by 1 percentage point is enhanced by 0.8% in a recession for every 1% increase in the average leverage in the economy relative to the steady state level of leverage. Compared to the change in average leverage in the economy during the Great Financial Crisis, which was 4% higher, a Fed information shock is found to be 3% more effective.

The results stem from the interaction of two opposing forces. Firstly, a negative TFP recession shock amplifies the presence of financially constrained firms with low productivity, leading to a larger proportion of firms that are highly responsive to aggregate fluctuations, as depicted in Figure 17. Secondly, the shock increases the average leverage in the economy, thereby increasing the share of firms with lower sensitivity to non-monetary communication. The extent of these effects depends on the strength of the two channels and the dynamics of general equilibrium. Based on the calibration of my model, I find that the reduced sensitivity of high leverage firms to non-monetary communication is insufficient to counterbalance the larger number of firms that are highly responsive to aggregate fluctuations during a

[129] Another approach is to simulate the separate transition paths of a Fed information shock and a negative aggregate TFP shock. By subtracting the impulse responses of the TFP shock alone from the joint transition path, we can isolate the specific effects of the policy shocks during a recession.

Figure 17: State dependency of non-monetary communication



Notes: Dependence of aggregate response of Fed information on initial distribution. I compute the change in aggregate capital for different initial distributions as described in the main text.

recession.

6.2 Revisiting the state dependency of pure monetary policy

I use the model to revisit the distributional effects of pure monetary policy. Previous literature has focused on studying the effect of monetary policy in a recession compared to normal times without taking into account the potential confouding effect of a Fed information component (Koby and Wolf, 2020; Ottonello and Winberry, 2018). In practice however, as the Fed releases an easing statement, investors may misinterpret the information released triggering an negative shock.[130] Because this shock produces direct effects on the marginal cost of capital and distributional effects over time, the effectiveness of an expansionary Taylor rule shock in a recession may be dampened by a negative market response.

I estimate the response of aggregate investment to different types of (expansionary) monetary policy innovation in a recession and compare them in normal times. I consider

[130] Figure 38 in Appendix E shows that this case is indeed widespread from 1990 to 2018.

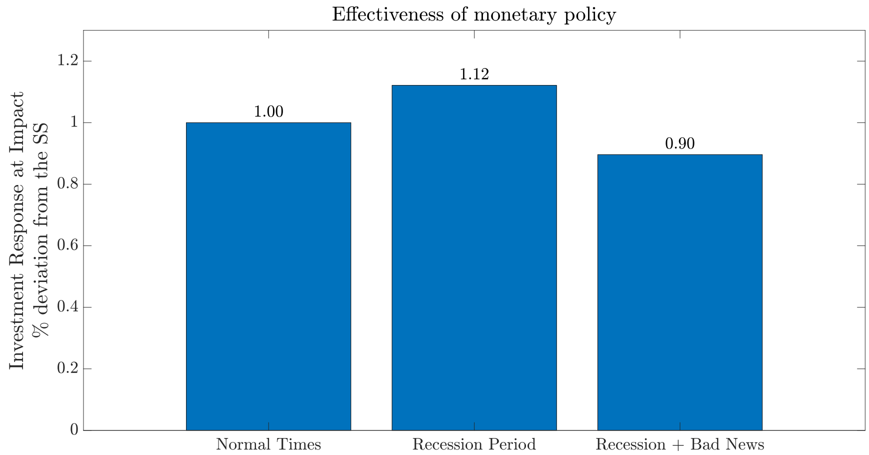
two types of monetary policy surprises. One with a positive one standard deviation Taylor rule shock with no contamination and, a second surprised, mixed with a negative market response (half standard deviation). I simulate separately the transition path of the two monetary policy surprises jointly with a negative aggregate TFP shock. I calibrate the standard deviation and the persistence parameters of the TFP shock to lower output at impact by roughly 4% and to generate a recession for around eight quarters in the model.[131] I obtain the effect of an expansionary Taylor rule shock under recession by subtracting the impulse responses of the aggregate TFP shock from the joint transition path. I normalize the response of aggregate investment to the two shocks in normal times to 1 to ease the interpretation. I plot the results of this exercise in Figure 18.

Figure 18 shows two facts. First, given my calibration, a an expansionary Taylor rule shock that cuts the nominal rate by 10bp in a recession is 12% more effective in stimulating investment than in normal times. The result depends on the strength of real and financial frictions. A TFP-induced recession produces two effects on the economy that may affect the potency of a monetary policy shock. First, it increases the share of financially constrained firms (i.e., firms that issue equity increases) that, given the results in figure 16, are relatively more sensitive to interest rate changes. Second, it increases the relative cost of capital financing due to the presence of fixed adjustment costs which, in turn, discourages firms from investing in response to any expansionary policy shock during a recession. This mechanism is reminiscent of the one in Caballero and Engel (1999) and discussed in Koby and Wolf (2020).[132] Given my calibration, the distributional effects of leverage dominate the dampening effect of real frictions.

[131] Similar to this paper, Koby and Wolf (2020) calibrates the standard deviation of the TFP shock to lower output at impact by 5%.

[132] In a downturn, firms are less sensitive to expansionary shocks because they are closer to their target capital and find it more expensive to adjust investment. As the fixed cost of investment does not change during a recession, the burden of paying the fixed cost is relatively higher in a recession than in normal times.

Figure 18: Revisiting state dependency of monetary policy



Notes: Response at impact of aggregate investment to an expansionary monetary policy shock under three different scenario. In the first column, the response of aggregate investment to a positive Taylor rule shock in normal times, which I normalize to 1. In the second column, the response of aggregate investment to an exogenous Taylor rule shock in a recession. In the last column, the response of investment to to an exogenous Taylor rule shock in a recession followed by a negative market reaction.

Second, Figure 18 shows that a negative market response to a FOMC statement may dampen the effectiveness of an expansionary monetary policy shock in a recession, and this effect is not negligible. Based on my calibration, a negative miscomunication in an FOMC statement dampens the elasticity of investment to an interest rate cut by more than 20% compared to the equivalent non-market response case. The economic intuition is a negative market reaction increases the cost of capital at the margin for all firms in the economy. It follows that even though a recession increases the share of financially constrained firms in the economy, a steepening in the marginal cost of capital dampens the effectiveness of a monetary policy cut in a period of recession.

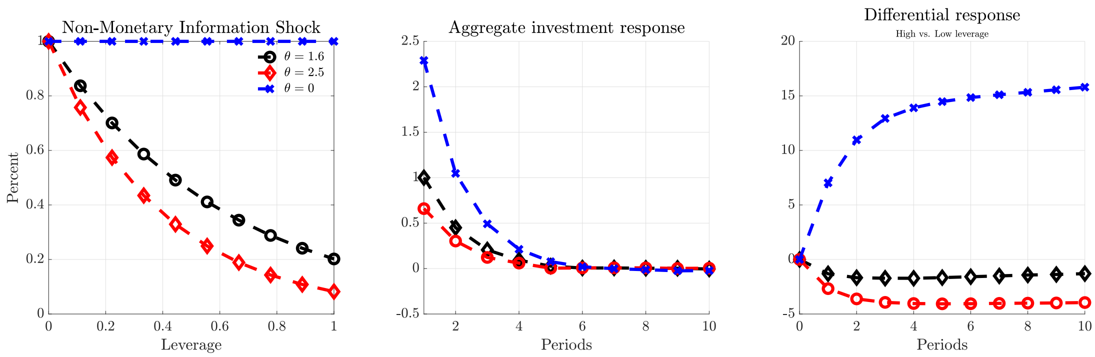
6.3 A counterfactual experiment

The heterogeneous responses of bond prices to a Fed information shock are crucial to explain the heterogeneity of firm-level investment observed in the data. With the price of debt being less sensitive to a Fed information shocks, high-leverage firms have less incentive to increase their debt positions and replace it with equity issuance. Nevertheless, high-leverage firms in the model have a larger propensity to invest, since they face a relatively steeper marginal costs of capital curve. This implies that if the price of debt for high leverage firms increased more in response to a Fed information shock, they would be able to save out of financial frictions, thus increasing their capital position by more. This source of heterogeneity is therefore, a dampener for Fed information shocks.

Figure 19 quantify the dampening effect of this channel in a the counter-factual experiment. I simulate the response of aggregate investment to the same shock using different parameters of θ_l. The parameter θ_l in the price of debt function controls the extent to which high leverage firms benefit less from a change in the market sentiment. I compare the results on aggregate and average investment of the benchmark model, $\theta_l = 1.5$, with two different values of $\theta_l = \{0, 2.5\}$. In the benchmark model $\theta_l = 1.5$, a shock to the risk premium affects the price of debt for high-leverage firms 4 time less than it does for a firm at 0 leverage. It follows that investment increases in the economy (i.e., I standardize the increase at 1pp at impact) and low-leverage firms contribute relatively more to the aggregate response.

If $\theta_l = 0$ (blue line), Fed information shocks increase debt prices equally across firms, regardless of the future leverage conditions. Now, firms with high-leverage have greater incentives to acquire more resources from the bond market to replace equity issuance. As high-leverage firms reduce their reliance on external equity issuance, they experience a decrease in their marginal cost of capital, thereby increasing their capital position. There

Figure 19: Counterfactual experiments to a Fed information shock



Notes: The results to a set of counter-factual experiments in the model for various values of θ_l. Black lines represents benchmark calibration, $\theta_l = 1.5$. Blue lines represents the model responses when $\theta_l = 0$. Red lines represents the model responses when $\theta_l = 2.5$. I report the heterogeneous effects of the shock along the leverage dimension in the first graph. The second graph illustrates the aggregate response to investment. All aggregate responses are re-scaled so that aggregate investment increases by one percentage point under the benchmark case. In the third graph, the average differential firm leverage response of the investment between high and low leverage firms. The averages are calculated by equally weighting firms that constitute more than 1 percent of the total firms.

are two effects that follow from this. First, high-leverage firms will be more sensitive to Fed information shocks and will increase their investments more than low-leverage firms (third column). Second, because high leverage firms increase investment by more, aggregate investment increases significantly more in response to the shock. According to my calibration, aggregate investment would increase more than twofold if $\theta_l = 0$, as compared to the benchmark case.

If $\theta_l = 2.5$ (red line) instead, Fed information shocks worsen the lower sensitivity of high leverage firms to price shocks. Firms with higher leverage find that issuing debt is even less beneficial compared to the benchmark case. Because of this, the differential investment response between high and low leverage decreases more, and aggregate investment increases by around 40 per cent less than in the benchmark scenario.

7 Conclusion

Monetary policy has experienced a notable evolution, shifting from the conventional Keynesian theory to a more contemporary framework. The new theory of monetary policy highlights the significance of beliefs and expectations in shaping economic outcomes. Through non-monetary communication strategies, central banks can impact firms' investment decisions by shaping investors' perceptions and confidence in the economic outlook. This emphasizes the role of psychological and informational factors in the transmission of monetary policy and underscores the importance of understanding how expectations and beliefs influence investment behavior.

In this paper, I study and quantify the role of financial frictions in the transmission of monetary policy on investment depending on the channel through which the policy is transmitted. While previous studies have examined the heterogeneous effect of monetary policy on firms' investment through the interest rates, this paper aims to provide a more comprehensive understanding of how financial frictions interact with monetary policy to shape investment decisions.

I show that financial frictions play a different role in the transmission of monetary policy depending on the channel. Using Compustat data, I show that in response to a pure monetary policy shock resulting in a 1% increase in average Q, a firm with 10 pp more leverage before the shock accumulate around 0.03% more capital stock after 2 years. Conversely, in response to a Fed information shock leading to the same increase in average Q, a firm with 10 pp higher leverage before the shock accumulates around 0.03% less capital after approximately the same period of time. Furthermore, I document that the transmission channel of Fed information to firms' capital investment is primary non-fundamental.

Finally, I develop a dynamic general equilibrium model with firm idiosyncratic productivity and financial frictions to rationalize the empirical findings and quantify the distributional effects of monetary policy announcements depending on the channel of monetary policy. I use the model to revisit the state dependency of monetary policy transmission. In my calibration, a negative market sentiment to an easing Taylor rule shock reduces the effectiveness of conventional monetary policy interventions in a period of recession by almost 20% compared to the no bad news case.

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Chapter 1

A Construction of the dataset and cleaning

A.1 Forecast Error

We extract earnings per share (EPS) forecasts at both firm-quarter and firm-year level from the Institutional Broker's Estimate System (IBES), together with Street actual earnings. We focus our attention on IBES-based actual measures, as suggested by Bradshaw and Sloan (2002), since Street measure has become a more common measure of earnings per share, compared to the previous GAAP accounting principle, to which Compustat-based EPS relies on. We are aware of the issues that are coming from the use of adjusted detail history in IBES and thus, we follow the cleaning methodology of Q.S. Drechsler (provided by WRDS). We start from the unadjasted dataset and extract EPS forecast. Then, we collect both quarterly and yearly horizon forecasts. Payne and Thomas (2003) pointed out that the joint presence of stock splits and rounding in the adjusted detail history of IBES can generate missclassified observation and rounding issues in their measures. A common solution is to adjusted measure of unadjasted EPS, by downloading the historical stock-split adjustment factors from CRSP. In this way we put the estimates on the same per share basis as reported earnings by companies. Finally, we define our consensus forecast as a median of analyst earnings forecasts, by combining a firm-fiscal combination between the reported date of actual Street profits and the date of forecast announcement, that differs between quarterly (0 to 100 days) and yearly (270 to 370 days) forecasts horizons, following Joshua Livnat (2006). We thus combine IBES dataset and Compustat dataset, by using linking tables (*iclink*) between IBES ID *ticker* and Compustat *gvkey*. To do this, we need to calculate the link date ranges between these two combination of identification codes, which is provided by WRDS.

We derive three measures of forecast errors, based on this IBES measures of consensus estimates and actual earnings per share (EPS), as it follows:

(1) **% Total Assets** is the simple difference between consensus estimates and actual EPS:

$$\textbf{\% Total Assets}_{it} = \frac{(\mathrm{act}_{it} - \mathrm{medest}_{it}) * 100}{at_{it}}$$

where act_{it} is the actual value of firm i EPS at time t, medest_{it} is the consensus estimate of EPS, based on a median of 0 to 100 days window for quarterly horizon individual forecasts and of 270 to 370 days window for yearly horizon individual forecasts of EPS and P_{it} is the price per share for firm i at the end of time t.

(2) **% Market Value** is a percentage measure, scaled by price per share at time t for each firm i, as it follows:

$$\textbf{\% Market Value}_{it} = \frac{(\mathrm{act}_{it} - \mathrm{medest}_{it}) * 100}{P_{it}}$$

(3) **% Lagged Sales** is a percentage measure, scaled by sales at $t-1$ (per quarter) for each firm i, as it follows:

$$\textbf{\% Lagged Sales}_{it} = \frac{(\mathrm{act}_{it} - \mathrm{medest}_{it}) * 100}{\mathrm{sales}_{i,t-1}}$$

Figure 20 shows the different distribution between these three measures of forecast errors.

A.2 Firm-level variables

We construct the other firm-level variables in the Compustat database following the usual practices in the literature. Firm size is the log of total assets, variable $atq_{i,t}$. Nominal sales is the variable $saleq_{i,t}$. Cost of good sold is the variable $cogsq_{i,t}$. Selling, general and administrative expenditures is the variable $xsga_{i,t}$. The market value of a firm is the price of the stock times the numbers of stocks as reported in Compustat $mkval_{i,t}$. Capital stock is equal to the book value of capital. We use the perpetual inventory method to calculate the capital value for each firm i at a time t. We measure the initial value of firm i's capital stock as the earliest available entry of $ppegtq_{i,t}$, and then iteratively construct capital stock from the change in $ppentq_{i,t}$. We construct a sectorial dummies following previous literature: (i) agriculture, forestry and fishing: sic < 999; (ii) mining: sic $\in [1000, 1499]$; (iii) construction: sic $\in [1500, 1799]$; (iv) manufacturing: sic $\in [2000, 3999]$; (v) transportation, communications, electric, gas, and sanitary services: sic $\in [4000, 4999]$; (vi) wholesale trade: sic $\in [5000, 5199]$; (vii) retail trade: sic $\in [5200, 5999]$; (viii) services: sic $\in [7000, 8999]$.

We deflate capital stock, sales, and total assets using the implied price index of gross value added in the U.S. non-farm business sector. To control for outliers in the regressors, we trim the variables at the 1% top-level and sales growth at the 1% top and bottom level as standard in the main reference literature.

A.3 Sample selections

The sample period is 1990Q1 to 2018Q4. We perform the following cleaning steps:

(1) We keep only US-based firms, $fic_{i,t} =$"USA".

(2) To avoid firms with strange production functions, drop regulated utilities and financial

companies, we drop all firm-quarters for which the 4-digit sic code is in the range [4900,5000) or [6000,7000).

(3) To get rid of years with extremely large values for acquisitions to avoid the influence of large mergers, we drop all firm-quarters for which the value of acquisitions $acq_{i,t}$ is greater than 5% of total assets $atq_{i,t}$.

(4) We drop all firm-quarters for which the measurement of Total Assets $atq_{i,t}$, Sales $saleq_{i,t}$, Property, Plant and Equipment (Net) $ppentq_{i,t}$, Cash and Short-Term Investments $cheq_{i,t}$, Debt in Current Liabilities $dlcq_{i,t}$, Total Long-Term Debt $dlttq_{i,t}$, Total Inventories $invtq_{i,t}$ are missing or negative.

(5) We drop all firm-quarters before a firm's first observation of Property, Plant, and Equipment (Gross) $ppegtq_{i,t}$.

A.4 Estimation of firm-level markup

We follow De Loecker et al. (2020) and De Loecker and Warzynski (2012) and use a production function approach. Assume that each firm i production technology is:

$$\mathbf{Q}_{it} = \mathbf{Q}_{it}(\mathbf{K}_{it}, \bar{K}_{it}, \gamma_{it}), \tag{54}$$

where $\mathbf{K}$ is a vector of variable inputs of production (labor, intermediate inputs,...), $\bar{K}$ is capital stock and γ represents each firm productivity. The firm solves the following cost minimization problem:

$$\mathcal{L}(\mathbf{K}_{it}, \bar{K}_{it}, \gamma_{it}) = \mathbf{R}_{it}\mathbf{K}_{it} + r\bar{K} + F_{it} - \lambda(\mathbf{Q}(.) - \bar{\mathbf{Q}}_{it}), \tag{55}$$

where $\mathbf{R}$ is the price vector of variable inputs, r the cost of capital, and F fixed cost. Solvinng the Lagrangian objective function for the variable inputs $\mathbf{K}$ and assuming the production function is Cobb-Douglas, firm i's markup can be written as:

$$\mu_{it} = \theta_{it}^{\mathbf{K}} \frac{P_{it} Q_{it}}{R_{it}^{\mathbf{K}} \mathbf{K}_{it}}, \tag{56}$$

where θ is the output elasticity of the variable inputs, $P_{it}Q_{it}$ is firm's revenues, and $R_{it}^{\mathbf{K}}\mathbf{K}_{it}$ is firm's costs of variable inputs.

Our preferred measure of markups at the firm-quarter level is constructed as follow:

$$\mu_{it} = \widehat{\theta_{it}} \frac{\text{Sales}_{it}}{\text{Cost of goods sold}_{it}} = \widehat{\theta_{it}} \frac{\text{saleq}}{\text{cogsq}}, \tag{57}$$

where $\widehat{\theta_{it}}$ is downloaded directly from De Loecker et al. (2020).

Alternatively, we define variable input to include also selling and general expenses as follow:

$$\mu_{it} = \theta_{it} \frac{\text{Sales}_{it}}{\text{Costs of goods sold + Overhead costs}_{it}} = \theta_{it} \frac{\text{saleq}}{\text{cogsq + xsgaq}}, \tag{58}$$

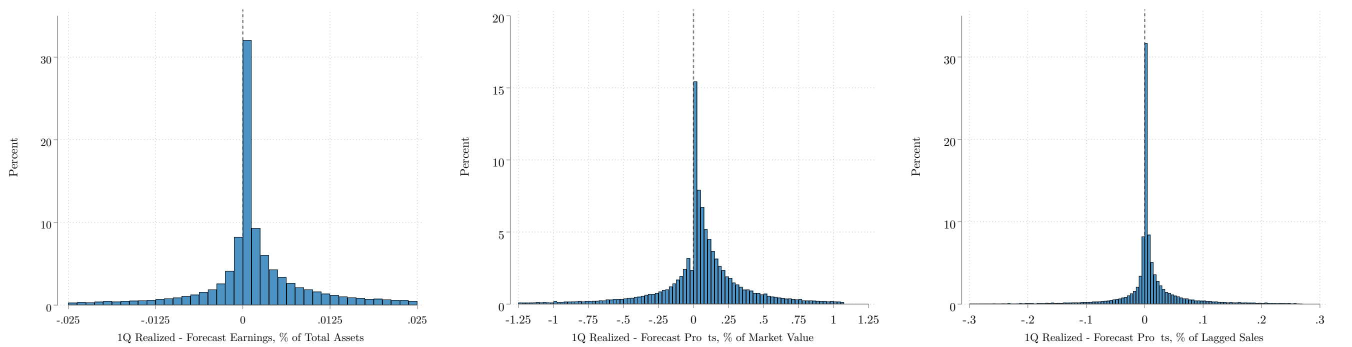
where $\widehat{\theta_{it}}$ is also estimated including selling and general expenses in the definition of variable input.

Lastly, we also consider the gross-margin defined as follow:

$$\mu_{it} = 1 - \frac{\text{Costs of goods sold}_{it}}{\text{Sales}_{it}} = 1 - \frac{\text{cogsq}}{\text{saleq}}. \tag{59}$$

A.5 Distribution of forecast errors from IBES

Figure 20: Distribution of forecast errors



Notes: The figure plots the histogram of the forecast errors drawn from a 1990-2018 sample of approximately 1,800 U.S.-based public, non-financial firms for a total of approximately 86,000 firm-quarter observation. The histogram does not include the top 5% and the bottom 5% of the forecast error distribution. Realized profits are quarterly earnings; forecast profits are the median analyst forecasts at quarterly frequency. Profits and analyst forecasts are from IBES. Forecast errors are computed as the difference between realized profits and forecast profits. Forecast errors are expressed as percentage of total assets (left panel), market value (center panel) and lagged sales (right panel).

