Customer Capital and the Aggregate Effects of Short-Termism

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Abstract

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 annual total market capitalization by \$3.1 trillion on average.

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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 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

[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).

[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).

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 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 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 and, thus, firm size. 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 a là 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

[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).

(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 the absence of endogenous growth. To the best of our knowledge, this is the first paper to use this class of models to study the aggregate effects of short-termism on firms' markup and pricing decisions.

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 A), the empirical robustness (Appendix B), the simple model (Appendix C), and the estimation and quantitative analysis (Appendix D).

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 A 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:

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

where $\widehat{\theta}_{st}$ is the estimated sectoral output elasticity of variable input V in sector s at time t, and $\frac{P_{ist}Q_{ist}}{P_{ist}^{V}Q_{ist}^{V}}$ 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 A provides further details on the estimation and measures of markup.

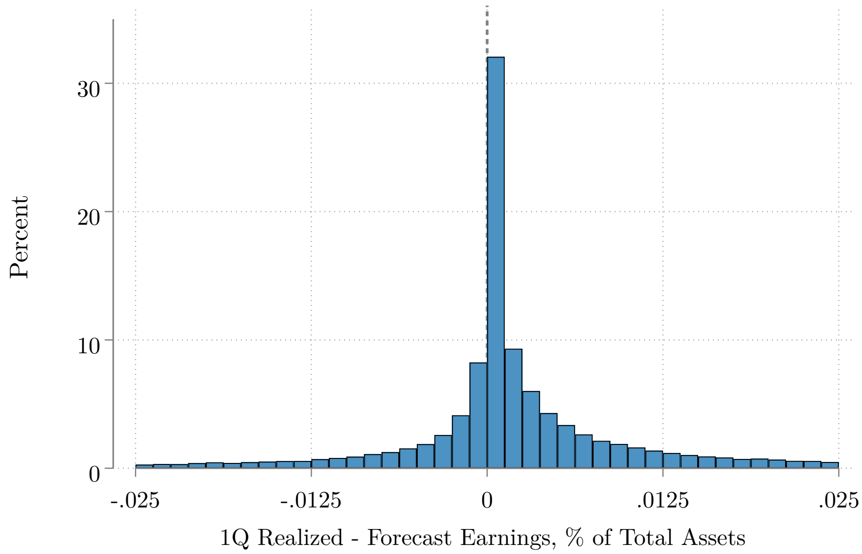
Forecast error. We follow Terry (2022) and use IBES profits forecasts and realized earnings to construct our main measure of the one-quarter forecast error for firm i at quarter t:

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

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 rescaling the difference between realized earning and analyst consensus by other measure of

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 A for additional details on data and measure construction.

firm size such as market value (Compustat variable *prccq*, i.e. price per share) or lagged sales (Compustat variable *saleq*). Appendix A 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 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 6 in Appendix A shows that the bunching pattern described in Figure 1 is robust to the other measures of forecast error

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 A for additional information on variables construction.

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:

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

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

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

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 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 4 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

[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*).

[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).

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 5 in Appendix B shows that the estimated discontinuity in markup growth is robust 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 6 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 7 in Appendix B shows that the discontinuity is increasing in sectors with lower levels of inventories, in line with Table 6. 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 8 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

[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 10 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).

[11] Moreover, Table 9 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).

overly reliant on any single product market (Hoberg and Phillips, 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 7 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 7 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 $[0.02, 0.05]$.

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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 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).

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

[14]Nevertheless, Table 11 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 8 and Table 12 in Appendix B show that the same qualitative patterns hold for sales and cost growth.

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]

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:

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

[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).

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:

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

where the cost of missing profit targets, $\theta_\pi y_t \mathbb{P}\left(\Pi_t < \Pi_t^f\right)$ 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]

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

[17]Derivations in the Appendix C.