B Empirics: Robustness checks

B.1 Alternative Measures

Table 9: Alternative Measures of Markup

	DEU - Demean (1)	DEU - (Cogs+Xsga) (2)	Gross Margin (3)
Mean Change at Cutoff (p.p.)	0.839^{***}	0.823^{***}	1.776^{***}
	(0.124)	(0.100)	(0.148)
Firm, Quarter FEs	Yes	Yes	Yes
Observations	76121	69533	71794

Notes: The Table reports the estimated discontinuity in markup growth (in p.p.) for firms just hitting profit targets. We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is the demean markup in Column (1), DEU with overhead costs in Column (2) and gross margin in Column (3). These measures are all at the firm-quarter level, $\Delta \log \mu_{i,t}$, and the running variable is forecast error, fe_{it}. Markups are estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. Standard errors, clustered at the firm level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

Table 10: Alternative Measures of Forecast Errors

	% Market Value (1)	% Lagged Sales (2)
Mean Change at Cutoff (p.p.)	0.756***	0.960***
	(0.122)	(0.087)
Firm, Quarter FEs	Yes	Yes
Observations	80174	80188

Notes: The Table reports the estimated discontinuity in markup growth (in p.p.) for firms just hitting profit targets. We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The regressor is forecast error scaled by market value in Column (1) and forecast error scaled by lagged sales in Column (2). These measures are all at the firm-quarter level, $\Delta \log \mu_{i,t}$, and the dependent variable is markup, which is estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. Standard errors, clustered at the firm level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $* * *$ = 1% level. See Appendix E for additional information on variables construction.

B.2 Additional Controls

Table 11: Inventories - Alternative Measures

	DEU (1)	DEU - Demean (2)	DEU - (Cogs+Xsga) (3)	Gross Margin (4)
Mean Change at Cutoff (p.p.)	0.826***	0.793***	0.911***	1.796***
	(0.110)	(0.116)	(0.100)	(0.161)
Firm, Quarter FEs	Yes	Yes	Yes	Yes
Observations	62237	62258	58882	59870

Notes: The Table reports the estimated discontinuity in markup growth (in p.p.) for firms just hitting analysts' forecasts. We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is the unexplained component of markup growth projected on inventories. We use alternative measures of markup (DEU in Column (4), DEU including overhead costs in Column (5) and gross margin in Column (6)). These measures are all at the firm-quarter level, $\Delta \log \mu_{i,t}$, and the running variable is forecast error, fe_{it}. Also in this case, for robustness check, we employ three alternative measures of forecast errors as the regressor (scaled by total assets in Column (1), by market value in Column (2) and by lagged sales in Column (3)). In these cases, markups are estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. Standard errors, clustered at the firm level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level. See Appendix E for additional information on variables construction.

Table 12: RDD Coefficient with sectoral characteristics

	HHI (1)	Elasticity (2)	Calvo (3)	Inventory (4)	Markup (5)
δ	0.153***	-0.218**	0.121*	-0.226***	0.469**
	(0.054)	(0.093)	(0.068)	(0.053)	(0.208)

Notes: The Table presents the correlation between the markup discontinuity across sectors (at NAICS5 level) and the following regressors: inventories in Column (1), HHI in Column (2), elasticity of substitution in Column (4), and adjustment price frequency in Column (5). Column (3) measures the relationship between the markup discontinuity and the markup level across quintiles of the markup distribution. Markup measures are estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. Discontinuity coefficients are obtained from the local linear regression model, Equation (3). Inventories are the variable *invtq* in Compustat. HHI is computed from sales (*saleq* in Compustat). The elasticities of substitution are from Broda and Weinstein (2006) while the sectoral adjustment price frequencies are from Pasten et al. (2020). $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level. See Appendix E for additional information on variables construction.

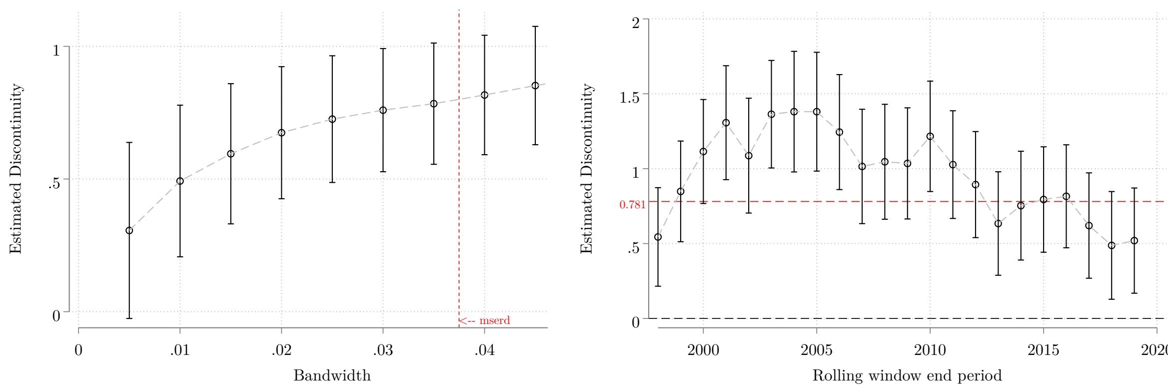
Table 13: Diversification

	Below Median (1)	Above Median (2)	Below Median Ind (3)	Above Median Ind (4)
Mean Change at Cutoff (p.p.)	0.585***	1.109***	0.630***	0.948***
	(0.140)	(0.224)	(0.147)	(0.213)

Notes: The Table reports the discontinuity in markup growth estimated using Equation (3) after splitting the sample in two subsamples (above and below median) on the basis of the firm diversification indices constructed by Choi et al. (2021). Columns (1) and (2) consider a global index of diversification (industrial, geography, finance and accounting, regulation and legal compliance, business operations and miscellaneous), while Columns (3) and (4) consider industrial diversification only. Importantly, a diversification index above the median means that a firm is relatively less diversified than a firm below the median. Markup measures are estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

B.3 Optimal Bandwidth and Discontinuity Over Time

Figure 21: Optimal Bandwidth



Notes: The panel on the left illustrates how the estimated discontinuity in markup growth (in p.p.) for firms just hitting analysts' forecasts changes for different levels of bandwidth (on the horizontal axis). We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and a bandwidth ranging between 0.005 and 0.05. The vertical dashed line represents the optimal bandwidth according to Calonico et al. (2020) used in the main specification. In the panel on the right we estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020) and a 32-quarter rolling window. The dependent variable is markup growth at the firm-quarter level, $\Delta \log \mu_{i,t}$, and the running variable is forecast error, fe_{it}. Markups are estimated using Compustat data from 1990 to 2018, following DEU and using cost of good sold as variable input. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. The confidence intervals at the 90% are computed clustering at the firm level. See Appendix E for additional information on variables construction.

B.4 Sales vs Costs

Table 14: Sales vs Costs - Alternative Measures of Forecast Errors

	% Market Value		% Lagged Sales	
	Δ log Sales	Δ log Costs	Δ log Sales	Δ log Costs
	(1)	(2)	(3)	(4)
Mean Change at Cutoff (p.p.)	1.2046***	0.3037*	1.4302***	0.7033***
	(0.176)	(0.159)	(0.158)	(0.144)
N	79159	79024	79174	79039
Firm, Quarter FEs	Yes	Yes	Yes	Yes

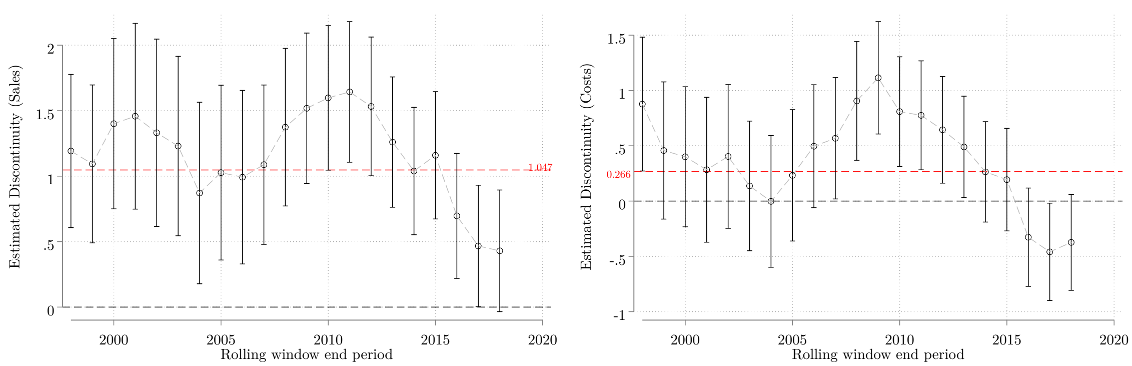
Notes: The Table reports the estimated discontinuity in sales and costs growth (in p.p.) for firms just hitting analysts' forecasts. We estimate Equation (3) using a local linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). In Columns (1) and (3) (Columns (2) and (4)), the dependent variable is sales (costs) growth at the firm-quarter level. The running variable is forecast error, fe_{it}. Sales (costs) growth is computed as the log difference in sales (costs), defined as *saleq* (*cogs*) from Compustat. The dataset runs from 1990 to 2018. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' market value (Columns (1) and (2)) or by lagged sales (Columns (3) and (4)). All specifications include firm and quarter fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

Table 15: Sales vs Costs - Alternative Measures of Cost

	% Total Assets	% Market Value	% Lagged Sales
	(1)	(2)	(3)
Mean Change at Cutoff (p.p.)	0.1352	0.2319	0.6517***
	(0.147)	(0.142)	(0.139)
N	69752	72244	72258
Firm, Quarter FEs	Yes	Yes	Yes

Notes: The Table reports the estimated discontinuity in costs growth (in p.p.) for firms just hitting analysts' forecasts. We estimate Equation (3) using a local linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is costs growth at the firm-quarter level. Costs growth is computed as the log difference in costs, defined as cost of good sold plus overhead costs($cogs + xsag$ in Compustat from 1990 to 2018). The running variable is forecast error, fe_{it}. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets (Column (1)), market value (Column (2)) or by lagged sales (Columns (3)). All specifications include firm and quarter fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

Figure 22: Sales vs Costs - Estimated Discontinuity over Time



Notes: The Figure plots the discontinuity in sales and costs growth (in p.p.) for firms just hitting analysts' forecasts over time. We estimate Equation (3) using a local linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020) and a 32-quarter rolling window. In the left (right) panel, the dependent variable is sales (costs) growth at the firm-quarter level. Sales (costs) growth is computed as the log difference in sales (costs), defined as *saleq* (*cogs*) from Compustat. The dataset runs from 1990 to 2018. The running variable is forecast error, fe_{it}. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. For each window, we report the estimated discontinuity and the 90% confidence intervals using standard errors clustered at the firm level. The horizontal dashed red line represents the estimated discontinuity from the main specification using the whole sample. See Appendix E for additional information on variables construction.

B.5 Boom vs Recession

Table 16: Markup Growth - Boom vs Recession

	Boom	Recession	Difference
	(1)	(2)	(3)
Mean Change at Cutoff (p.p.)	0.718***	1.765***	
	(0.126)	(0.437)	
Difference in Mean Change at Cutoff (p.p.)			0.825***
			(0.145)
Firm, Quarter FEs	Yes	Yes	Yes
Observations	69306	6781	66083

Notes: The Table reports the estimated discontinuity in markup growth (in p.p.) for firms just hitting analysts' forecasts, splitting the sample in two subsamples, Boom (Column (1)) and Recession (Column (2)). We estimate Equation (3) using a local linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is markup growth at the firm-quarter level, $\Delta \log \mu_{i,t}$, the running variable is forecast error, fe_{it}. The first two columns consider only quarters of economic boom (recession), as of NBER dates, while Column (3) reports the estimated difference in discontinuities between Recession and Boom. The coefficient is estimated via OLS augmenting the main specification in Equation (3) with a triple interaction $\xi \mathbb{1}(fe_{it} \geq 0)\mathbb{1}(\text{Recession} = 1)$. The sample is restricted to include the observations within the optimal bandwidth used in the main specification. Standard errors, clustered at the firm level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

Table 17: Sales vs Costs - Boom vs Recession

	Δ log Sales		Δ log Costs		Alternative Δ log Costs	
	Boom	Recession	Boom	Recession	Boom	Recession
	(1)	(2)	(3)	(4)	(5)	(6))
Mean Change at Cutoff (p.p.)	0.8424***	3.3617***	0.1086	1.8156***	-0.0084	1.3210**
	(0.182)	(0.632)	(0.162)	(0.561)	(0.154)	(0.552)
N	69500	6755	69332	6737	63561	6191
Firm, Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The Table reports the estimated discontinuity in sales and costs growth (in p.p.) for firms just hitting analysts' forecasts, splitting the sample in two subsamples, Boom (Columns (1), (3) and (4)) and Recession (Columns (2), (4) and (6)). We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is sales growth at the firm-quarter level in Columns (1) and (2). Columns (3) and (4) use cost of good sold while Columns (5) and (6) use cost of good sold plus overhead cost. Data are from Compustat, from 1990 to 2018. The running variable is forecast error, fe_{it}. Forecast errors is the differences between realized profits and the median analyst forecasts from IBES, scaled by firms' total assets. Boom and recession are defined according to the NBER dates. All specifications include firm and quarter fixed effects. Standard errors, clustered at the firm level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level. See Appendix E for additional information on variables construction.

C Derivation Toy Model

Given the real interest rate R, short-term costs θ_π and analysts forecasts Π_t^f, manager chooses p_t to maximize the present value of profits today and tomorrow:

$$\max_{p_t} \quad V^M\Big(p_t \mid \Pi_t^f, \theta_\pi\Big) := (p_t - c)\bar{b}^\theta p_t^{-\eta} + \phi_e y_t - \theta_\pi y_t \mathbb{P}\Big(\Pi_t < \Pi_t^f\Big) + \frac{1}{R}(\bar{p} - c)\frac{(\delta\bar{b})^\theta}{\bar{p}^\eta} p_t^{(1-\eta)\theta}$$

where the price tomorrow $\bar{p}$ solves the static profit maximization problem:

$$\max_{\bar{p}} \quad (\bar{p} - c) b_{t+1}^\theta \bar{p}^\eta \quad \text{s.t.} \quad b_{t+1} = \delta \bar{b}^\theta p_t^\eta$$

The FOC with respect to $\bar{p}$ pins down the optimal manager price tomorrow:

$$\bar{p} = \frac{\eta}{\eta - 1} c$$

Given $\bar{p}$, the FOC with respect to p_t pins down optimal manager price:

$$\left(1-\eta\frac{p_t-c}{p_t}\right)-\frac{\eta}{p_t}\phi_e+\left[\theta_\pi\mathbb{P}\left(\Pi_t<\Pi_t^f\right)+\theta_\pi f_\nu\frac{\partial\Pi_t}{\partial p_t}\right]-\frac{1}{R}(\bar{p}-c)\frac{\delta^\theta}{\bar{p}^\eta}(\eta-1)\theta p_t^{(\eta-1)(\theta-1)}=0$$

Simplifying and rearrenging:

$$\left(1-\eta\frac{p_t-c}{p_t}\right)-\frac{\eta}{p_t}\phi_e+\left[\theta_\pi\mathbb{P}\left(\Pi_t<\Pi_t^f\right)+\theta_\pi f_\nu\frac{\partial\Pi_t}{\partial p_t}\right]=\frac{1}{R}(\bar{p}-c)\frac{\delta^\theta}{\bar{p}^\eta}(\eta-1)\theta p_t^{(\eta-1)(\theta-1)}$$

The term on the left hand side is the marginal benefit of increasing prices today while, on the right hand side is the marginal cost of increasing prices today.

D Quantitative Model

D.1 Algorithm for Stationary Equilibrium

We use a value function iteration procedure to compute the stationary equilibrium of the model. We calculate the distribution of firms across the idiosyncratic state-space using a non-stochastic simulation approach, as outlined in Young (2010). The algorithm comprises three steps and is utilized to estimate the model, as detailed in the paper.

Grid. We use a three-dimensional grid to represent the state variables of the firm: its customer base, productivity, and observed demand noise. We discretize the continuous exogenous processes for productivity (a) and observed demand shock (ε) into a discretized Markov chain using the method outlined in Tauchen (1986). We set the number of grid points for a to 7 and for ε to 9. This results in a transition matrix of dimensions 63 x 63, with column sums equaling one.

The customer base grid, denoted as b, consists of a set of 161 points within a finite interval of non-equally spaced points, designed to provide denser coverage in the lower range of the customer distribution. We set the maximum customer value to 24 and the minimum to 1. To ensure that the ergodic distribution of firms does not exclude firms at the boundaries, we implement appropriate checks. Once the grids are established, we employ value function iteration to seek a solution.

Algorithm. We implement the following algorithm to compute the stationary equilibrium of the model following Terry (2022):

(1) Guess short-term incentives θ_π;

   a) Guess an initial value for the analysts forecasts $\Pi^f_{0,t}$ and solve manager policy;

      i) Guess a value function for the manager the $V_0^M(a, \varepsilon, b)$;

      ii) Find the policy function (b', m) that it solve the Bellman equation for each element in the grid;

      iii) Calculate the new value function $V_1^M(a, \varepsilon, b)$;

      iv) Update the value function and iterate until $\max ||V_1^M - V_0^M||$ is arbitrary small;

   b) Update analysts forecasts $\Pi^f_{1,t}$ given managers policies;

      i) Calculate the implied firms' realized profits Π_t over the states;

      ii) Calculate the expected profits $\Pi^f_{1,t}$ using the unconditional probabilities from the transition matrix;

   c) Update the analysts forecasts and iterate until $\max ||\Pi^f_{1,t} - \Pi^f_{0,t}||$ is arbitrary small;

(2) Compute the implied mean firm value objective of boards given θ_π via (19).

(3) If the board objective is optimized, realized short-term incentives θ_π^* are computed. If not, update the guess for θ_π and return to 1.a.

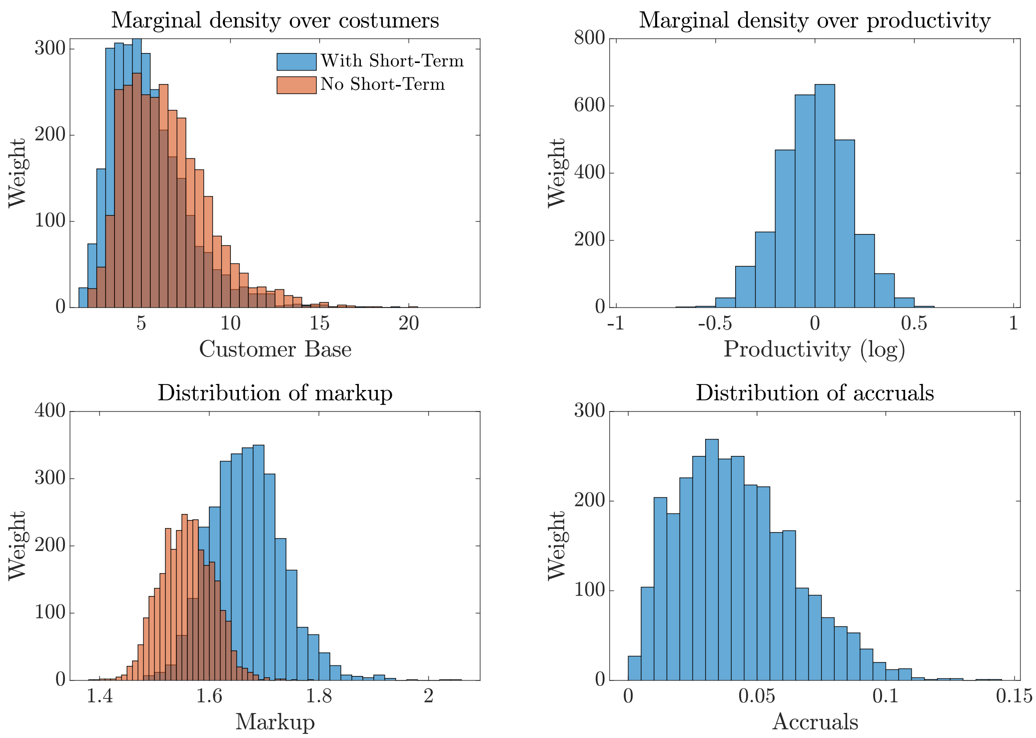
(4) Given a solution for b', m calculate the distribution Γ of firms over (a, ε, b) in the stationary equilibrium using Young (2010).

A solution to this problem deliver the policy function for b', m and a policy functions over the space grid (a, ε, b). For the counter-factual experiments, we only solve the model without finding the short-term parameter θ_π in the algorithm.

Simulation. We conduct simulations for firms based on the optimal solution to calculate target moments. Specifically, we simulate a panel of 3,000 firms over a span of 150 quarters each, discarding an initial 50-quarter burn-in period. As target moments are characterized by differentiable functions of means, we compute the covariance of the underlying means while employing firm-based clustering, following the approach of Hansen and Lee (2019). Subsequently, we estimate the covariance matrix Σ for these moments using the Delta method. The resulting optimal weighting matrix is determined as the inverse of the covariance matrix, denoted as $W = \Sigma^{-1}$.

D.2 Ergodic Distribution and Manager Policies

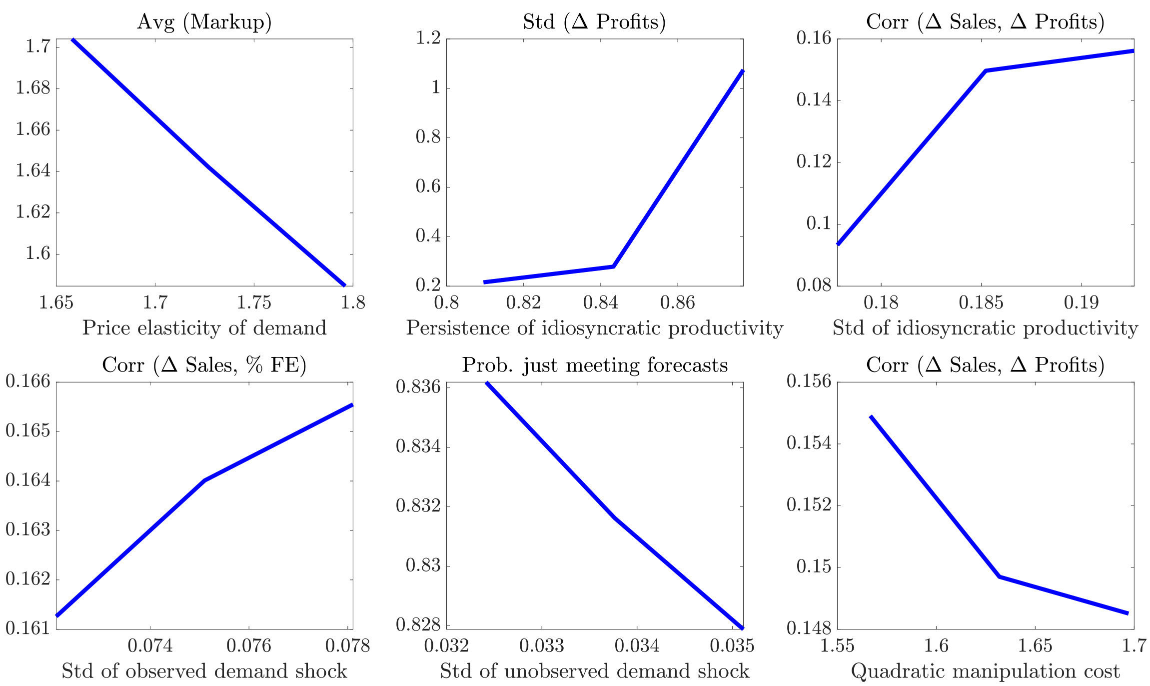
Figure 23: Density and Manager Policy



Notes: In red bars, the histogram of the policy functions for markup and costumers with no short-term incentives ($\theta_\pi = 0$), while in blue bars the histogram of the policy functions with short-term incentives (θ^*_π). The first row of the figure plots the marginal density over customers (left) and productivity (right). The second row plot the distribution of markups and the manager's accruals manipulation policies. These policies are based on the model's parameterization reported in Table 2. We average over time before plotting the histogram. All plots are generated from averaging 3000 simulated firms over 50 quarters before plotting.

D.3 Parameters Identification from SMM

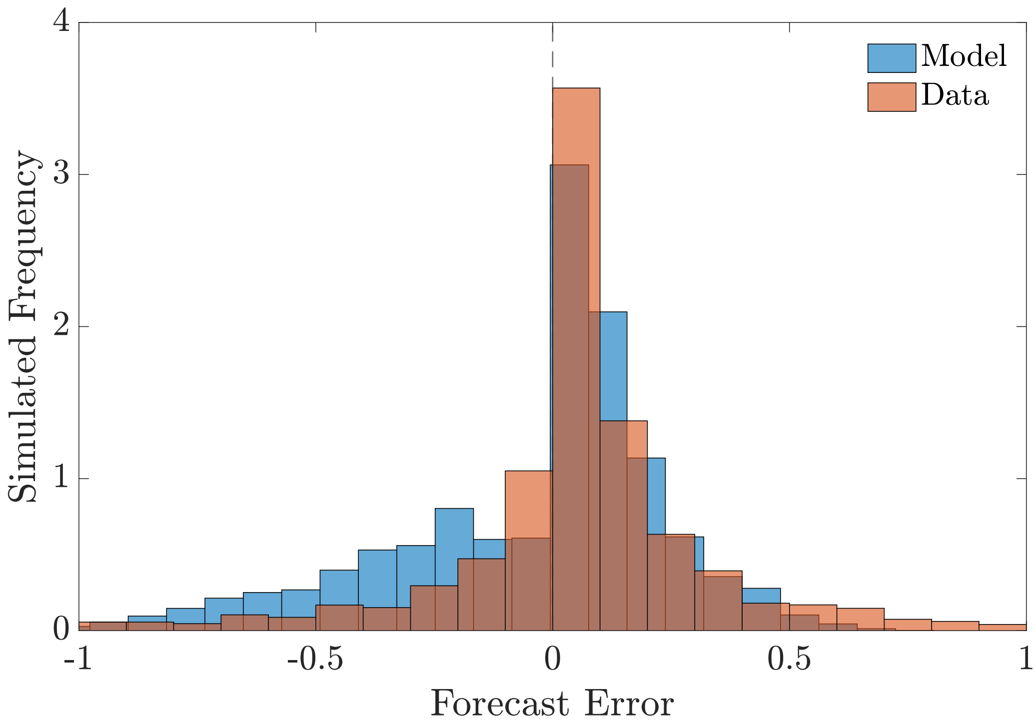
Figure 24: Identification of the other parameters



Notes: Figure 24 plots selected simulated smoothed target moments on the remaining estimated parameters, varying the value above and below the baseline estimate in Panel A of Table 2.

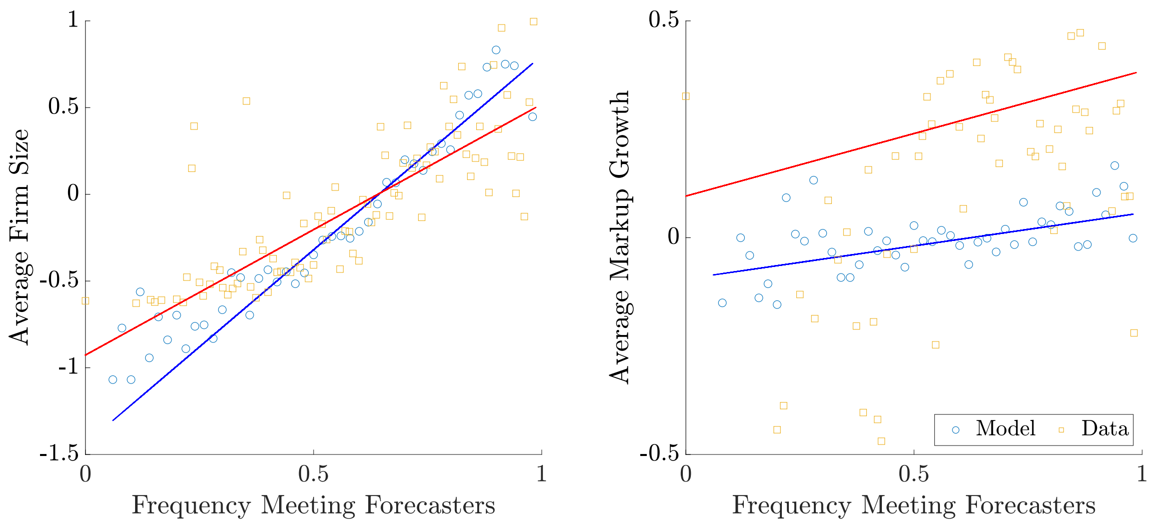
D.4 Model Fit and Untargeted Moments

Figure 25: Forecast Error Distributions



Notes: Figure 25 compares the distribution of forecast errors generated in the model (blue) and data (red). The bunching of firm profits at zero or just above forecasts is targeted in estimation. The distribution of forecast error in the data is computed on the 2013-2018 panel sample of 1,587 firms for 48,016 firm-quarters. Realized profits are quarterly earnings; forecast profits are the median analyst forecasts at quarterly frequency from IBES. Forecast errors are computed as the percentage difference between realized profits and forecast profits using Haltiwanger formula. The distribution of forecast errors in the model is computed on a panel of simulated data of 3,000 firms for 50 quarters. Simulated data are generated from a model based on the parameterization reported in table 2. Forecast errors in the model are computed as the percentage difference between reported profits and forecast profits using Haltiwanger formula.

Figure 26: Untargeted Moments



Notes: Figure 26 plots the relationship between frequency of meeting forecasters' expectations and size (left-hand side) and markup growth (right-hand side). Variables are computed on a panel of simulated data of 3,000 firms for 50 quarters. Simulated data are generated from a model based on the parameterization reported in table 2. Forecast errors in the model are computed as the percentage difference between reported profits and forecast profits using Haltiwanger formula. Frequency of meeting forecasters is the average number of times a firm meet forecasters over 50 quarters in simulated data; size is the average number of costumers registered by the firm over 50 quarters; markup growth is the average markup change within a quarter for each of the simulated firms over thee 50 quarters.

Table 18: Discontinuity in markup growth in the model

	Model (1)	Model (2)	Data (3)	Data (4)
Mean Change at Cutoff (p.p.)	1.036**	1.062**	0.841***	0.790***
	(0.463)	(0.461)	(0.139)	(0.114)
Standardized (p.p.)	5.284	5.485	5.061	4.813
Firm, Quarter FEs	No	Yes	No	Yes
Mean $\lvert\Delta \log \mu\rvert$ (p.p.)	12.236	12.236	8.300	8.300
Median $\lvert\Delta \log \mu\rvert$ (p.p.)	8.402	8.402	3.179	3.179
Observations	139650	139650	79014	79014

Notes: The Table reports the estimated discontinuity in markup growth (in p.p.) for firms just hitting analysts' forecasts. We estimate Equation (3) using a Local Linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). The dependent variable is markup growth at the firm-quarter level, $\Delta \log \mu_{i,t}$, and the running variable is forecast error, fe_{it}. Forecast errors is the differences between realized profits and the median analyst forecasts from simulated data. Markups are defined as the ratio between price and productivity scaled by wages. Data is generated from 3000 simulated firms over 50 quarters. Column (2) includes firm and quarter fixed effects while column (1) does not. The table reports also the estimated discontinuity in markup growth (in p.p.) after standardizing the outcome variable by its mean and standard deviation. Mean (median) $|\Delta \log \mu_{i,t}|$ refer to the average (median) of the absolute markup growth rates. Standard errors, clustered at the firm level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $* * * = 1\%$ level.

D.5 Robustness and Extensions

Table 19: Estimated parameters and moments - Decreasing Accrual Costs

A. Estimated parameters	Symbol	Estimate	(Std. Error)
Price elasticity of demand	η	1.8091	0.0072
Persistence of idiosyncratic productivity	ρ_a	0.7874	0.0113
Std of idiosyncratic productivity	σ_a	0.1865	0.0030
Std of observed demand shock	σ_e	0.0522	0.0008
Std of unobserved demand shock	σ_u	0.0213	0.0001
Quadratic manipulation cost	ϕ_m	1.2942	0.0172
Private benefit manager	ϕ_e	0.0306	0.0004
B. Targeted moments	Data	(Std. Error)	Model
Std. deviation of sales growth	0.1591	0.0029	0.2411
Correlation of sales growth, profits growth	0.4924	0.0148	0.0781
Correlation of sales growth, forecast error	0.0610	0.0066	0.1312
Std. deviation of profits growth	0.4921	0.0075	0.4967
Correlation of profits growth, markup growth	0.1784	0.0150	0.1724
Correlation of profits growth, forecast error	0.1082	0.0090	0.2446
Std. deviation of markup growth	0.0915	0.0028	0.1691
Correlation of markup growth, forecast error	0.0887	0.0074	0.1634
Std. deviation of forecast error	0.5707	0.0091	0.2453
Probability of meeting forecasts	0.7094	0.0028	0.7729
Probability of just meeting forecasts	0.7707	0.0046	0.8561
Mean of markup	1.5540	0.0189	1.5886
C. Quantitative impact			p.p.
Mean markup increase from short-term pressure			7.353
Mean shareholders profit gain from short-term pressure			5.614
Welfare loss from short term pressure			[3.389,4.965]
Market capitalization loss from short-term pressure			9.042
Average effect			-0.811
Distribution effect			9.853

Notes: Panel A's SMM parameter estimates use efficient moment weighting. Panel B's data moments use a 2003-2018 Compustat-IBES panel of 1,587 firms for 48,016 firm-quarters. Standard errors are firm clustered. Panel C's are the estimates of the impact of short-termism comparing the average moments in the model with short-term incentives (θ_π^*) to the moments in the model without short-term incentives ($\theta_\pi = 0$). Model moments are computed over a 50-quarter simulated panel of 3,000 firms, with a burn-in period of 25 years. Moment units are proportional (0.01 = 1%).

Table 20: Estimated parameters and moments - Sales Benefit

A. Estimated parameters	Symbol	Estimate	(Std. Error)
Price elasticity of demand	η	1.8565	0.0001
Persistence of idiosyncratic productivity	ρ_a	0.8549	0.0052
Std of idiosyncratic productivity	σ_a	0.1424	0.0005
Std of observed demand shock	σ_e	0.1035	0.0005
Std of unobserved demand shock	σ_u	0.0210	0.0021
Quadratic manipulation cost	ϕ_m	0.8109	0.0833
Private benefit manager	ϕ_e	0.0995	0.0019
B. Targeted moments	**Data**	**(Std. Error)**	**Model**
Std. deviation of sales growth	0.1591	0.0029	0.2485
Correlation of sales growth, profits growth	0.4924	0.0148	0.0204
Correlation of sales growth, forecast error	0.0610	0.0066	0.0642
Std. deviation of profits growth	0.4921	0.0075	0.5476
Correlation of profits growth, markup growth	0.1784	0.0150	0.2210
Correlation of profits growth, forecast error	0.1082	0.0090	0.2401
Std. deviation of markup growth	0.0915	0.0028	0.1773
Correlation of markup growth, forecast error	0.0887	0.0074	0.2231
Std. deviation of forecast error	0.5707	0.0091	0.2596
Probability of meeting forecasts	0.7094	0.0028	0.7617
Probability of just meeting forecasts	0.7707	0.0046	0.8396
Mean of markup	1.5540	0.0189	1.5613
C. Quantitative impact			**p.p.**
Mean markup increase from short-term pressure			12.983
Mean shareholders profit gain from short-term pressure			13.843
Welfare loss from short term pressure			[5.190,7.873]
Market capitalization loss from short-term pressure			14.461
Average effect			-2.208
Distribution effect			16.669

Notes: Panel A's SMM parameter estimates use efficient moment weighting. Panel B's data moments use a 2003-2018 Compustat-IBES panel of 1,587 firms for 48,016 firm-quarters. Standard errors are firm clustered. Panel C's are the estimates of the impact of short-termism comparing the average moments in the model with short-term incentives (θ_π^*) to the moments in the model without short-term incentives ($\theta_\pi = 0$). Model moments are computed over a 50-quarter simulated panel of 3,000 firms, with a burn-in period of 25 years. Moment units are proportional ($0.01 = 1\%$).

Table 21: Estimated parameters and moments - CES model

A. Estimated parameters	Symbol	Estimate	(Std. Error)
Price elasticity of demand	η	2.2336	0.0064
Persistence of idiosyncratic productivity	ρ_a	0.6552	0.0049
Std of idiosyncratic productivity	σ_a	0.2131	0.0035
Std of observed demand shock	σ_e	0.1166	0.0017
Std of unobserved demand shock	σ_u	0.0523	0.0005
Quadratic manipulation cost	ϕ_m	0.8205	0.0001
Private benefit manager	ϕ_e	0.0250	0.0001
B. Targeted moments	**Data**	**(Std. Error)**	**Model**
Std. deviation of sales growth	0.1591	0.0029	0.3620
Correlation of sales growth, profits growth	0.4924	0.0148	0.4590
Correlation of sales growth, forecast error	0.0610	0.0066	0.3235
Std. deviation of profits growth	0.4921	0.0075	0.7293
Correlation of profits growth, markup growth	0.1784	0.0150	-0.1062
Correlation of profits growth, forecast error	0.1082	0.0090	0.2732
Std. deviation of markup growth	0.0915	0.0028	0.0423
Correlation of markup growth, forecast error	0.0887	0.0074	-0.2758
Std. deviation of forecast error	0.5707	0.0091	0.1793
Probability of meeting forecasts	0.7094	0.0028	0.7103
Probability of just meeting forecasts	0.7707	0.0046	0.8585
Mean of markup	1.5540	0.0189	1.7774
C. Quantitative impact			**p.p.**
Mean markup increase from short-term pressure			2.091
Mean shareholders profit gain from short-term pressure			0.112
Welfare loss from short term pressure			[1.670,1.741]
Market capitalization loss from short-term pressure			-0.112
Average effect			-0.112
Distribution effect			-0.000

Notes: Panel A's SMM parameter estimates use efficient moment weighting. Panel B's data moments use a 2003-2018 Compustat-IBES panel of 1,587 firms for 48,016 firm-quarters. Standard errors are firm clustered. Panel C's are the estimates of the impact of short-termism comparing the average moments in the model with short-term incentives (θ_π^*) to the moments in the model without short-term incentives ($\theta_\pi = 0$). Model moments are computed over a 50-quarter simulated panel of 3,000 firms, with a burn-in period of 25 years. Moment units are proportional (0.01 = 1%).

Chapter 2

A Empirics

A.1 Data

We use three main sources of information:

- We use data on 18 currencies from December 1993 to December 2019. The currencies considered are: Euro, Japanese Yen, Argentinian Peso, Brazilian Real, Canadian Dollar, Swiss Franc, Australian Dollar, Chilean Peso, Indian Rupee, Mexican Peso, British Pound, South African Rand, Russian Ruble, Swedish Krona, Turkish Lira, New Zealand Dollar, Singapore Dollar, Norwegian Krone. The panel is not balanced.

  We obtain data for the spot and one-month forward exchange rates at a daily frequency from Datastream and Thompson Reuters. All exchange rates are defined against the US Dollar. To calculate the one-month interest rate, we took the difference between the logarithm of the one-month forward exchange rate and the logarithm of the spot exchange rate. We then computed monthly averages for the spot exchange rates and the one-month interest rate differentials.

- We use data from the U.S. Commodity Futures Trading Commission (CFTC) on investors' currency positions. The U.S. Commodity Futures Trading Commission (CFTC) data provides detailed information on several aspects within the currency futures market, including net open interest positions held by asset managers, institutional investors, and leveraged funds, as well as measures of concentration and the number of reportable traders. Data is reported on a weekly basis and spans the years 2006 to 2016 for 11 currency pairs. These pairs include both major and non-major USD currency pairs, reflecting the diversity of assets traded within the currency futures market. Major currency pairs typically involve the U.S. dollar and another major global currency, such as the Euro or Japanese Yen, while non-major pairs may involve currencies from emerging markets or smaller economies. Table 22 in Appendix A reports summary statistics on key variables. Figures 27, 28 and 29 in Appendix A respectively show the net open positions, the concentration ratio, and the number of reportable traders in the future FX market per currency and trader group.

- We use data on exchange rate expectations from the ECB Professional Forecasters survey. The survey runs at quarterly frequency since 2002Q1 until 2020Q4. It provides information on the expectations of professional forecasters regarding the euro-dollar exchange rate at different time horizons, including the current quarter and one to four quarters ahead. The dataset includes exchange rate forecasts from approximately forty professional forecasters.

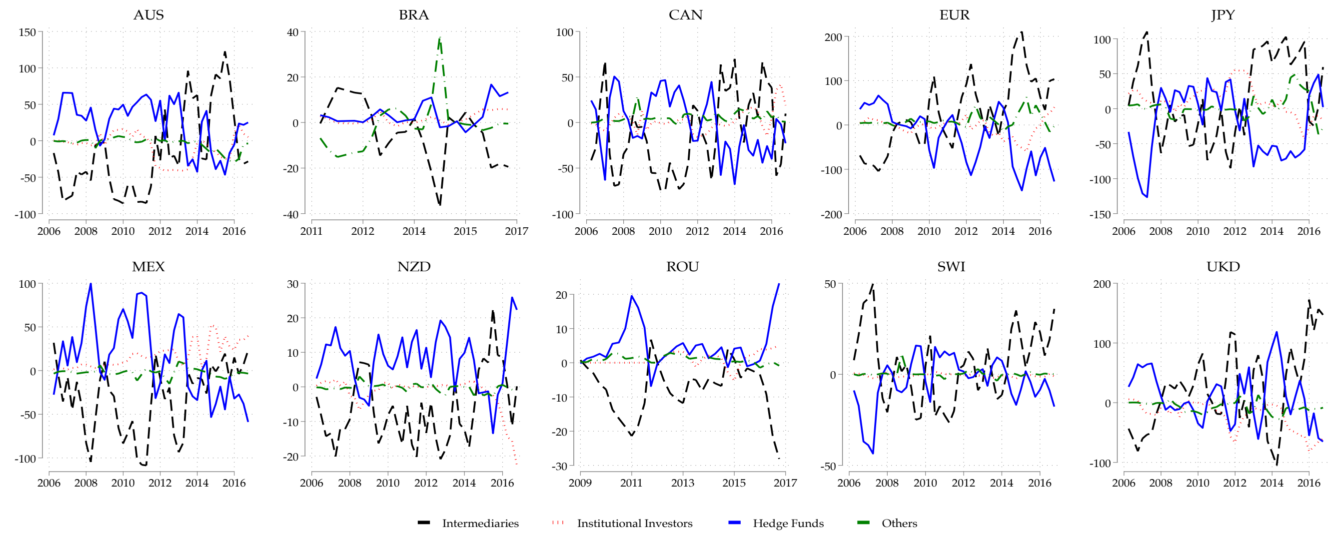
A.2 Additional Figures and Tables

Table 22: Summary Statistics

	Currency										
	AUS	BRA	CAN	EUR	JPY	MEX	NZD	ROU	SWI	UKD	Total
Imbalances (Mil $): Intermediaries	-16.187	-6.434	-12.622	28.306	18.102	-32.057	-6.518	-7.947	5.374	22.884	-0.135
Institutional Investors	-7.796	2.055	2.180	-5.056	11.952	17.415	-1.776	1.024	-0.638	-22.889	-0.541
Hedge Funds	24.308	3.976	-1.946	-26.019	-20.756	15.288	7.938	5.004	-3.836	10.268	1.153
Others	-4.226	0.307	5.804	9.966	2.195	-2.215	-0.282	0.969	0.263	-7.537	0.524
Concentration: Top 4 (Net)	0.433	0.700	0.368	0.295	0.392	0.537	0.553	0.566	0.411	0.396	0.448
Top 8 (Net)	0.564	0.795	0.484	0.399	0.513	0.680	0.704	0.676	0.537	0.523	0.572
Number: Intermediaries	7.795	4.693	7.442	13.417	8.921	7.069	6.761	6.327	6.180	7.289	7.832
Institutional Investors	6.117	0.084	5.430	15.686	7.775	6.196	2.744	0.000	1.983	7.331	6.444
Hedge Funds	15.600	6.129	13.881	25.064	19.689	16.121	9.867	4.883	8.896	16.649	14.734
Others	5.364	2.340	7.249	12.576	6.350	6.864	4.198	0.482	0.199	5.110	5.949

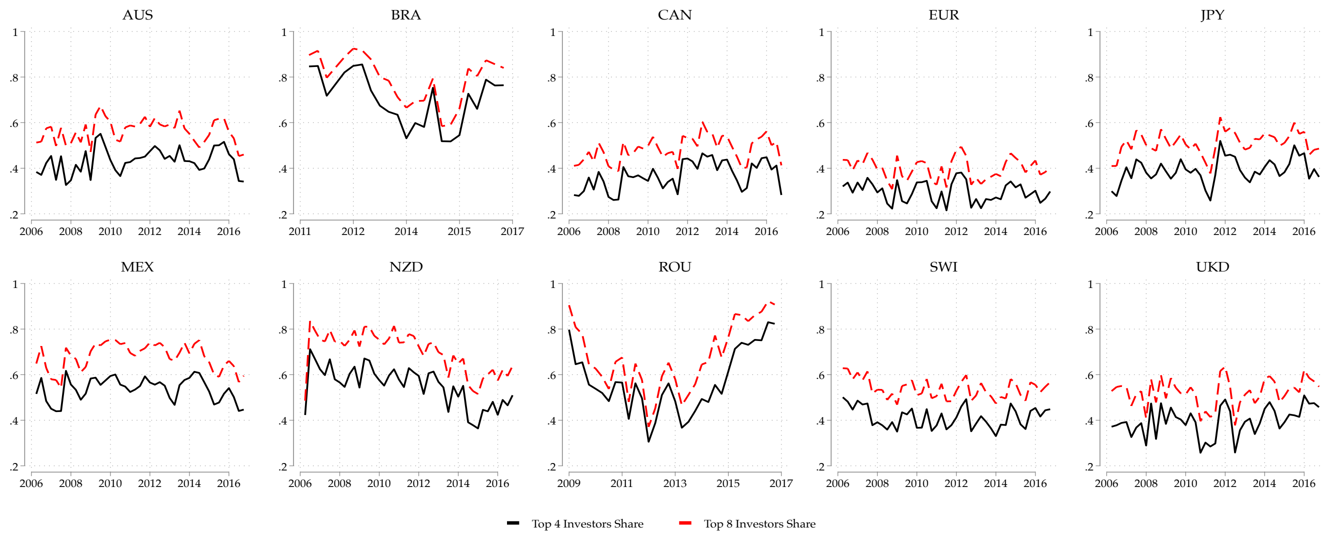
Notes: Report the means of the main variables in the CFTC dataset by currency pair. Net open interest positions are in millions of dollars ($), concentration ratios are expressed in percentages, and the number of traders is in count. The reported mean statistic is calculated based on a panel of weekly observations spanning from 2006 to 2018.