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 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]

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

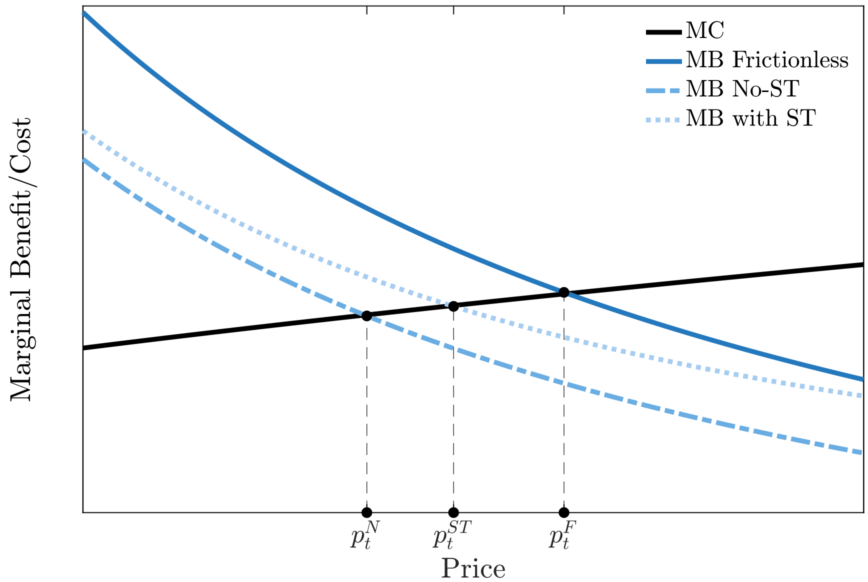
Equation 10 states that at the optimum, the manager sets the price p_t to equate the marginal benefit (on the left-hand side) with the marginal cost of increasing the price today (on the right-hand side). The marginal cost of increasing the price is determined by the fact that higher prices reduce the 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 is positive when the board sets a cost for not meeting analysts' forecasts ($\theta_\pi > 0$), resulting in the manager

[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.

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 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

[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.

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 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

[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.

[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.

increasing in firm's size and depends on the parameter θ_π, which is optimally chosen by the board. Thus, the manager solves the following dynamic problem:

$$V^M\left(a_{j,t},\varepsilon_{j,t},b_{j,t}|\theta_\pi,\Pi^f_{j,t}\right)=\max_{\{p_{j,t},m_{j,t}\}}\Bigg\{\theta_d\left(p_{j,t}y_{j,t}+m_{j,t}-\frac{w_t}{a_{j,t}}y_{j,t}\right)+\phi_e\frac{y_{j,t}}{a_{j,t}}-\phi_m m^2_{j,t} \quad (16)$$

$$-\theta_\pi\frac{y_{j,t}}{a_{j,t}}\mathbb{P}\left(\Pi_{j,t}<\Pi^f_{j,t}\right)+\frac{1}{R_t}\mathbb{E}_t V^M\left(a_{j,t+1},\varepsilon_{j,t+1},b_{j,t+1}|\theta_\pi,\Pi^f_{j,t}\right)\Bigg\},$$

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:

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

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:

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

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

[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.

distribution, Γ_h. Hence, the board of directors sets θ_π to solve the following problem:

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

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^f_t and short-term costs θ_π;

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

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;

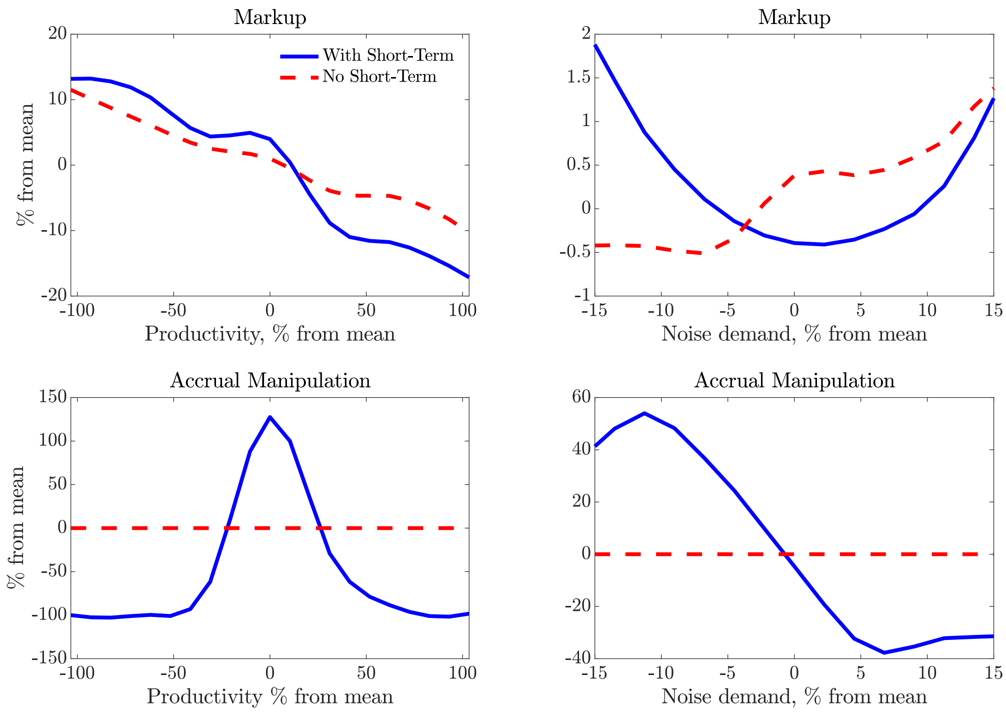
iv) The firm distribution $\Gamma(a, \varepsilon, b)$ is consistent with the idiosyncratic stochastic processes and managers' policy function, $p^*(a, \varepsilon, b)$ and $m^*(a, \varepsilon, b)$.