Figure 27: Net Open Interest Position by Currency Pairs



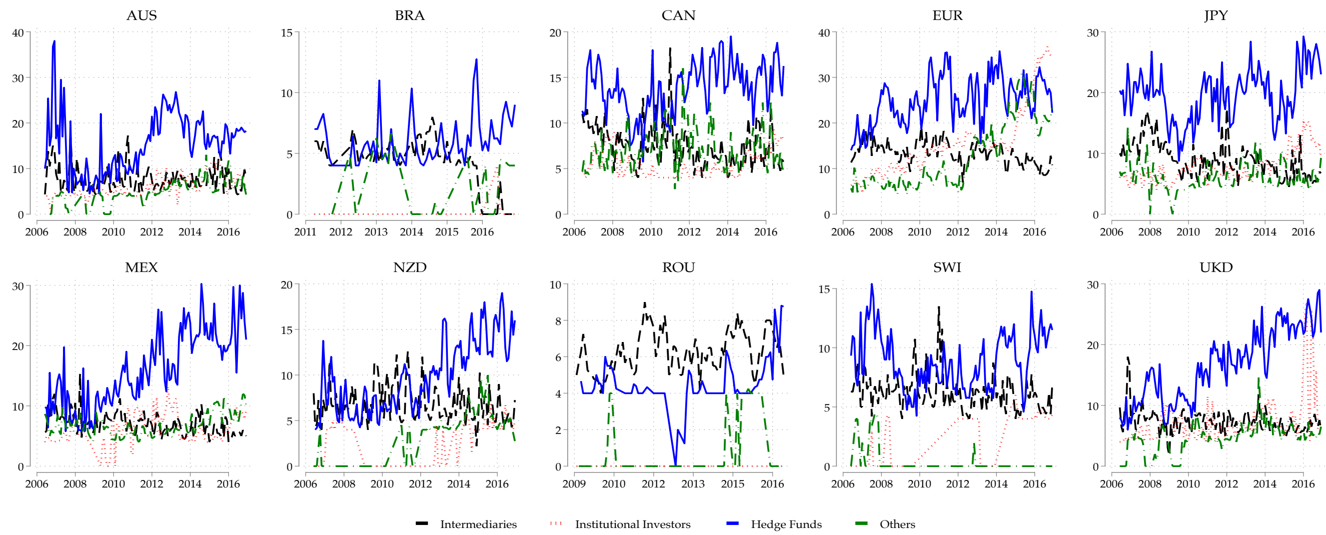
Notes: The figure shows the net positions for the reportable traders in the future FX market by currency pair. Net Positions are calculated after offsetting each trader's equal long and short positions. We report net positions for Dealers (black dashed line), Institutional Investors (red dotted line), Hedge Funds (blue line) and Other Reportable Traders (green dashed line). The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016. Data are quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

Figure 28: Concentration Ratios by Currency Pairs



Notes: The figure shows the average percentages of open interest held, referred to as Concentration Ratios, by the largest four (black line) and eight (red line) reportable traders in the future FX market by currency pair. These concentration ratios are based on 'Net Position' and are calculated after offsetting each trader's equal long and short positions. The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016. Data are quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

Figure 29: Number of Traders by Currency Pairs



Notes: The figure shows the numbers of reportable traders in the future FX market by currency pair. For each currency pair, we report the number of Dealers (black dashed line), Institutional Investors (red dotted line), Hedge Funds (blue line) and Other Reportable Traders (green dashed line). The data is sourced from the U.S. Commodity Futures Trading Commission (CFTC) and spans from 2006 to 2016. Data are quarterly averages for each currency pair. Appendix A provides additional details regarding the data used.

Table 23: Expectation Dispersion

	Whole Sample	Average across Quarters	Median across Quarters
Same Quarter	0.028	0.024	0.020
Across all Horizons	0.041	0.038	0.035

Notes: The table reports the standard deviation of EUR/USD exchange rate expectations from the ECB Professional Forecasters survey. Data covers the period from 2002Q1 to 2020Q4 and is collected at a quarterly frequency for various horizons ranging from the same quarter to one year ahead. The expectations are expressed in logarithmic form to maintain consistency with the log-linearized model. Expectations are demeaned at the quarterly-horizon level. The first row focuses on same-quarter expectations, while the second row considers all horizons pooled together. The first column reports the dispersion (standard deviation) in exchange rate expectations across the whole sample period. The second and third columns compute the dispersion for each quarter and report the average and median dispersion across all quarters, respectively.

B Derivations and Additional Results

B.1 Derivation Demand Functions - Rational Expectation Case

Each investor j solves the following problem:

$$\max_{b_t^j} E_t^j(w_{t+1}^j|\Omega_t^j) - \frac{\rho}{2} Var_t^j(w_{t+1}^j|\Omega_t^j)$$

$$\text{s.t. } w_{t+1}^j = (\omega - b_t^j)i_t + (i_t^\star + s_{t+1} - s_t)b_t^j$$

We assume that investors have symmetric rational expectation information sets, so that all j indexes on expectation and variance are dropped. We take the derivative of the objective function w.r.t. b_t^j. If the investor is strategic ($j = S$), they internalize the effect of their demand on the exchange rate. Thus, the demand schedule is:

$$b_t^{S,i} = \frac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho Var_t(s_{t+1}) + \frac{\partial s_t}{\partial b_t^{S,i}}},$$

where the $\frac{\partial s_t}{\partial b_t^j}$ represents the price impact. If the investor is competitive ($j = C$), the demand schedule follows a standard mean-variance specification:

$$b_t^C = \frac{E_t(s_{t+1}) - s_t + i_t^\star - i_t}{\rho Var_t(s_{t+1})}.$$

We can now derive an expression for the price impact of a strategic investor. Assume there are N strategic investors, each with positive mass λ_i. Then, the market clearing condition for the foreign bond market is:

$$(1-\lambda)b_t^C + \sum_i^N \lambda_i b_t^{S,i} + (x_t + \bar{x})\bar{W} = B(1+s_t).$$

Substituting the demand schedule and applying the Implicit function theorem, we can write:

$$(1-\lambda)\frac{\partial b_t^C}{\partial s_t}\frac{\partial s_t}{\partial b_t^{S,i}} + \lambda_i = B\frac{\partial s_t}{\partial b_t^{S,i}}$$

Thus:

$$\frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i}{B - (1-\lambda)\frac{\partial b_t^C}{\partial s_t}} \qquad \text{with } \frac{\partial b_t^C}{\partial s_t} \equiv -\frac{1}{\rho Var_t(s_{t+1})}$$

Therefore:

$$\frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i \rho Var_t(s_{t+1})}{B\rho Var_t(s_{t+1}) + (1-\lambda)} \equiv \frac{1}{N}\frac{\lambda\rho\sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)} > 0$$

where the last equality holds in case of a symmetric oligopoly (i.e. $\lambda_i = \frac{\lambda}{N}\forall i$). The price impact is positive for $\forall(B, \lambda, N, \lambda_i, \rho, \sigma)$.

Lastly, in international portfolio choice models, the value of the supply of foreign assets in domestic currency (indirectly) depends on the value of the exchange rate when foreign assets are denominated in foreign currency. Differently from standard models of strategic trading (Kyle, 1989), strategic investors internalize not only their price effect on the quantity demanded but also on the quantity (value) supplied. Compared to closed economy models or cases in which foreign assets are denominated in domestic currency, the presence of this valuation effect on the supply implies a weakly lower price impact. Let pi^F and pi^D be the price impact on a foreign and a domestic asset, respectively.

$$pi^F \equiv \frac{\partial s_t}{\partial b_t^{S,i}} = \frac{\lambda_i \rho \sigma_t^2}{B\rho\sigma_t^2 + (1-\lambda)} \qquad pi^D \equiv \frac{\partial p_t}{\partial b_t^{S,i}} = \frac{\lambda_i \rho \sigma_t^2}{(1-\lambda)}$$

where p_t is the price of the domestic asset. It is easy to show that $pi^F \leq pi^D \quad \forall (B, \rho, \sigma_t^2, \lambda_i, \lambda)$. The intuition is fairly simple. The increase in the price of a currency (foreign currency appreciates) increases the nominal value of the supply of foreign assets when denominated in domestic currency. The supply shift dampens the initial rise in price, reducing the magnitude of the price impact. The overall effect of tradings on the exchange rate is lower due to the presence of a valuation effect. In other words, the residual net demand faced by strategic investors is more elastic than in a case with no valuation effects. The main implication is that strategic investors still reduce their exposure to foreign assets compared to competitive investors but not as much as in the case there was no valuation effect.

B.2 Effect of Strategic Behavior on Noise and Fundamental Shock

The presence of strategic investors amplifies (dampens) the response of the exchange rate to noise (fundamental) shocks.

Proof. Consider the law motion of the exchange rate in Equation (29). s_t can be rewritten as a forward looking sum of fundamentals and noises as follow:

$$s_t = -\mu \sum_{k=0}^{\infty} \mu^k (\Delta i_{t+k}) + \frac{1-\mu}{b} \sum_{k=0}^{\infty} \mu^k (x_{t+k}),$$

where $\Delta i_{t+k} = i_{t+k} - i^{\star}_{t+k}$. Therefore, the response of the exchange rate to a unit shock in noise and fundamental at impact is:

$$\text{IRF } (s_{t+j}, j = 0) = \begin{cases} \dfrac{\mu}{1-\mu\rho_u}, & \text{for } \varepsilon_u = -1 \\ \\ \dfrac{(1-\mu)}{(1-\mu\rho_x)b}, & \text{for } \varepsilon_x = 1 \end{cases}$$

Taking the derivative w.r.t. μ, we find:

$$\frac{\partial \text{IRF}(s_{t+j}, j = 0)}{\partial \mu} = \begin{cases} \dfrac{1}{(1-\mu\rho_u)^2} > 0 \\ \\ -\dfrac{(1-\rho_x)}{(1-\mu\rho_x)^2 b^2} < 0 \end{cases}$$

Since μ is decreasing (increasing) function of λ (N), the response of the exchange rate to a unit shock in fundamental is dampened while noise shock are amplified as λ increases (N decreases). ■

B.3 Monotonicity of Unconditional Variance

The unconditional volatility of the exchange rate is non-monotonic in the presence of strategic investors.

Proof. Consider the law of motion of the exchange rate, Equation 29, and substitute the process for fundamental and noise:

$$s_t = -\mu \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} \mu^k \rho^j \varepsilon^u_{t+k-j} + \frac{1-\mu}{b} \sum_{k=0}^{\infty} \sum_{j=0}^{\infty} \mu^k \rho_x^j \varepsilon^x_{t+k-j}.$$

After some algebra, s_t can be written as summation of its backward and forward components:

$$s_t = -\frac{\mu}{1-\mu\rho_u} \left[\sum_{k=0}^{\infty} \mu^k \varepsilon^u_{t+k} + \sum_{k=1}^{\infty} \rho_u^k \varepsilon^u_{t-k} \right] + \frac{1-\mu}{b(1-\mu\rho_u)} \left[\sum_{k=0}^{\infty} \mu^k \varepsilon^x_{t+k} + \sum_{k=1}^{\infty} \rho_x^k \varepsilon^x_{t-k} \right].$$

Thus, the unconditional variance of the exchange rate is:

$$\mathrm{Var}(s) = \frac{\mu^2 \sigma_u^2}{(1-\mu\rho_u)^2} \left[\frac{1}{1-\mu^2} + \frac{\rho_u^2}{1-\rho_u^2} \right] + \frac{(1-\mu)^2 \sigma_x^2}{(1-\mu\rho_x)^2 b^2} \left[\frac{1}{1-\mu^2} + \frac{\rho_x^2}{1-\rho_x^2} \right],$$

which is a combination of the variances of fundamental and noise shocks. Taking the derivative of $\mathrm{Var}(s)$ w.r.t. μ, we find:

$$\begin{aligned}\frac{\partial \mathrm{Var}(s)}{\partial \mu} =& \frac{\mu \sigma_u^2}{(1-\mu\rho_u)^3} \left[\frac{1}{1-\mu^2} + \frac{\rho_u^2}{1-\rho_u^2} \right] + \frac{\mu^3 \sigma_u^2}{(1-\mu\rho_u)^2 (1-\mu^2)^2} - \\ & \frac{(1-\mu)(1-\rho_x)\sigma_x^2}{(1-\mu\rho_x)^3 b^2} \left[\frac{1}{1-\mu^2} + \frac{\rho_x^2}{1-\rho_x^2} \right] + \frac{\mu(1-\mu)^2 \sigma_x^2}{(1-\mu\rho_x)^2 (1-\mu^2)^2 b^2}.\end{aligned}$$

The unconditional volatility of the exchange rate is increasing in λ iff:

$$\frac{(1+\mu\rho_x)\sigma_x^2}{(1-\mu\rho_x)^2(1+\mu)(1+\rho_x)b^2} - \frac{\mu\sigma_x^2}{(1-\mu\rho_x)^2(1+\mu)^2 b^2} >$$
$$\frac{\mu\sigma_u^2}{(1-\mu\rho_u)^2}\frac{(1+\mu\rho_u)}{(1-\mu^2)(1-\rho_u^2)} + \frac{\mu^3\sigma_u^2}{(1-\mu\rho_u)^2(1-\mu^2)^2},$$

that can be rewritten as follows:

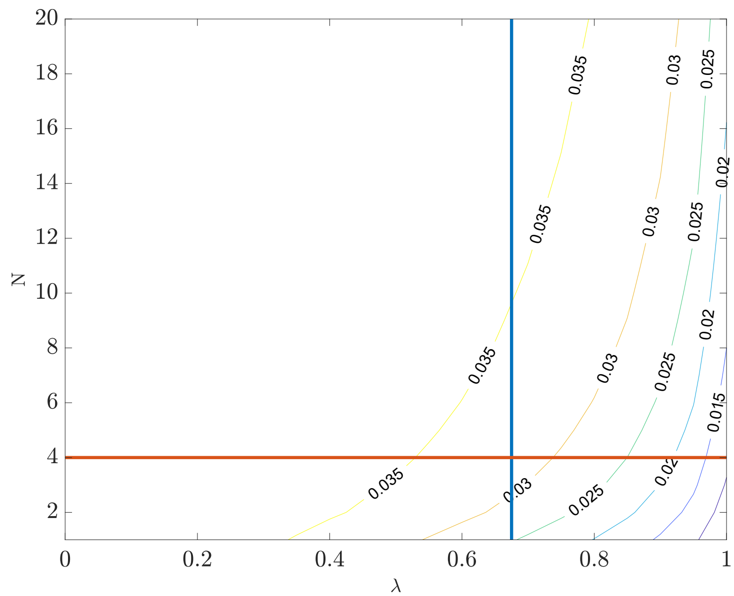
$$\frac{\mathrm{Var}(x)}{\mathrm{Var}(\Delta i)}\frac{1}{b^2} > \left[\frac{(1+\mu^2\rho_x)(1-\rho_x)}{\mu(1+\mu\rho_u)(1-\mu^2)+\mu^3(1-\rho_u^2)}\frac{(1-\mu\rho_u)^2(1-\mu)^2}{(1-\mu\rho_x)^2}\right]^{-1}. \tag{60}$$

■

Equation (60) suggests that the unconditional variance of the exchange rate increases as λ increases when the variance of the noise shock is sufficiently high compared to the variance of the fundamental process.

The non monotonic case is not relevant given standard parametrizations, including ours. Let define $\underline{\sigma_x}$ as the minimum value of the volatility of the noise process at which the relationship between the level of strategic behavior and exchange rate variance becomes non-monotonic. Figure 30 shows the value of $\underline{\sigma_x}$ for different combinations of N and λ. In our calibration, we find that the volatility of the noise shock should be at least 75% lower in order to break the monotonic relationship between strategic behavior (λ and/or N) and the unconditional variance of the exchange rate. In cases where λ or N take on other values, he minimum value of σ_x is at least 50% lower compared to the value implied by Figure 32 in Appendix D. For instance, in a market with a high level of strategic behavior (λ approximately 1), we find that σ_x is approximately 0.05. However, monotonicity in the relationship between strategic behavior and unconditional variance breaks if σ_x falls below 0.025.

Figure 30: $\underline{\sigma_x}$ for different combinations of N and λ.



Notes: The figure shows the minimum value of the volatility of the noise process, σ_x, that guarantees that the volatility of the exchange rate is monotonically increasing in the presence of strategic behavior (higher λ and/or lower N). The threshold is computed using Equation (60). We compute the minimum value of σ_x for different levels of λ and N. The horizontal and vertical lines pin down the combination of λ and N used in the parametrization of the basic framework. Remaining parameters are constant, see Table 5.

Furthermore, it is important to note that the threshold value mentioned earlier is dependent on the parameters ρ_x, ρ_u and b. The robustness of the monotonic relationship between strategic behavior and unconditional variance is also guaranteed by the conservative nature of our calibration. In standard calibrations, only more persistent noise processes or less persistent fundamental processes would align with the observed data. Similarly, higher values of home bias (lower b) would be consistent with the data. Higher values of ρ_x, lower values of ρ_u and lower b all contribute to reducing the threshold, thereby relaxing the condition for monotonicity.

B.4 Excess Return Predictability - UIP

Another empirically robust evidence in exchange rate dynamics is the predictability of excess returns, commonly referred to as deviations from the Uncovered Interest Parity (UIP). Our model predicts systematic deviations from UIP due to a non-zero net supply of foreign assets, regardless of the presence of strategic investors. However, strategic behavior amplifies these UIP deviations compared to a competitive market.

Through the lens of our model, the one-period excess return, $q_{t+1} = s_{t+1} - s_t - (i_t - i_t^*)$, can be expressed as follow from Equation (29):

$$E_t q_{t+1} = \frac{\Phi}{B}(Be^{s_t} - X_t), \tag{61}$$

where the right-hand side represents the deviation from UIP. The deviations from UIP can be interpreted as the risk premium demanded by investors for holding foreign assets to clear the market. The risk premium consists of two main components: the net supply of foreign assets (adjusted for the demand of noise traders) and the market structure captured by Φ, which increases with λ or decreases with N. Our model predicts that UIP does not hold even in a fully competitive market when λ is zero. Moreover, as the market becomes more populated with strategic investors, UIP deviations become larger. The presence of strategic investors leads to a higher insensitivity in the total demand for foreign assets. Consequently, a larger risk premium is necessary to absorb the net supply of foreign assets compared to a competitive market. This results in a higher predictability of excess returns.

We use the calibrated model and simulated data to estimate a standard one-period Fama regression:

$$q_{t+1} = \alpha + \beta(i_t - i_t^{\star}) + \epsilon_t. \tag{62}$$

where q_{t+1} is the realized excess return. While UIP implies that the Fama coefficient, β, is zero, empirical evidence typically finds a negative number. Our model predicts that β is given by:

$$\beta = -(1-\mu)\frac{1}{1-\mu\rho_u} < 0,$$

which is negative and decreasing in the level of strategic behavior.[133] Figure 31 plots the estimated excess return predictability coefficient β for different levels of λ. As anticipated, the coefficient is negative, consistent with the estimates found in the literature. Moreover, its magnitude is monotonically increasing in the level of strategic investors.

We now provide an analytic proof that the excess return is more predictable as λ increases.

Proof. Consider the law motion of the exchange rate, Equation 29:

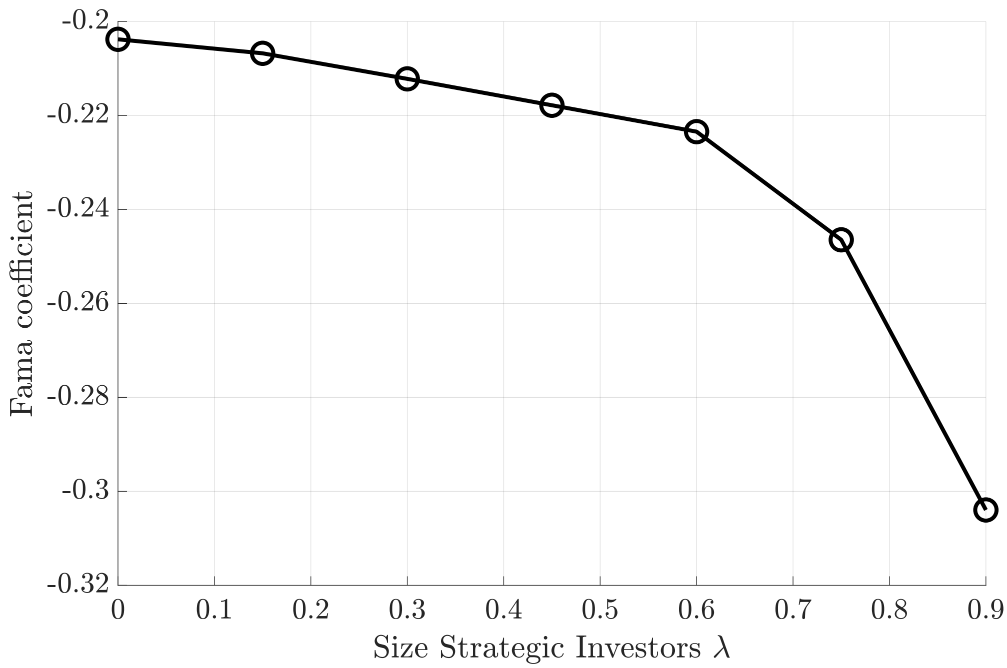
$$s_t = \mu[E_t(s_{t+1}) + i_t^{\star} - i_t] + (1-\mu)\frac{\bar{x}}{b} + (1-\mu)\frac{1}{b}x_t,$$

where only the first term depends on fundamentals. Manipulating it, we can derive the j-period change in currency price as follows:

$$\Delta s_{t+j} = -\mu\sum_{k=0}^{\infty}\mu^k(\Delta i_{t+j+k} - \Delta i_{t+k}).$$

[133] Interestingly, β is equal to zero if the supply of asset is constant when denominated in domestic currency, meaning that B is not multiplied by e^{s_t}. In this particular case, the excess return depends solely on the noise component X_t, which is orthogonal to fundamental shocks. Therefore, β is equal to zero even if there are systematic deviations in UIP. In other words, risk premium is still positive (UIP does not hold), but it is not predictable ($\beta = 0$).

Figure 31: Excess Return Predictability



Notes: The right panel shows the estimated one-period Fama coefficient using Equation 62 and simulated data from our model for different levels of strategic behavior. We run 5000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 5.