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

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.

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 opportunistically 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 9 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

[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.

[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.

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.

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 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

[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.

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.

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:

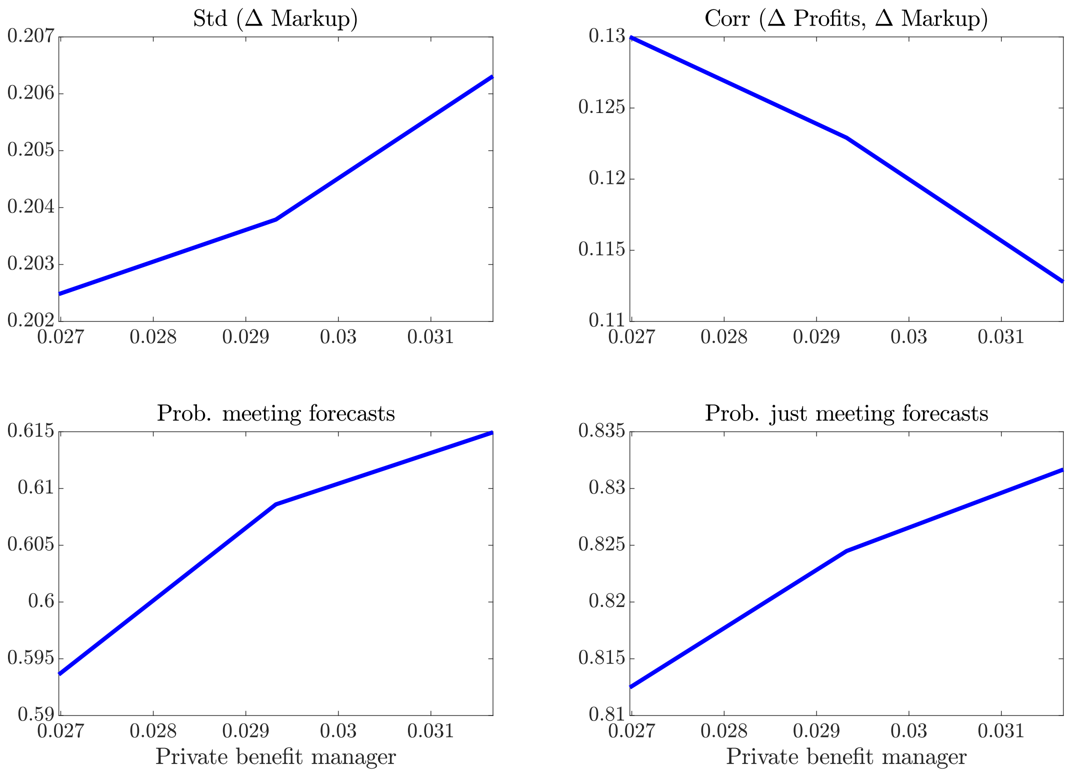
$$\hat{\theta}_{\text{SMM}} = \theta : \min_{\theta} \quad \Big(m(\tilde{x} \mid \theta) - m(\tilde{x})\Big) W \Big(m(\tilde{x} \mid \theta) - m(\tilde{x})\Big)', \tag{20}$$

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 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 10 in Appendix D plots the relationship between the other estimated parameters 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).