With Δs_{t+j} in hand, we can then calculate:

$$\begin{aligned}
\beta_1 = \frac{\text{Cov}(\Delta s_{t+1} - \Delta i_t; \Delta i_t)}{\text{Var}(\Delta i_t)} &= \left[\text{Cov}\left(-\mu \sum_{k=0}^{\infty} \mu^k (\Delta i_{t+k+1} - \Delta i_{t+k}); \Delta i_t\right) - \text{Var}(\Delta i_t)\right] / \text{Var}(\Delta i_t) \\
&= \left[-\mu \sum_{k=0}^{\infty} \mu^k \text{Cov}(\Delta i_{t+k+1} - \Delta i_{t+k}; \Delta i_t) - \text{Var}(\Delta i_t)\right] / \text{Var}(\Delta i_t) \\
&= \left[-\mu \sum_{k=0}^{\infty} \mu^k \rho_u^k (\rho_u - 1)\text{Var}(\Delta i_t) - \text{Var}(\Delta i_t)\right] / \text{Var}(\Delta i_t) \\
&= -(1-\mu)\frac{1}{1-\mu\rho_u} < 0,
\end{aligned}$$

which is negative for each value of μ and increasing (decreasing) in μ (in λ). ■

Notice that predictability reversal does not arise in our model, differently from Bacchetta and Van Wincoop (2010) and Engel (2016). Formally define the j-period ahead excess return as $q_{t+j} = s_{t+j+1} - s_{t+j} - (i_{t+j} - i^*_{t+j})$, and consider the following regression:

$$q_{t+j} = \alpha + \beta_j (i_t - i^*_t) + \epsilon_{t+j}. \tag{63}$$

The coefficient of interest, β_j, is:

$$\begin{aligned}
\beta_j =& \frac{\text{Cov}(q_{t+j}, \Delta i_t)}{\text{Var}(\Delta i_t)} \\
& \frac{1}{\text{Var}(\Delta i_t 9}(\text{Cov}(\Delta s_{t+j}, \Delta i_t) - \text{Cov}(\Delta i_{t+j-1}, \Delta i_t)) \\
& \frac{1}{\text{Var}(\Delta i_t)}\left[\text{Cov}\left(-\mu \sum_{k=0}^{\infty} \mu^k (\Delta i_{t+k+j} - \Delta i_{t+k+j-1}); \Delta i_t\right) - \text{Cov}(\Delta i_{t+j-1}, \Delta i_t)\right] \\
& \frac{1}{\text{Var}(\Delta i_t)}\left[\left(-\mu \sum_{k=0}^{\infty} \mu^k \text{Cov}(\Delta i_{t+k+j} - \Delta i_{t+k+j-1}); \Delta i_t\right) - \text{Cov}(\Delta i_{t+j-1}, \Delta i_t)\right] \\
& -\mu \sum_{k=0}^{\infty} \mu^k (\rho_u^{k+j} - \rho_u^{k+j-1}) - \rho_u^{j-1} \\
& -\mu \rho_u^{j-1}(\rho_u - 1)\frac{1}{1-\mu\rho_u} - \rho^{j-1} = -\rho^{j-1}\frac{1-\mu}{1-\mu\rho_u} \leq 0.
\end{aligned}$$

Lastly, notice that $\frac{\partial \beta_j}{\partial j} = -(j-1)\rho_u^{j-1}\left(\frac{1-\mu}{1-\mu\rho_u}\right) < 0$. Therefore, for $j \to \infty$, the coefficient $\beta_j \to 0$ monotonically, excluding any reversal.[134]

[134] This is not surprising considering the absence of any friction, such as infrequent portfolio adjustment (Bacchetta and Van Wincoop, 2010, 2019).

C Solution Method of Dispersed Information Model

We solve the model with higher order expectations using the recursive solution algorithm in Nimark (2017). We approximate the equilibrium of the model to an arbitrary precision with finite number of higher order expectations $\bar{k} < \infty$.

We recursively computes the exchange rate process and the law of motion of the expectations hierarchy for arbitrarily high orders of expectations following these steps:

Step 1. Define the zero order process ($k = 0$) for the exchange rate s_t as a function of the current fundamentals $\Delta i_t^{(0)}$:

$$\begin{aligned} s_t &= G_k \Delta i_t^{(0)} + R_1 \mathbf{w_t} \\ \Delta i_t^{(0)} &= M_k \Delta i_{t-1}^{(0)} + N_k \mathbf{w_t} \end{aligned}$$

where $\mathbf{w_t}$ is the vector of aggregate shocks, including both fundamental and noise shocks; R_1 and N_k represent the variance matrices associated with the zero-order state space representation; the matrix $G_k \equiv G_0 = -\mu$, and $M_k \equiv M_0 = \rho$ are stored separately in the zero-iteration period.

Because investors learn from the exchange rate s_t, the measurement equation for investor j at time t includes a noisy signal about Δi_t as well as s_t:

$$\mathbf{s_{j,t}} = D_0 \Delta i_t^{(0:k)} + R_1 \mathbf{w_t} + R_2 w_{j,t} \quad w_{j,t} \sim N(0, I)$$

where $D_0 = [1, G_0]'$ and $w_{j,t}$ is the idiosyncratic noise shock.

Step 2. Using the measurement equation and the law of motion of hierarchy, compute the

Kalman gain K_k for the k^{th} step, as well as the matrices M_{k+1} and N_{k+1}:

$$M_{k+1} = \begin{bmatrix} M_0 & \mathbf{0}_{q\times kq} \\ \mathbf{0}_{kq\times q} & \mathbf{0}_{kq\times kq} \end{bmatrix} + \begin{bmatrix} \mathbf{0}_{q\times kq} & \mathbf{0}_{q\times q} \\ K_k D_k M_k & \mathbf{0}_{kq\times q} \end{bmatrix} + \begin{bmatrix} \mathbf{0}_{q\times q} & \mathbf{0}_{q\times kq} \\ \mathbf{0}_{kq\times q} & (I - K_k D_k) M_k \end{bmatrix}$$

$$N_{k+1} = \begin{bmatrix} N_0 \\ (K_k D_k N_k + K_k R_1) \end{bmatrix}.$$

to get the k^{th} step law of motion

$$\Delta i_t^{(0:k)} = M_{k+1} \Delta i_{t-1}^{(0:k)} + N_{k+1} \mathbf{w}_t, \quad \mathbf{w}_t \sim N(0, I)$$

where the matrix D_k is defined as:

$$D_k = \begin{bmatrix} 1 & \mathbf{0}_{q\times kq} \\ G_k & \end{bmatrix}$$

Step 3. The k-order process for the exchange rate s_t^{k+1} is:

$$s_t^{k+1} = G_{k+1} \Delta i_t^{(0:k+1)} + R_1 w_t$$

where

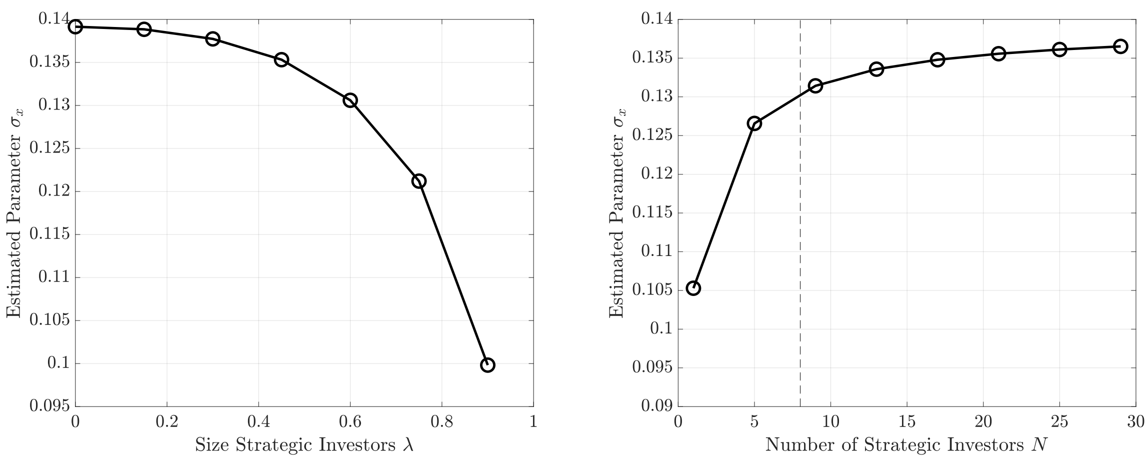
$$G_{k+1} = G_0 + \mu G_k M_k H_{k+1} \qquad \text{and} \qquad H_k \equiv \begin{bmatrix} \mathbf{0}_{(kq)\times q} & I_{kq} \end{bmatrix}$$

Step 4. Repeat Steps $2 - 3$ for $k = 1, 2, ..., \bar{k}$ where the number of iterations $\bar{k}$ can be chosen to achieve any desired degree of accuracy.

D Additional Tables and Figures

D.1 Strategic Behavior and Noise Volatility

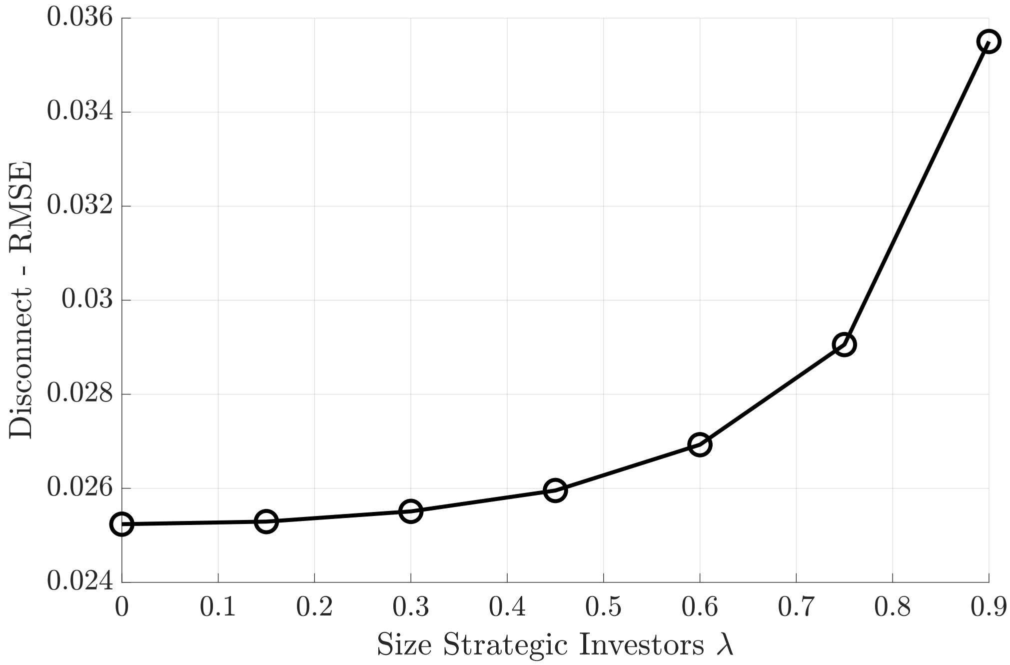
Figure 32: Relationship between Strategic Behavior and Noise Volatility



Notes: The figure shows the volatility of the noise component, σ_x, required to match the target volatility of the exchange rate change in the basic framework, for different levels of strategic behavior. The left panel considers different levels of strategic behavior in terms of λ for a number of strategic investors equal to $N = 4$. The left panel considers different levels of strategic behavior in terms of N for a total size of strategic investors equal to $\lambda = 0.675$. All other parameters are constant and summarized in Table 5.

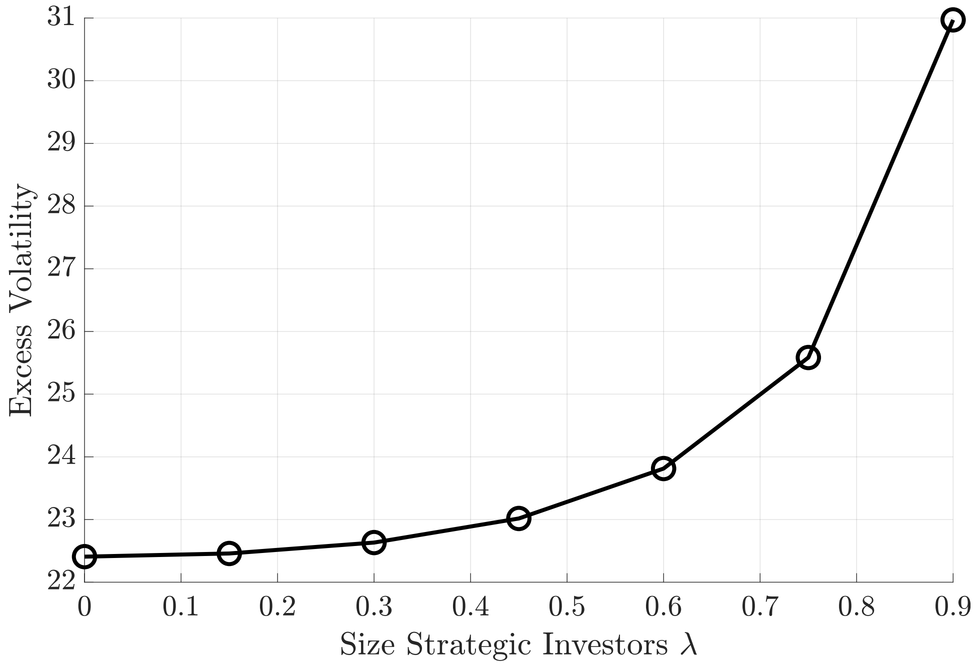
D.2 Strategic Behavior and Exchange Rate Dynamics

Figure 33: Exchange Rate Disconnect - RMSE



Notes: The figure shows the estimated Root-Mean Square Error (RMSE) of the disconnect regression in Equation 31 using simulated data. We run 3000 simulations and, for each iteration, the model runs for 8000 periods with 4000 burn-in. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 5.

Figure 34: Excess Volatility - Exchange Rate Change



Notes: The figure shows the excess volatility ratio computed using simulated data from our model. We run 3000 simulations and, for each iteration, the model runs for 8000 periods with 3000 burn-in. The excess volatility ratio is computed using the ratio between the volatility of the exchange rate change and the volatility of changes in the fundamental, $\frac{\text{Var}(\Delta s)}{\text{Var}(\Delta u_t)}$. Data are simulated for different levels of strategic behavior λ. Remaining parameters are common across scenarios, see Table 5.

Table 24: Testing Model Predictions

	(1) Excess Volatility	(2) Disconnect - R2
λ	182.898***	-0.247***
	(69.564)	(0.068)
Constant	52.115	0.232***
	(39.098)	(0.038)
Currency & Year FEs	Yes	Yes
Observations	900	900

Notes: The table reports the relationship between λ and the variables of interest. λ represents the net concentration ratio by the top eight reporting traders operating in the future FX market. Variable of interest are: exchange rate excess volatility (Columns (1)); exchange rate disconnect/R^2 (Column (2)). The exchange rate disconnect is measured using the Adjusted R^2 from the regression in Equation (31), while excess volatility is calculated as the ratio of exchange rate volatility from Equation (32) to the volatility of the interest rate differential. λ is measured monthly from 2006 to 2016 using the U.S. CFTC data. To measure excess volatility and disconnect, we use a two-year periods rolling window and exchange rate data at monthly level. Values of the excess volatility ratio and disconnect are winsorized at 1%. All regressions include currency and year fixed effects. Standard errors in parenthesis are clustered at the currency level. Significance level:* $p<0.10$, ** $p<0.05$, *** $p<0.01$. Currencies considered are: Euro, Japanese Yen, Brazilian Real, Canadian Dollar, Swiss Franc, Australian Dollar, Mexican Peso, British Pound, Russian Ruble, and New Zeland Dollar. Appendix A provides additional information on the data used.

D.3 Cross-Currency Model Predictions

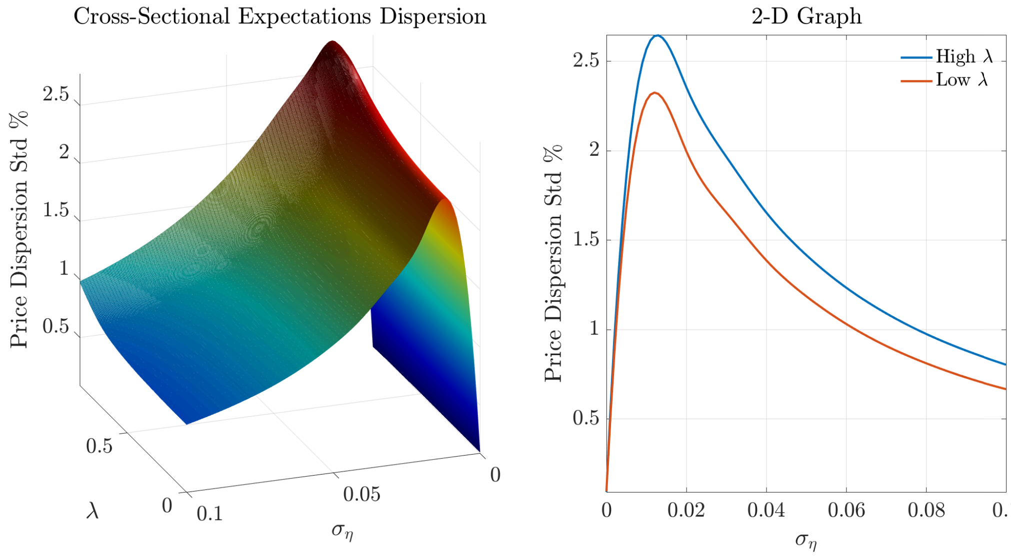
D.4 Parametrization Quantitative Model

Table 25: Parametrization Quantitative Model

	Value	**Moment - Target**	**Data**	**Model**
λ	0.675	Share transactions 1st quintile – NYFXC		
N	4	Number of investors 1st quintile – NYFXC		
ρ_u	0.85	Average persistence AR(1) Δi_t		
σ_u	0.005	Average StD innovation AR(1) Δi_t		
σ_t	0.028	Average StD ER change		
σ_η	0.006	Same Quarter Expectation Dispersion	0.02	0.01
σ_x	0.022	σ_t (Volatility ER change)	0.028	0.029
ρ_x	0.9	ER RW/Average Disconnect		
ρ	50	Average UIP level		
b	0.33	Home Bias		
$\bar{k}$	10			

Notes: The table summarizes the parametrization used in Section 5. For each parameters, we report the value used in the model, the corresponding moment and data used to calibrate, and, if applicable, the target moment used to estimate it. Appendix A provides additional information on the data used.

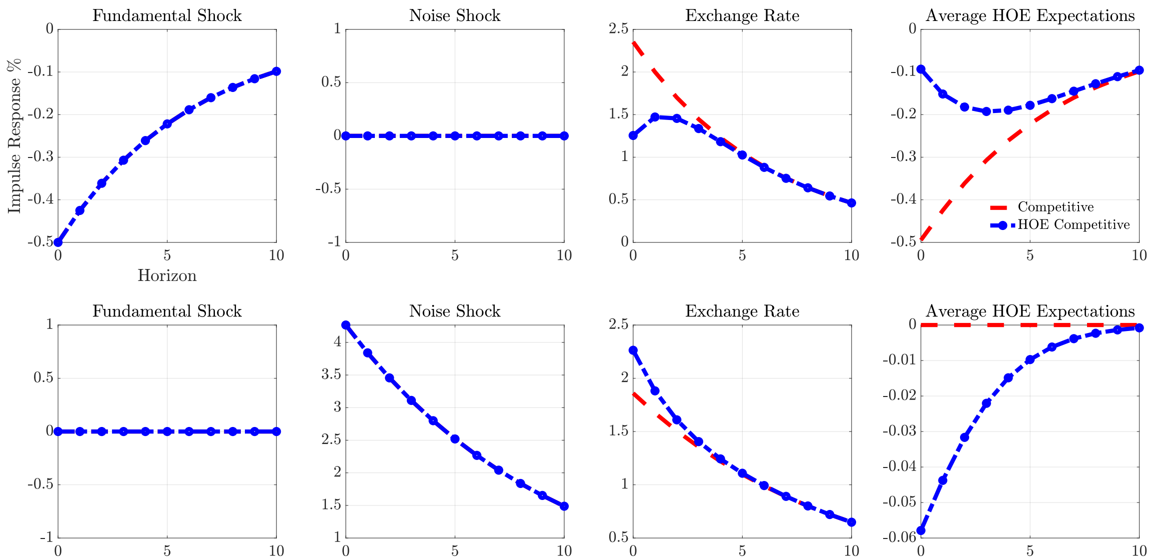
Figure 35: Exchange Rate Expectation - Dispersion



Notes: The figure shows the dispersion (standard deviation) across investors in the one-period exchange rate expectations for different level of strategic behavior (λ) and precision of the signal on fundamentals (σ_η) implied by the model in Section 5. The left panel shows the dispersion in expectations for values of $\lambda \in [0, 1]$, and $\sigma_\eta \in [0, 0.1]$. The right panel shows the dispersion in expectation for two levels of strategic behavior ("Low" with $\lambda = 0$, and "High" with $\lambda = 0.6$) and a precision of the signal σ_η between 0 and 0.1. The figure is generated for a representative calibration with $\sigma_u = 0.01$ and $\rho_x = 0$. All remaining parameters are reported in Table 25 in Appendix D.

D.5 Impulse Response under High Order Expectations (HOE)

Figure 36: Impulse Response to Exogenous Shocks



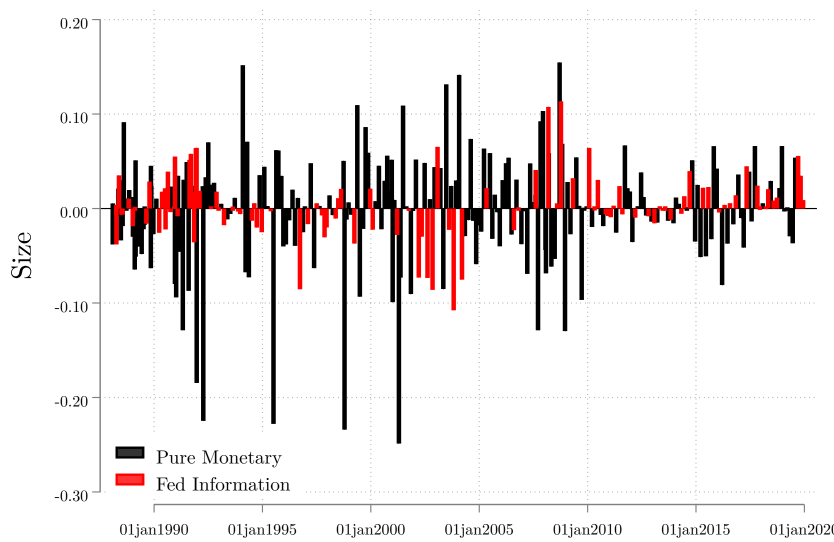
Notes: The top panel (bottom) shows the response to a fundamental (noise) shock. The first (second) column show the dynamics of a one standard deviation shock in fundamental (noise). The third column shows the dynamics of the exchange rate. The fourth column shows the response of the average first order ($k = 1$) expectation of future exchange rate defined in Equation (35). The blue dashed-dot line shows the response in an economy with dispersed information $\sigma_\eta > 0$. The red dashed line shows the response in an economy without dispersed information, $\sigma_\eta = 0$. In both scenario, markets are fully competitive ($\lambda = 0$). Remaining parameters are common across scenarios, see Table 25 in Appendix D.

Chapter 3

E Construction of the dataset and cleaning

E.1 Decomposition of Fed announcement shocks from 1990-2018

Figure 37: Historical decomposition of the monetary policy shocks



Notes: The figure shows point estimates of the historical decomposition of Fed announcement components: the pure monetary policy shock (black line) and Fed information shocks (red line). Shocks are identified following Jarociński and Karadi (2020) approach. All the macro data series for the identification, and the time series of the shocks are available in their replication file. Since shocks are up to scale, I normalize both series of shocks to 1 standard deviation. The grey bar are the NBER recession periods from 1990 to 2019.

E.2 Firm-level variables on Compustat

I construct the firm-level variables in the Compustat database as follows.

- **Capital Stock.** Capital stock is equal to the book value of capital. I use the perpetual inventory method to calculate the capital value for each firm i at a time t. I measure the initial value of firm i's capital stock as the earliest available entry of $ppegtq_{i,t}$, and then iteratively construct $k_{i,t}$ from $ppentq_{i,t}$ as:

$$k_{i,t+1} = k_{i,t} + ppentq_{i,t+1} - ppentq_{i,t}$$

- **Leverage.** Leverage is the ratio of debt in current liabilities $dlcq_{i,t}$ and long-term debt $dlttq_{i,t}$ on total assets, $atq_{i,t}$. I average leverage within the year.

- **Cash liquidity.** I calculate cash holdings as the ratio of cash and short-term investments $cheq_{i,t}$ on total assets $atq_{i,t}$. I average cash liquidity within the year.

- **Investment Rate.** Investment rate is the ratio of the variation of capital stock as calculated in (i) on the past value of capital $k_{i,t-1}$.

- **Rating.** Rating is the S&P domestic long term issuer credit rating $spcsrc_{i,t}$. I divide the sample in three groups based on 2-quarters lag ratings. I assign value 2 if *spcsrc* is between A+ and A-, value 1 if *spcsrc* is between B+ and B-, value 0 otherwise.

- **Dividends.** Dividends is the sum of common dividends $dvy_{i,t}$ and preferred dividends, $dvpq_{i,t}$.

- **Firm Size.** I construct a measure of size for each firm following Gertler and Gilchrist (1994). For each firm i, I calculate the moving average of the sales over the past ten years. For each quarter t, a firm i is a large firm (value 0) if it is above the 30th percentile of the distribution for average sales of that year or is a small firm (value 1) if it is below the threshold.

- **Total assets.** Total assets is the variable $atq_{i,t}$ in Compustat.

- **Sectoral dummies.** I construct a sectoral dummies following Ottonello and Winberry (2018): (i) agriculture, forestry and fishing: sic < 999; (ii) mining: sic $\in [1000, 1499]$; (iii) construction: sic $\in [1500, 1799]$; (iv) manufacturing: sic $\in [2000, 3999]$; (v) transportation, communications, electric, gas, and sanitary services: sic $\in [4000, 4999]$; (vi) wholesale trade: sic $\in [5000, 5199]$; (vii) retail trade: sic $\in [5200, 5999]$; (viii) services: sic $\in [7000, 8999]$.

- **Average Q.** The average Q is the sum of the market value of the firm *mkval* net of Common/Ordinary Equity *ceqq*, total assets atq and investment tax credit *txditcq*, divided by *atq*.

I deflate capital stock, sales, and total assets using the implied price index of gross value added in the U.S. non-farm business sector. To control for outliers in the regressors, I trim the variables, leverage, cash holdings, total assets at the 1% top-level and sales growth at the 1% top and bottom level as standard in the main reference literature. I transform all regressors in logarithm before the estimation.

E.3 Sample selections

The sample period is 1990Q1 to 2018Q4. I perform the following cleaning steps:

- I keep only US-based firms, $fic_{i,t} =$"USA".

- To avoid firms with strange production functions, drop regulated utilities and financial companies, I drop all firm-quarters for which the 4-digit sic code is in the range [4900,5000) or [6000,7000).

- To get rid of years with extremely large values for acquisitions to avoid the influence of large mergers, I drop all firm-quarters for which the value of acquisitions $acq_{i,t}$ is greater than 5% of total assets $atq_{i,t}$.

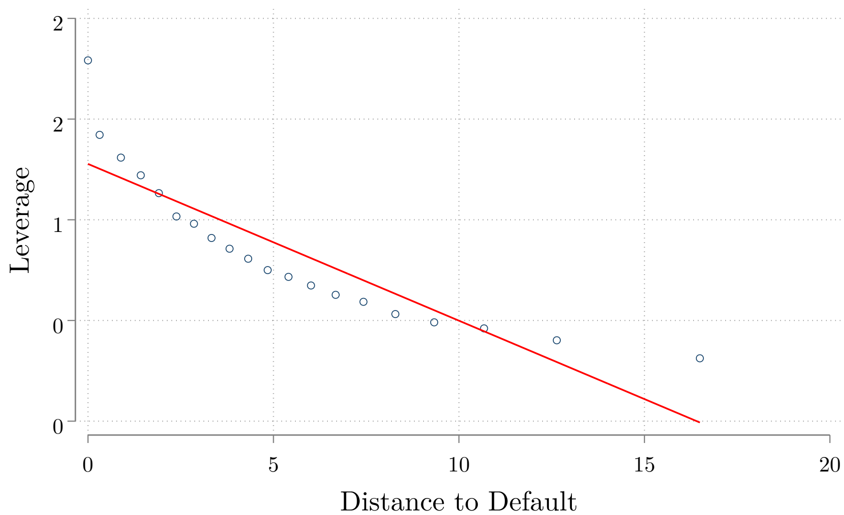
- I drop all firm-quarters for which the measurement of Total Assets $atq_{i,t}$, Sales $saleq_{i,t}$, Property, Plant and Equipment (Net) $ppentq_{i,t}$, Cash and Short-Term Investments $cheq_{i,t}$, Debt in Current Liabilities $dlcq_{i,t}$, Total Long-Term Debt $dlttq_{i,t}$, Total Inventories $invtq_{i,t}$ are missing or negative.

- I drop all firm-quarters before a firm's first observation of Property, Plant, and Equipment (Gross) $ppegtq_{i,t}$.

After computing the yearly moving averages for leverage and liquid asset ratios but before estimating (1), I drop all firms observed between 1990Q1-2016Q4 for less than 40 quarters.

E.4 Firm leverage and distance to default in the data

Figure 38: Plot the relationship between firms' leverage and distance to default

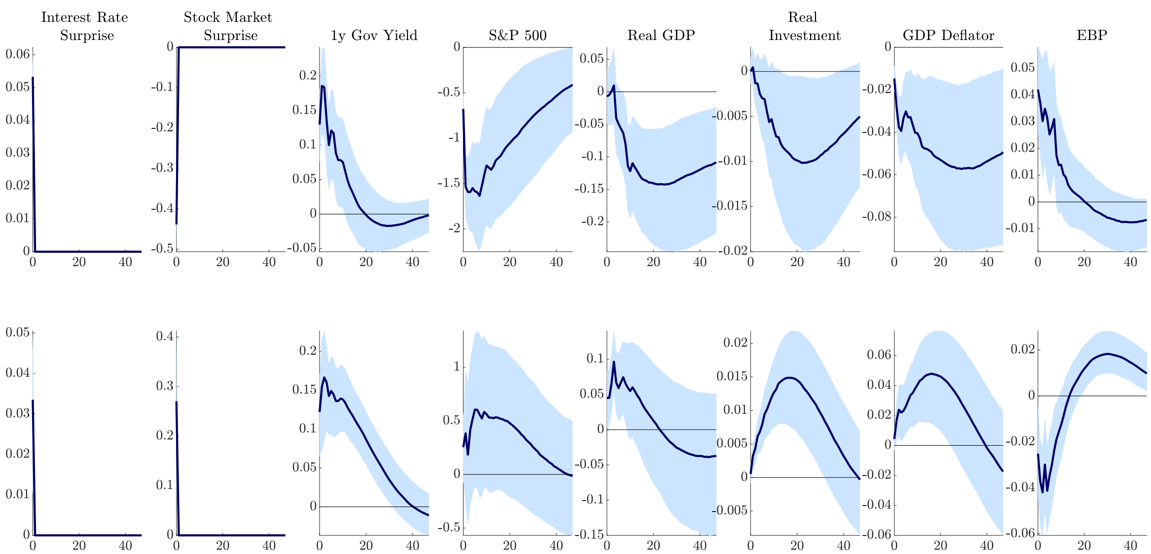


Notes: The figure illustrates the relationship between leverage and distance to default in the data. Leverage is calculated as the ratio of debt in current liabilities ($dlcq_{i,t}$) and long-term debt ($dlttq_{i,t}$) to shareholder equity (i.e., total assets minus liabilities), averaged within the year. The distance to default is estimated for each firm in Compustat, following the procedure outlined in **?**. A value of distance to default above 3 indicates that a firm faces a low or zero probability of default, while a value lower than 3 may suggest a higher probability of default.

F Additional results and robustness

F.1 Aggregate response to identified shocks

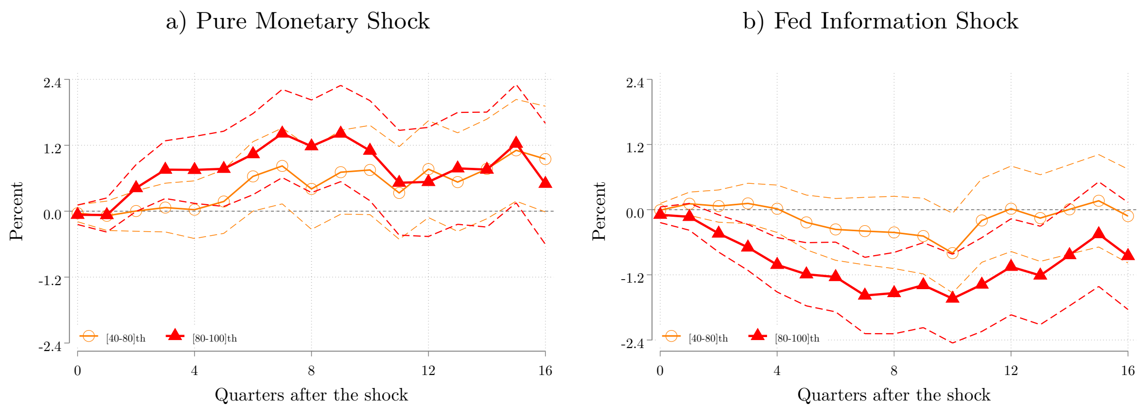
Figure 39: Aggregate IRFs to the identified shocks



Notes: The aggregate impulse responses to a contractionary one-standard deviation pure monetary policy shock (first row) and a non-pure monetary policy shock (second raw) identified using Jarociński and Karadi (2020) decomposition. I plot the median response along with the [14,86] percent confidence intervals. The results show that a pure monetary policy shock produces contractionary effects on the economy that are similar to a standard Taylor rule shock in a New-Keynesian framework. The variables real investment, real GDP, and prices unambiguously fall after the shock while the cost of borrowing rises. Instead, a non-pure monetary policy shock produces expansionary effects on the economy that are instead similar to a demand shock, the variables real investment, real GDP, and prices increase after the shock.

F.2 Heterogeneous effect of monetary policy by leverage group

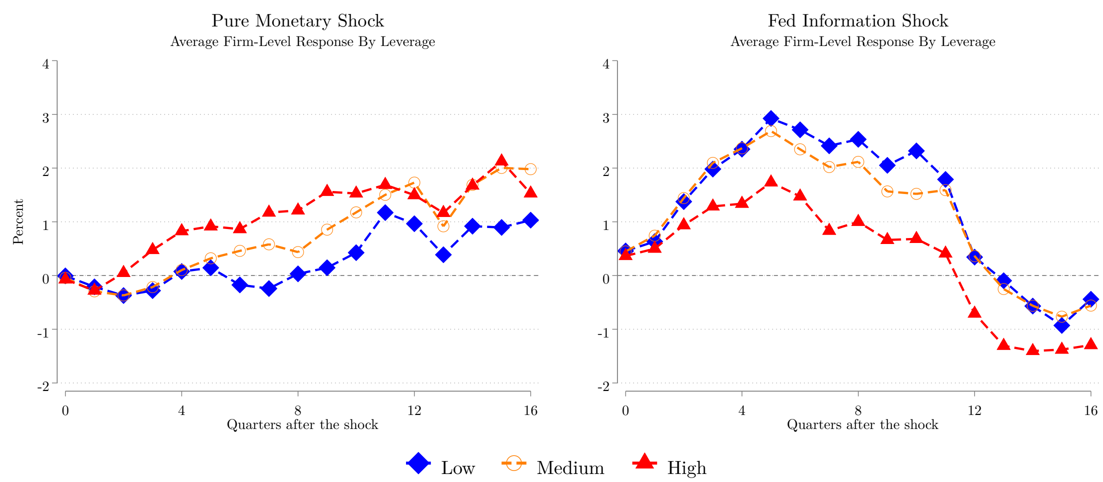
Figure 40: Heterogeneous response of investment by leverage group



$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t\times j,h} + \sum_{j=1}^{3}\Big[\beta^s_{h,g}\cdot \Delta \mathrm{q}_t + \alpha^s_{h,g}\Big]\mathbb{1}[i \in g_j] + \Gamma'_h W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms belonging to different leverage groups relative to a reference group. The orange line represents the average differential response of capital between a firm in the 40th to 80th percentile of the leverage distribution and a firm in the bottom 40%, while the red line represents the average differential response of capital between a firm above the 80th percentile of the leverage distribution and a firm in the bottom 40%. The point estimates and 90% confidence intervals for the $\beta_{h,g}$ coefficients for each leverage group are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructued following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

Figure 41: Average response to identified shocks by leverage group



Notes: The figures illustrate the average response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms that belong to different leverage groups. A firm is classified as low leverage if it falls within the 40th percentile of past year leverage, medium if it falls between the 40th and 80th percentile, and high if it is above the 80th percentile. The blue line is the average response of capital accumulation for a firm that is low leverage; the orange line is the average response of capital accumulation for a firm that is medium leverage; the red line is the average response of capital accumulation for a firm that is high leverage. The point estimates are calculated by summing the average response for low leverage firms with the differential responses for each leverage group, as obtained from Figure 40. Confidence intervals are not shown for clarity. Additional details on variable construction can be found in Appendix E.

Figure 42: Heterogeneous response of investment in the sample 1990-2008

a) Pure Monetary Shock b) Fed Information Shock

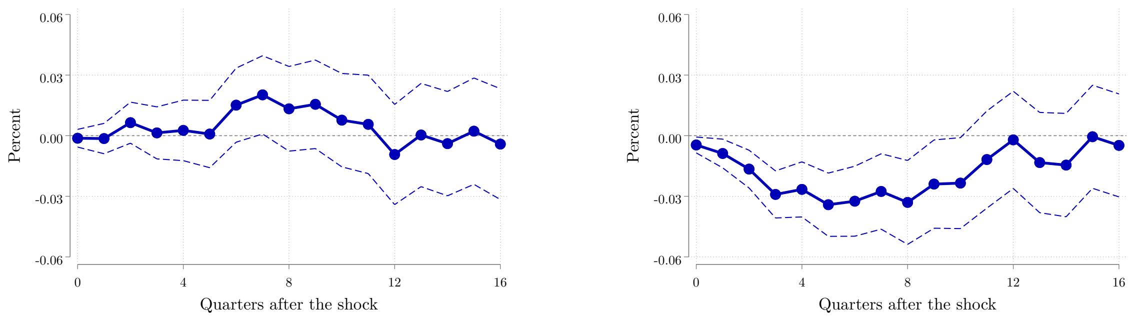
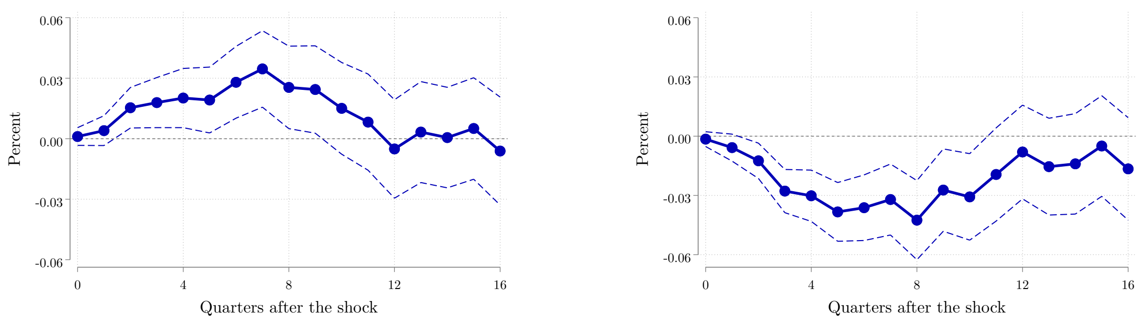


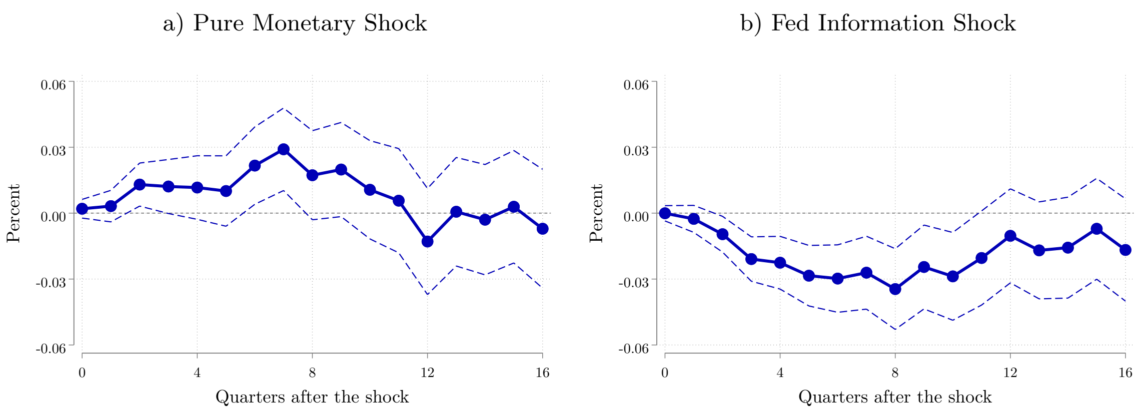
Figure 43: Heterogeneous response of investment in the sample 1994-2018

a) Pure Monetary Shock b) Fed Information Shock



Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in past leverage. Figure 42 illustrates the estimates in the period 1990Q1-2008Q4, while Figure 43 illustrates the estimates considering the period 1994Q1-2018Q4. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation 37 using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructued following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

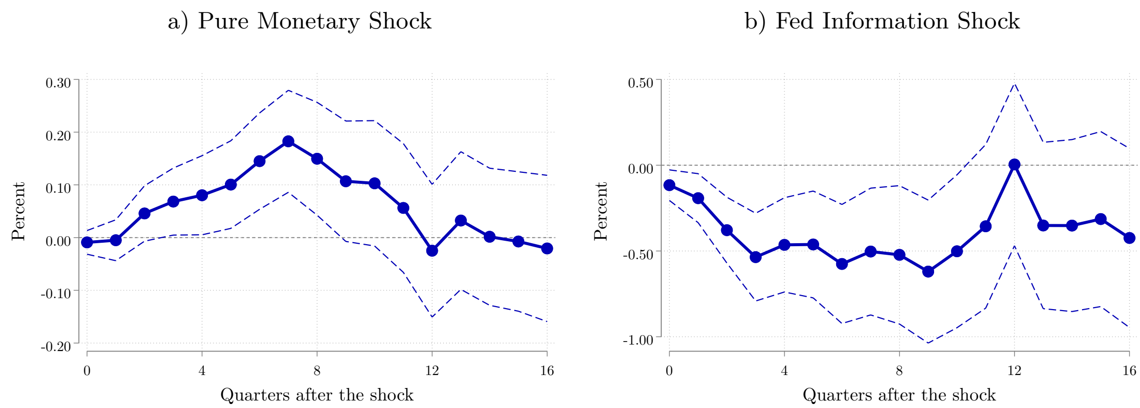
Figure 44: Heterogeneous response of investment without time fixed effects



$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + (\beta_h \Delta q_t + \delta_h)\text{lev}_{i,t-4} + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in past leverage. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and without time-sector fixed effects. $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are used as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructued following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Sample is from 1990 to 2018. Additional details on variable construction can be found in Appendix E.

Figure 45: Heterogeneous response of investment using Poorman identification



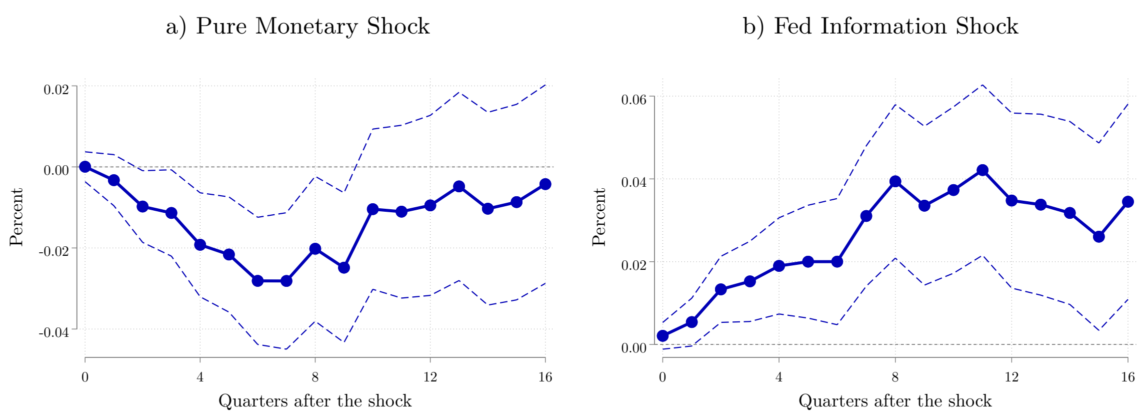
$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)\text{lev}_{i,t-4} + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in past leverage. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are the “Poorman identification" shocks from Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

G Relating to prior literature

G.1 Relating to Jeenas (2018a)

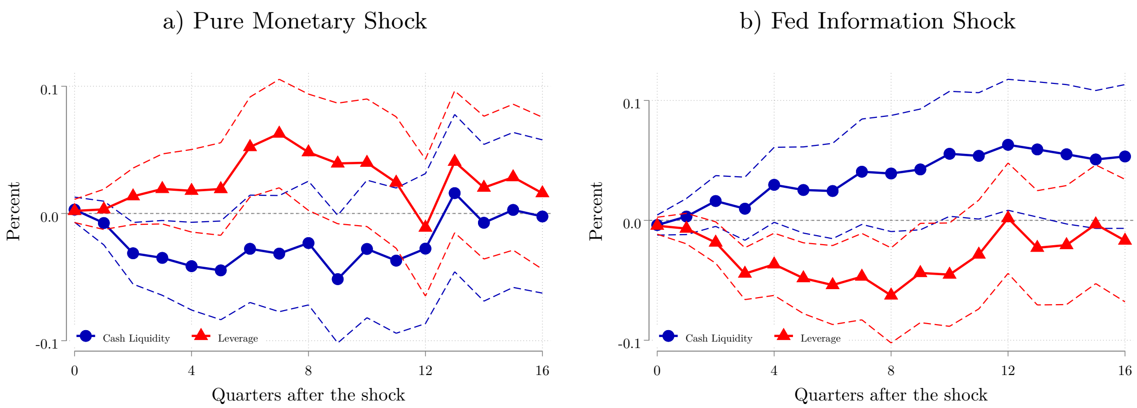
Figure 46: Heterogeneous response of investment using cash liquidity



$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)\text{cash}_{i,t-4} + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in cash liquidity (i.e., *cash* divided by *atq*). The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

Figure 47: Heterogeneous response of investment using cash liquidity and leverage

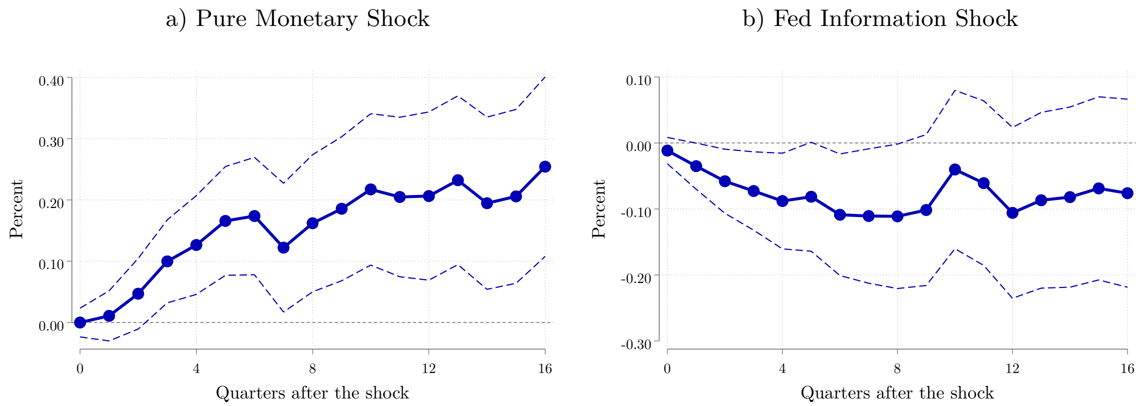


$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)[\text{cash}_{i,t-4} + \text{lev}_{i,t-4}] + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in cash liquidity (i.e., *cash* divided by *atq*) and leverage. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

G.2 Relating to Gertler and Gilchrist (1994)

Figure 48: Heterogeneous response of investment using size

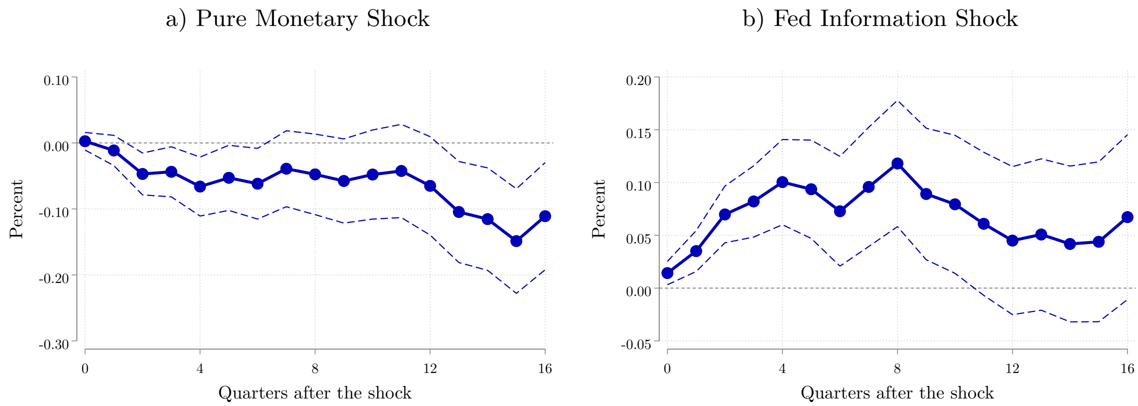


$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)\mathbb{1}_{\text{Small}_{i,t}} + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among small and large firms. Firms' size is determined based on their sales growth, following the approach of Gertler and Gilchrist (1994). A positive value of β_h indicates that small firms are relatively more sensitive than large firms to a shock, while a negative value indicates the opposite. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

G.3 Relating to Cloyne et al. (2018)

Figure 49: Heterogeneous response of investment using age

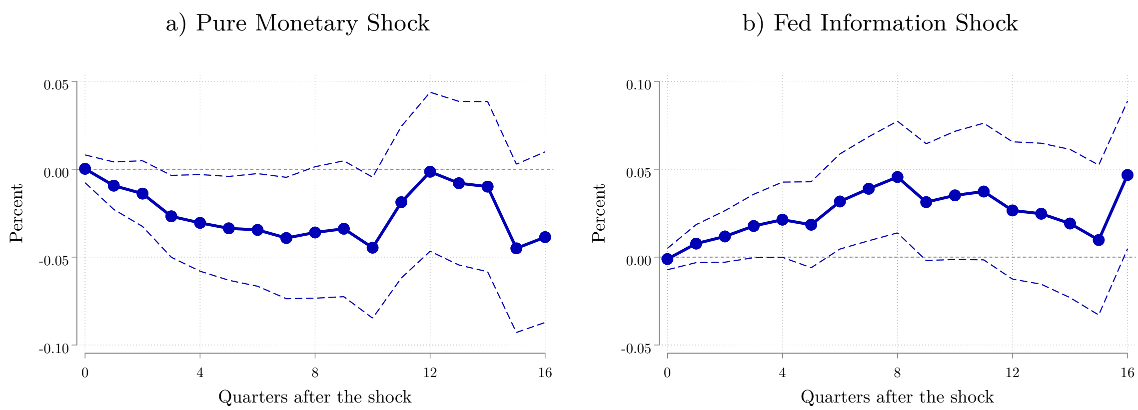


$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)\mathbb{1}_{\text{Young}_{i,t}} + \Gamma'_h W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among young and old firms. A firm is classified as "young" if it has been in existence for less than 25 years, while it is considered "old" if it has been in existence for more than 25 years. Firms' age in Compustat is constracted from the data available on Jay R. Ritter's website. A positive value of β_h indicates that young firms are relatively more sensitive than old firms to a shock, while a negative value indicates the opposite.The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

G.4 Relating to Ottonello and Winberry (2018)

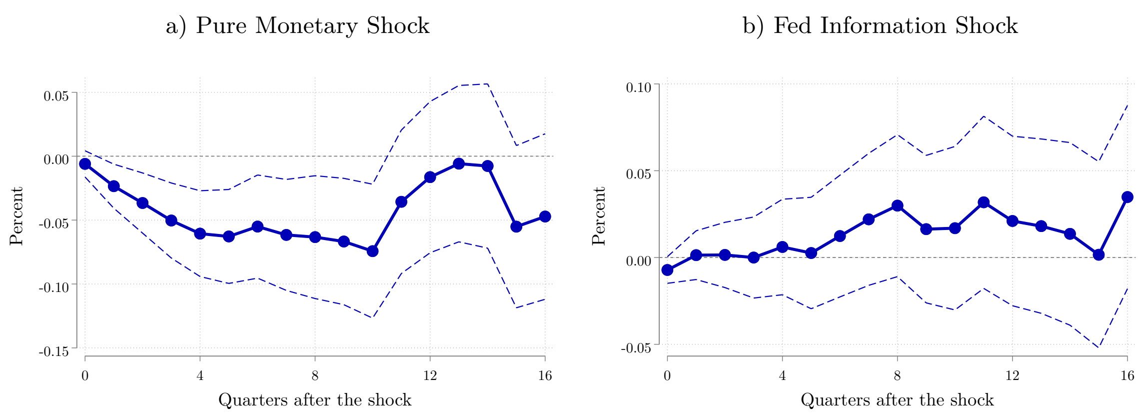
Figure 50: Heterogeneous response of investment using distance to default



$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)\mathrm{d2d}_{i,t-4} + \Gamma'_h W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in the distance to default. A positive value of β_h indicates that firms that are relatively more financially stable are more sensitive to a shock, while a negative value indicates the opposite. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

Figure 51: Heterogeneous response of investment using demeaned distance to default

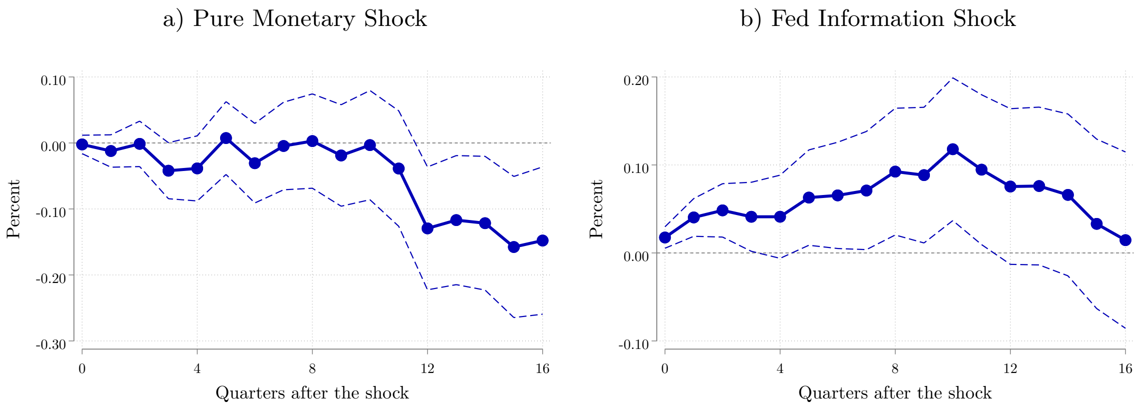


$$\Delta_h \log(k_{i,t+h}) = \alpha_{i,h} + \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)[\mathrm{d2d}_{i,t-4} - \mathbb{E}_i \mathrm{d2d}_{i,t-4}] + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) among firms with a 10 percentage point difference in the previously demeaned distance to default at the firm level. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

G.5 Relating to Whited (1992)

Figure 52: Heterogeneous response of investment using S&P credit rating



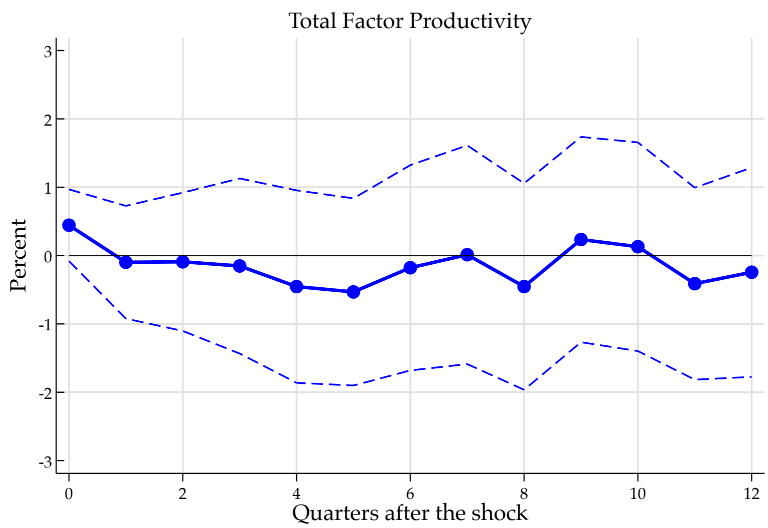
$$\Delta_h \log(k_{i,t+h}) = \alpha_{t,j,h} + (\beta_h \Delta q_t + \delta_h)\mathbb{1}_{\text{Good Rating}_{i,t-1}} + \Gamma_h' W_{i,t-1} + u_{i,t+h}$$

Notes: The figures illustrate the average heterogeneous response of capital accumulation to a pure monetary shock (panel a) and a Fed information shock (panel b) between firms with high credit score and low credit score. A positive value of β_h indicates that firms with a credit score > B+ are relatively more sensitive than firms with a lowe credit score, while a negative value indicates the opposite. The point estimates and 90% confidence intervals for the β_h coefficients are reported, obtained by estimating equation hereabove using 2SLS and employing $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ as instruments for Δq_t. The confidence intervals are constructed based on two-way clustered standard errors at the firm and quarter levels. The instruments $\varepsilon_t^{\text{mps}}$ and $\varepsilon_t^{\text{info}}$ are constructed following the identification approach of Jarociński and Karadi (2020). The variable Δq_t represents the quarterly percentage change in the average Q calculated across firms for each quarter in Compustat. Additional details on variable construction can be found in Appendix E.

H Additional results for the Fed information channel

H.1 Effect of Fed information on TFP

Figure 53: Response of aggregate TFP to a Fed information shock



Notes: Plot the response of aggregate TFP to a Fed information shock estimated using standard Local Projection. I use the **?** utilization-adjusted series of TFP as a measure of aggregate productivity. I control for 4 lags of GDP growth, inflation, interest rate and excess bond premium in the regression. The results do not change if aggregate controls are removed. The impulse response is computed at quarterly frequency. I report the 90% confidence intervals.

Table 26: Robustness of the Q-test to different measure of sentiment

	No Sentiment	With Sentiment 1	With Sentiment 2
	(1)	(2)	(3)
Fed Information Shock	1.431***	1.103	1.021**
	(0.486)	(0.676)	(0.435)
Pure Monetary Shock	-1.353***	-1.784***	-1.300***
	(0.481)	(0.641)	(0.406)
Fixed Effects	Firm	Firm	Firm
Controls	Size, Trend	Size, Trend	Size, Trend
Period	1990-2018	1990-2018	1990-2018
Observation	339268	173557	324807

Notes: The table reports panel OLS estimates of the coefficients of a regression of the change in the Tobin's Q on the monetary policy shocks. Average Tobin's Q is the ratio of total assets, the market value of equity from CRSP, minus the book value of equity and deferred taxes to total assets. Pure and Fed information shocks are identified using Jarociński and Karadi (2020) approach. Variations in investor sentiment are proxy by the change in volatility index (VIX). The dataset runs from 1990-Q1 to 2018-Q4. Standard errors, clustered two-way at the firm and quarter level, are reported in parentheses. $* = 10\%$ level, $** = 5\%$ level, and $*** = 1\%$ level. See Appendix E for additional information on variables construction.

Table 27: Robustness of the Q-test to different specification

	No Sentiment	With Sentiment 1	With Sentiment 2
	(1)	(2)	(3)
Fed Information Shock	1.431***	1.103	1.021**
	(0.486)	(0.676)	(0.435)
Pure Monetary Shock	-1.353***	-1.784***	-1.300***
	(0.481)	(0.641)	(0.406)
Fixed Effects	Firm	Firm	Firm
Controls	Size, Trend	Size, Trend	Size, Trend
Period	1990-2018	1990-2018	1990-2018
Observation	339268	173557	324807

Notes: The table reports panel OLS estimates of the coefficients of a regression of the change in the Tobin's Q on the monetary policy shocks. Average Tobin's Q is the ratio of total assets, the market value of equity from CRSP, minus the book value of equity and deferred taxes to total assets. Pure and Fed information shocks are identified using Jarociński and Karadi (2020) approach. Variations in investor sentiment are proxy by the change in volatility index (VIX). The dataset runs from 1990-Q1 to 2018-Q4. Standard errors, clustered two-way at the firm and quarter level, are reported in parentheses. $*$ = 10% level, $**$ = 5% level, and $***$ = 1% level. See Appendix E for additional information on variables construction.

I Model Details

I.1 Agents problem

Intermediate good producers. Denote $\{\varepsilon, \mathrm{S}\} = \{\varepsilon, \mathrm{K}, \mathrm{B}\}$ the state of a firm j in the economy. The intermediate good producers solve the following problem:

$$V(\varepsilon, S) = \max_{K', B'} \left\{ \mathcal{D}(\varepsilon, S, S') - (a_0 + \frac{a_1}{2}\mathcal{D}^2)\mathbb{1}_{\mathcal{D}<0} + \Lambda_{t,t+1} \sum_{\varepsilon'} \pi(\varepsilon'|\varepsilon) V'(\varepsilon', S'|\varepsilon) \right\} \tag{64}$$

subject to:

$$\mathcal{D}(\varepsilon, S, S') = \Pi(\varepsilon, S) - c_0 \left(\frac{I}{K} \right)^2 K + c_1 \mathbb{1}_{I \neq 0} - K' + (1-\delta)K + \mathcal{Q}B' \tag{65}$$

$$\Pi(\varepsilon, S) = (1-\tau)(p_t^w Z_t \varepsilon K^\alpha \mathrm{N}^{*\nu} - w_t N^* - \eta) - B + \tau(\delta K + i_t B) \tag{66}$$

$$N^*(\varepsilon, K) = \arg\max_{N \geq 0} \left\{ p_t^w Z_t \varepsilon K^\alpha N^\nu - w_t N \right\} \tag{67}$$

$$\mathcal{H}(\varepsilon, S, S') = (a_0 + a_1 \mathcal{D}^2)\mathbb{1}_{\mathcal{D}<0} \tag{68}$$

$$I = \mathrm{K}' - (1-\delta)K \tag{69}$$

$$B' \leq \theta_k K' \quad (\lambda') \tag{70}$$

where λ is the multiplier associated to the non-binding constrain. The optimality condition for capital can be obtained by taking the FOCs w.r.t to K' and combining with the envelope condition.

The FOC with respect to K' is:

$$-\frac{\partial \mathcal{D}}{\partial K'}(1 - a_1 \mathcal{D}\mathbb{1}_{\mathcal{D}<0}) = \Lambda_{t,t+1}\mathbb{E}V_{K'}(\varepsilon', S') + \theta_k \lambda' \tag{71}$$

The envelope condition allows to characterize intertemporal payoffs for the capital choice:

$$V_k(\varepsilon, S) = \frac{\partial \mathcal{D}}{\partial K}(1 - a_1 \mathcal{D}\mathbb{1}_{\mathcal{D}<0}) \tag{72}$$

Taking the derivatives and combining equations (71) and (72), we have that:

$$\begin{aligned} \left(1 - \varepsilon_t^{\text{risk}} e^{-\theta_l \frac{B'}{K'}} + c_0 \frac{I}{K}\right)(1 - a_1 \mathcal{D}\mathbb{1}_{\mathcal{D}<0}) = \\ \Lambda_{t,t+1}\mathbb{E}\left[\Pi_k(\varepsilon', S') + (1-\delta)\left(1 + c_0 \frac{I'}{K'}\right) + \frac{c_0}{2}\left(\frac{I'}{K'}\right)^2\right](1 - a_1 \mathcal{D}'\mathbb{1}_{\mathcal{D}'<0}) + \theta_k \lambda' \end{aligned} \tag{73}$$

which is equal to equation (**??**) in the paper.

Final good producers. Final good producers buy from retailers goods $\tilde{Y}_{i,t}$ at price $p_{i,t}$ and aggregate using a CES aggregator:

$$Y_t = \left[\int \tilde{Y}_{i,t}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$$

The demand of retail goods $\tilde{Y}_{i,t}$ is obtained solving:

$$\max_{\{\tilde{Y}_{i,t}\}} \quad P_t Y_t - \int p_{i,t}\tilde{Y}_{i,t} \qquad \text{s.t.} \quad Y_t = \left[\int \tilde{Y}_{i,t}^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$$

Taking the FOCs w.r.t to $\tilde{Y}_{i,t}$ we get the demand of the good $\tilde{Y}_{i,t}$.

$$\tilde{Y}_{i,t} = \left(\frac{p_{i,t}}{P_t}\right)^{-\theta} Y_t$$

and substituting in the constraint, we get the aggregate price P_t.

$$P_t = \left(\int p_{i,t}^{1-\theta}\right)^{\frac{1}{1-\theta}}$$

Because final good producers are perfectly competitive, zero profits condition holds.

Retailers Retailers transform homogeneous good products $Y_{i,t}$ using a linear technology $\tilde{Y}_{i,t} = Y_{i,t}$. Retailers sell the heterogeneous good $\tilde{Y}_{i,t}$ to a final good producer at a price $p_{i,t}$ to be determined in a monopolistic competitive market, i.e., they take the demand of goods as given. It follows that retailers solve the following problem:

$$\max_{\{p_{i,t}\}} \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{t,t+1} \left(p_{i,t}\tilde{Y}_{i,t} - p_t^w Y_{j,t} - \frac{\phi_p}{2}\left(\frac{p_{i,t}}{p_{i,t-1}} - 1\right)^2 Y_t \right) \qquad \text{s.t.} \quad \tilde{Y}_{i,t} = \left(\frac{p_{i,t}}{P_t}\right)^{-\theta} Y_t$$

The FOCs for the problem gives:

$$p_{i,t}\frac{d\tilde{y}_{i,t}}{dp_{i,t}} + \tilde{Y}_{i,t} - p_t^w \frac{d\tilde{Y}_{i,t}}{dp_{i,t}} - \phi\left(\frac{p_{i,t}}{p_{i,t-1}} - 1\right)\frac{Y_t}{p_{i,t-1}} + \mathbb{E}\Lambda_{t,t+1}\phi\left(\frac{p_{t+1}}{p_{i,t}} - 1\right)\frac{Y_{t+1}}{p_{i,t}}\left(\frac{p_{i,t+1}}{p_{i,t}}\right) = 0$$

Because all firms are symmetric and from pricing equation, it follows that:

$$(P_t - p_t^w)\frac{d\tilde{Y}_{i,t}}{dp_{i,t}} + Y_t - \phi\pi\frac{Y_t}{P_{t-1}} + \mathbb{E}\Lambda_{t,t+1}\phi(1+\pi_{t+1})\pi_t\frac{Y_{t+1}}{P_t} = 0$$

Finally, re-organizing the terms the New-Keynesian Phillips curve is:

$$\pi_t(1+\pi_t) = \frac{1}{\phi_p}[\theta p_t^w - (\theta - 1)] + \mathbb{E}\Lambda_{t,t+1}(1+\pi_{t+1})\pi_{t+1}\frac{Y_{t+1}}{Y_t}$$

Assume that the final good price is the numeraire, $P_t = 1$ and rewrite the NKPK in log-linearized form:

$$\log\Pi_t = \frac{\theta - 1}{\phi_p}\log\frac{p_t^w}{p} + \beta\mathbb{E}_t\log\Pi_{t+1}$$

Because retailers operate in a monopolistic environment, their profits are distributed to the household. I omit the household problem since it is described in the paper.

I.2 Equilibrium

A recursive competitive equilibrium of the model is as follows:

Definition 1. *A recursive competitive equilibrium of the model is as a set of the firms' value and policy functions $V(\varepsilon, K, B)$, $K^{*\prime}(\varepsilon, K, B)$, $B^{*\prime}(\varepsilon, K, B)$,$N^*(\varepsilon, K, B)$, a consumption and labor function C_t, N_t, a distribution of firms $\Gamma(\varepsilon, K, B)$ and, a set of prices w_t, i_t, p_t^w such that:*

i) (Firms optimization) Firms choose $K^{*\prime}(\varepsilon, K, B)$, $B^{*\prime}(\varepsilon, K, B)$ and $N^*(\varepsilon, K, B)$ to maximize the future stream of dividends given their constraints;

ii) (Household optimization) Given the equilibrium prices, households choose consumption and labor paths that are consistent with the equations the Euler Equation and Frish labor supply;

iii) (Retailers and final good producers) Retailers set the price $pi,_t$ for the intermediate goods taking the demand of the final good producers as given. Retailers and final good producer' solutions aggregate to produce the NKP Curve.

iv) *(Central bank and government) Central bank set the nominal interest rate* i_t *following a Taylor rule. Government collect taxes from the firms and redistribute lump-sum to the households;*

iv) *(Law of motion for the firms' distribution) The law of motion for the firm distribution* Γ *is generated by the stochastic process for idiosyncratic productivity and the firm policy function* $K^{*\prime}(\varepsilon, K, B)$, $B^{*\prime}(\varepsilon, K, B)$*:*

$$\Gamma' = Q\Gamma$$

where Q *is the transition matrix from the states* (ε, K, B) *to* (ε', K', B')*:*

$$Q((\varepsilon, K, B), \mathcal{E} \times \mathcal{K} \times \mathcal{B}) = \mathbb{1}\{K^*(\varepsilon, K, B) \in \mathcal{K}, B^*(\varepsilon, K, B) \in \mathcal{B}\}\pi(\varepsilon'|\varepsilon)$$

vi) *(Law of motion for aggregate state) The law of motion for the aggregate states follow the stochastic processes for the aggregate shocks;*

vii) *(Markets clearing) From the budget constraint, substituting dividends from wholesale producers and retailers. Aggregate prices* w_t *and* p_t^w *are consistent with market clearing conditions:*

$$Y_t = C_t + I_t + \int \mathcal{G} dj - \int \mathcal{H} dj + \frac{\phi}{2}\pi_t^2 Y_t$$

I solve for the stationary equilibrium of the model and, study the response of the model along the perfect foresight transition path to an anticipated change in the future aggregate technology and unexpected change in the nominal interest rate. I rely on computational methods to study the solution of this problem.

I.3 Computational methods

This section provides details on the computational methods that I use to find the solution to the model in this paper. I solve the model using value function iteration, both in the steady-state and along the perfect-foresight transition path. To calculate the response of the economy to an unexpected aggregate shock, I use a standard backward-forward shooting method following **?** algorithm. Finally, to calculate the distribution of firms over the idiosyncratic state-space, I use the non-stochastic simulation approach following Young (2010).

Firm's optimal solution. To find an approximation of the solution in the steady-state, I discretize the state for $(\varepsilon, K, \frac{B}{K})$. I convert the continuous exogenous process for ε into the discretized Markov chain using Tauchen (1986). I fix the number of grid points for ε, $N_\varepsilon = 5$. Instead, the grid for K and $\frac{B}{K}$ is made up of a set of (13 x 8) in an interval $(0, K^{\max}]$ and $[-\theta_k, \theta_k]$ non-equally spaced points so to have more points in the lower part of the capital and higher part of leverage. Once I have set up the grids, I use value function iteration to find a solution.

1. Guess an initial value for the wage w_0^*;

2. Given the value for wage w_0^*, solve the firms' problem using value function iteration:

   i) Approximate the $\mathbb{E}V(\varepsilon, K', \frac{B'}{K'})$ with an higher-order polynomials and guess an initial vector of coefficient c_0;

   ii) Given the expected value function, find the optimal combination $(K', \frac{B'}{K'})$ such that it solve the Bellman equation for each element in the grid $(\varepsilon, K, \frac{B}{K})$;

   iii) Given the solution, calculate the new expected value function;

iv) Update the coefficient of the expected value function using Newton method and find c_1;

v) Iterate until $||c_1 - c_0||$ is arbitrary small;

3. Given a solution for K', B' and a coefficient vector c, calculate the distribution Γ of firms over $(\varepsilon, K, \frac{B}{K})$ in the stationary equilibrium using Young (2010). Before computing the ergodic distribution, I interpolate the solution over a finer grids over the states.

4. Using the cross-sectional distribution of firms calculate a new equilibrium value for wage w_1^*. Iterate until $|w_1^* - w_0^*|$ is small enough.

A solution to this problem deliver the policy function for K', B' and a vector of coefficient c^* over the space grid (ε, K, B).

Perfect-Foresight transitional dynamics. I compute the dynamics of the economy to an unexpected aggregate shock using a standard backward-forward algorithm. The algorithm is in 4-steps:

1. Guess a path for aggregate consumption $\left(C_t^{OLD}\right)_{t=1}^{T}$ and calculate the path for aggregate prices w_t, i_t, p_t^w and inflation π_t consistent with the model equations.

2. Backward: Start from time T, calculate backward the policy functions for $K_{t,t+1}^{*\prime}$ and $B_{t,t+1}^{*\prime}$ for all time t.

3. Forward: Given the policy functions obtained, iterate forward to calculate the distribution of firms $\Gamma_t = \Gamma_t(\varepsilon, K, B)$ over time using Young's method.

4. Use the results in (2) to calculate a new equilibrium path for aggregate consumption $(C_t)_{t=1}^{T}$. Iterate (1-4) until $|C_t - C_t^{OLD}|$ is small enough.

One problem with the backward-forward shooting method is that updating the path for ”too quickly" may result in the overall procedure to diverge. I compute the new update path for consumption as a convex combination of the previous guess and the newly calculated path, with λ small:

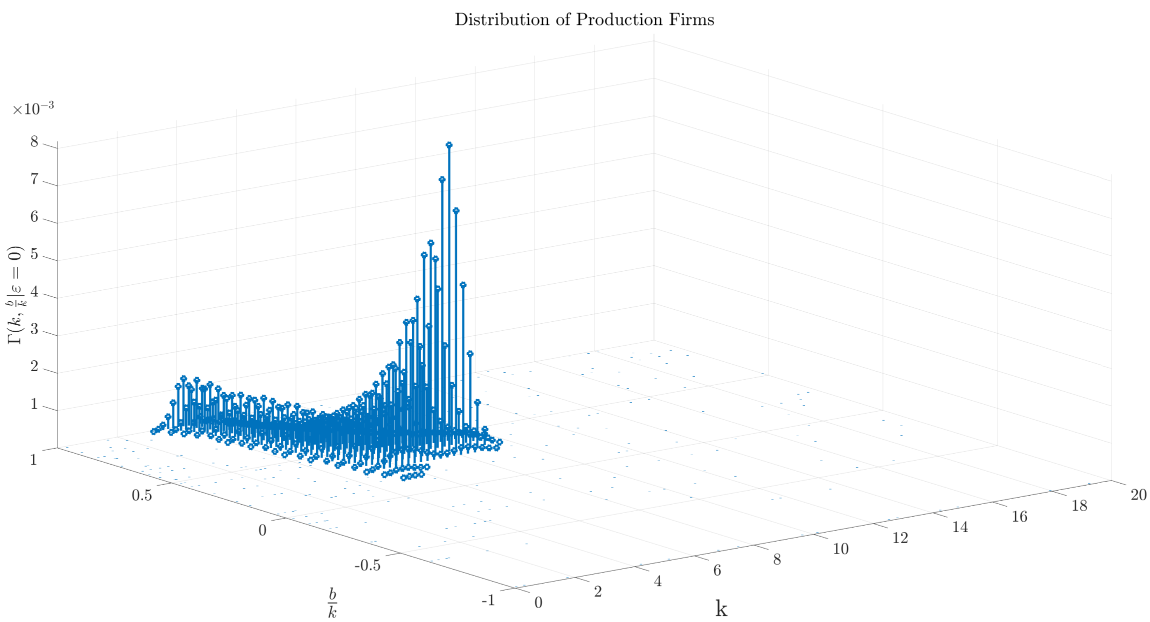
$$\left(C_t^{NEW}\right)_{t=1}^{T} = \lambda(C_t)_{t=1}^{T} + (1-\lambda)\left(C_t^{OLD}\right)_{t=1}^{T}$$

A solution to the algorithm delivers the impulse response function of the aggregate variable and the distribution of firms in response to an unexpected aggregate shock over time.

J Model results

J.1 Ergodic distribution of the model

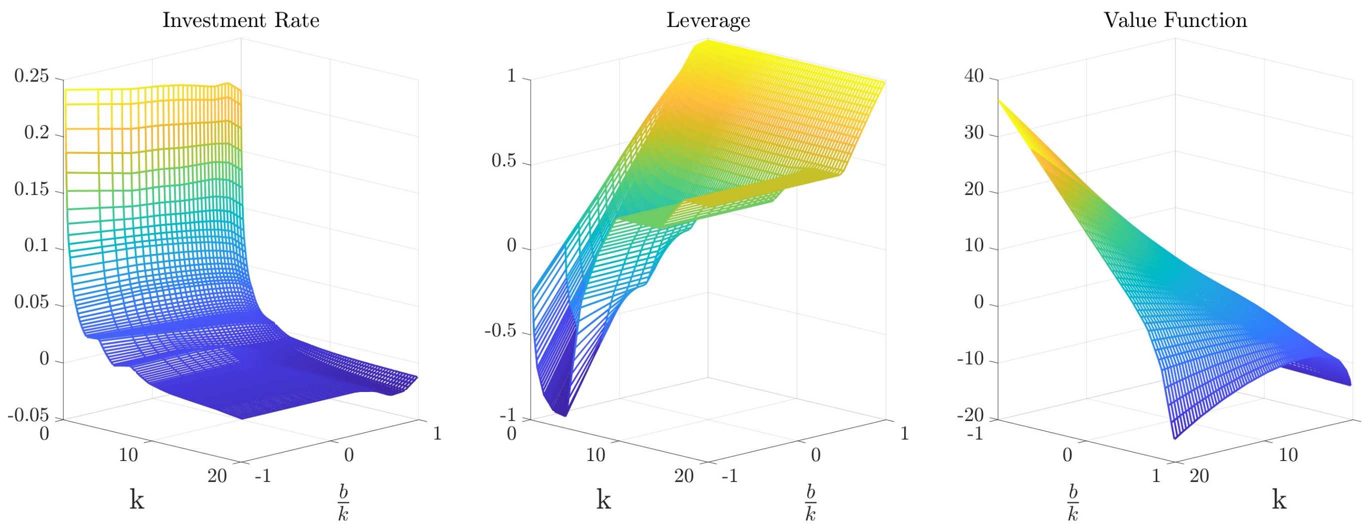
Figure 54: Ergodic distribution of the firms in the steady state.



Note: The ergodic distribution of the investment firms in the stationary equilibrium as a function of capital (x-axis) and leverage (y-axis). I approximate the ergodic distribution with Young (2010) method.

J.2 Policy function in the stationary equilibrium

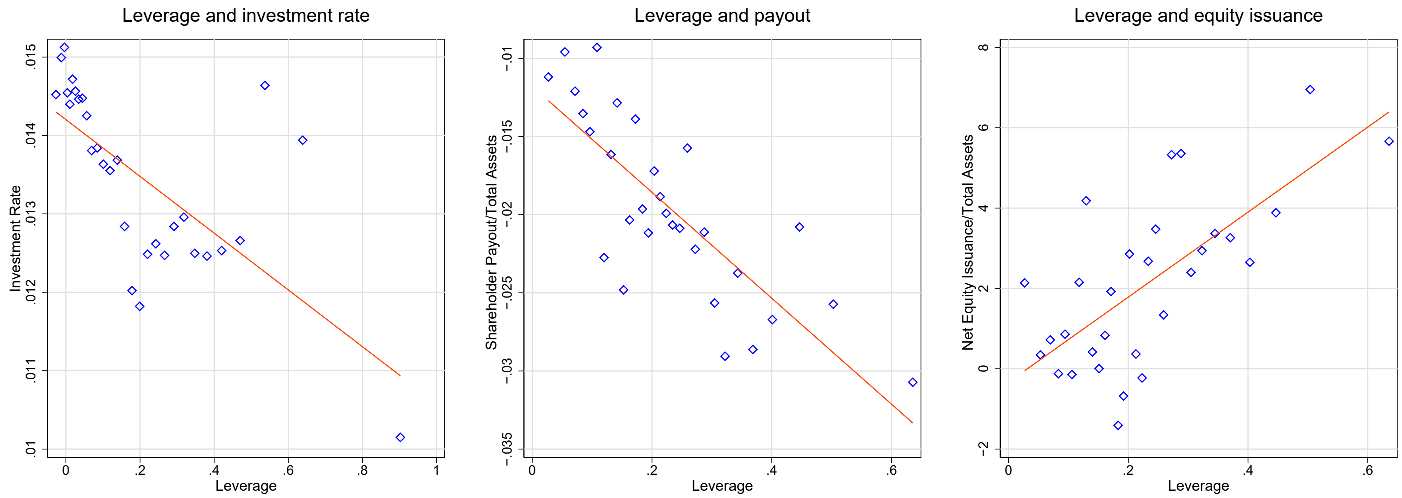
Figure 55: Policy functions in the steady state.



Note: Plot the optimal value and policy functions for investment rate and leverage in the stationary equilibrium over the state state grid $(k, \frac{b}{k})$. I fix the idiosyncratic productivity at the steady state level.

J.3 Cross-section correlation between leverage and other financial variables

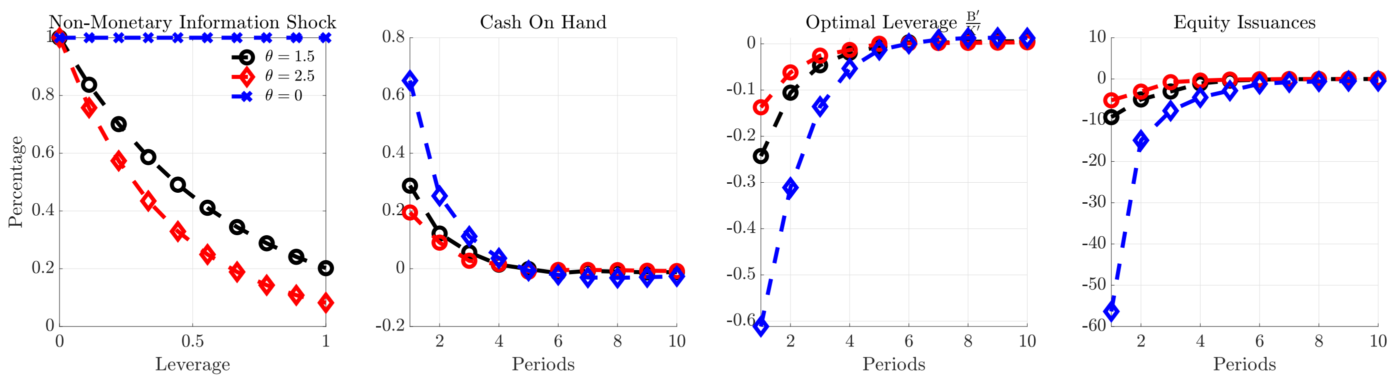
Figure 56: Leverage and other financial variables across US firms 1990-2016



Note: I plot the cross-sectional correlation between firms' leverage, investment rate, dividends payout, and equity issuance across Compustat firms from 1990 to 2016. To mimic steady state correlation, I compute firm averages over time on the entire time sample. Before plotting, I also trim the tails at 1.5% of the firm averages to avoid outliers.

J.4 Financial variable response to a non-monetary shock under different scenarios

Figure 57: Financial variable response for high leverage firms to a $\varepsilon_t^{\text{risk}}$ shock



Note: The average impulse response function for the price of debt, debt and equity issuance for high leverage firms in response to a non-pure monetary policy shock and different value of θ_l. Black lines represents benchmark calibration, $\theta_l = 1.5$. Blue lines represents the model responses when $\theta_l = 0$. Red lines represents the model responses when $\theta_l = 2.5$. High leverage firms are defined as firms that have more than 50% of leverage in the stationary distribution prior the shock hits. The averages are calculated by equally weighting firms that constitute more than 1 percent of the total firms.

J.5 Financial variables response to different monetary shocks

Figure 58: Financial variables response to a $\varepsilon_t^{\text{mps}}$ shock

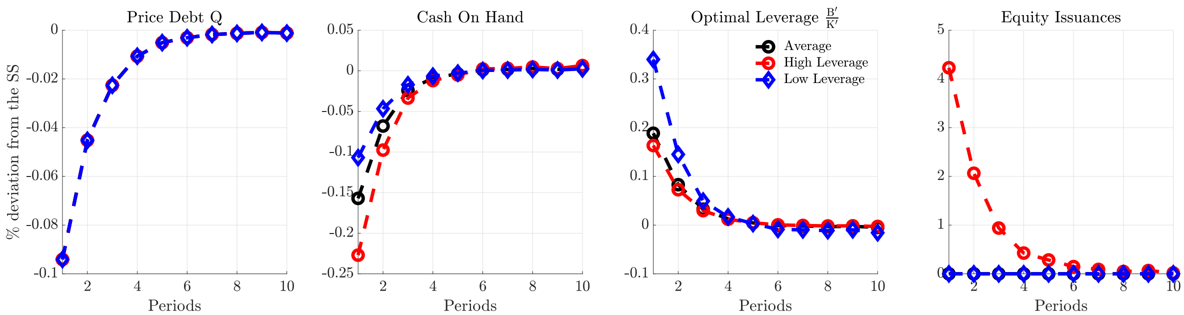
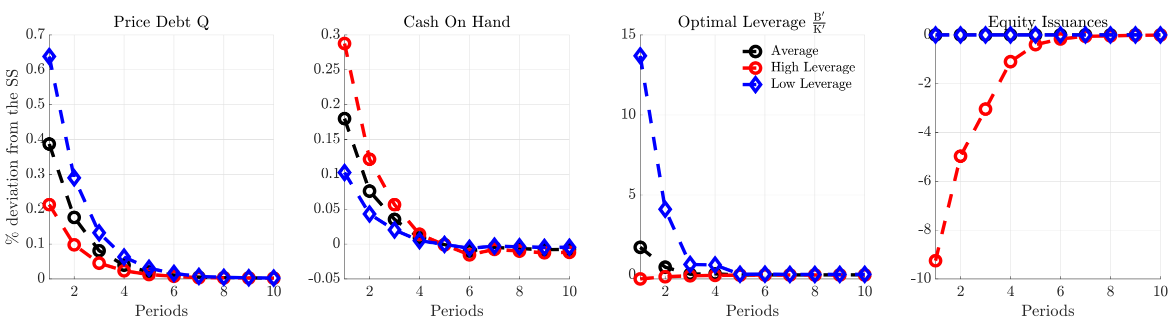


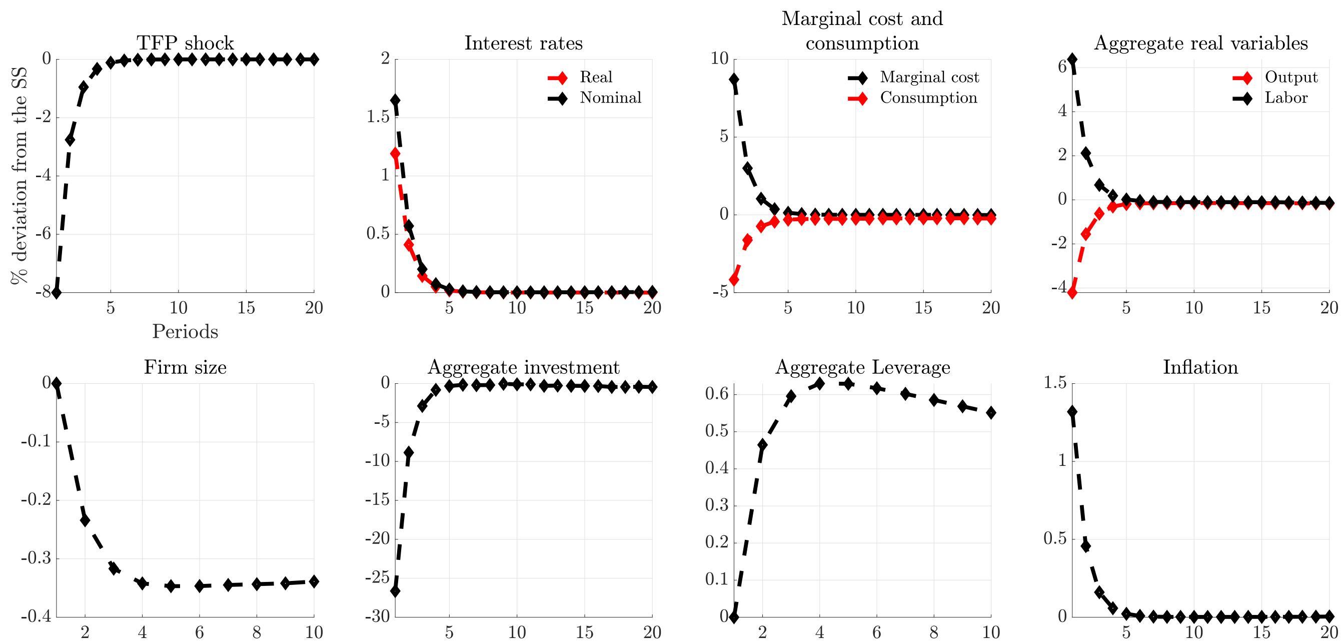
Figure 59: Financial variables response to a $\varepsilon_t^{\text{risk}}$ shock



Notes: The average impulse response function for the price of debt, debt and equity issuance across firms in response to a pure monetary policy shock (first column) and a Fed information shock (second column). The blue line shows the average firm-level responses of the main variables for firms that prior the shock have less than 50% of leverage (i.e., low leverage). The red line illustrates the average response for the same variables for firms with more than 50% leverage (i.e., high leverage). The averages are calculated by equally weighting firms that constitute more than 1 percent of the total firms.

J.6 Aggregate response to a productivity shock

Figure 60: IRFs to an aggregate productivity shock



Note: Plot the impulse response function of the model to a one standard deviation productivity shock in the model. The standard deviation is calibrated to generate a drop in output by 4 percent at impact whereas, the persistence of the shock is calibrated to induce a recession for eight quarters. Responses are presented as deviations with respect to the stationary equilibrium.