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.

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.

Appendix D.2 shows that the model can reproduce a set of untargeted moments consistent with the data. Figure 11 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 12 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 13 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 indicate that short-termism prompts firms to increase their markups, leading to an immediate benefit for shareholders. According to the baseline model, short-termism results in a 8.04% rise in average markups in the economy, a significant amount compared to recent evidence on markup and competition

[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.

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 loss from short term pressure	[3.474,5.959]
Market capitalization loss from short-term pressure	9.178
Average effect	-0.770
Distribution 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%).

(De Loecker et al. (2020) among others).[34] 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 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.[35] 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).[36] 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

[34] 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.

[35] In Compustat, we proxy profits as sales minus cost of good sold (*saleq* - *cogs* - *xsgaq*).

[36] 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.

and Paasche indexes.[37] 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 contrasting forces: an average effect and a distribution effect.[38] The average effect reflects the positive impact of short-termism on the individual firm market value, which increases because of short-term incentives, in line with markups and profits dynamics described above. The distribution effect is tied to the influence of short-termism on the average size of firms in the economy instead. As short-termism reduces manager's private benefit from increasing firm size, firms in a world with short-termism tend to be relatively smaller, thus, reducing market capitalization.[39] Table 3 shows that the distribution effect (-9.59%) dominates the average effect (0.751%), rationalizing the negative impact that short-term has on average 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

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[37] 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, $p^i y^i = \sum p^i_x y^i_x$, 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.

[38] We decompose the effect of short-termism on market cap into an average effect and distribution effect using the following within-between decomposition. 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, the average effect. The second term reflects the effect of short-termism on the ergodic distribution, the distribution effect.

[39] See Figure 9 in Appendix D for how the distribution of firms over customer capital (firm value) changes when we move from an economy with short-termism to an economy without short-termism. In the presence of short-termism, firms' value increases for all levels of customer capital while the distribution shifts to the right.

be responsible for an aggregate loss of approximately \$3.1 trillion dollars.

It is important to stress that these results should be considered as the upper bound of the effect of short-term pressure on welfare and prices, as managers have can only manipulate markups to meet analysts' forecasts. 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 14 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 15 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.[40] 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 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.

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

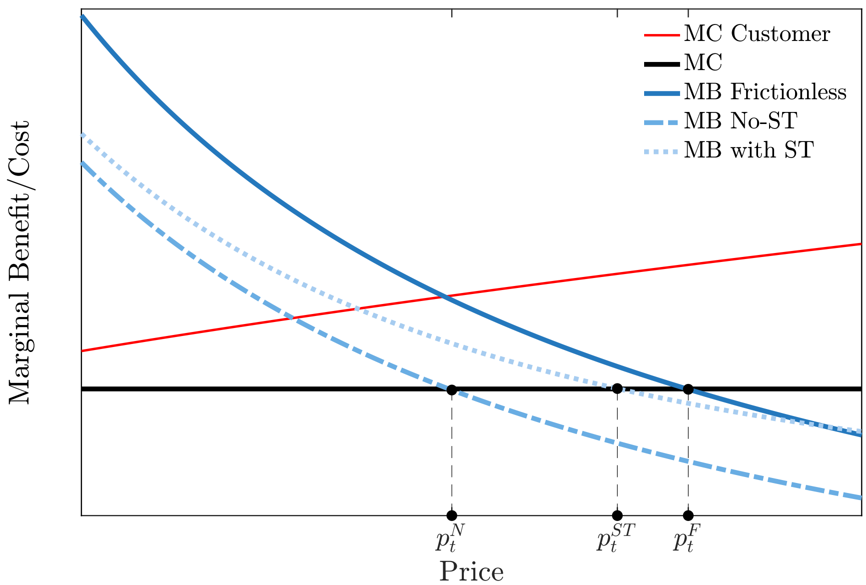
where the right hand side is now equal to zero as in any standard static pricing problem, meaning that the cost of raising prices today is only the lower current demand. Importantly, even though the investing motifs has disappeared, Figure 5 shows that the effect of short-termism is qualitatively the 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.[41] 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 16 in Appendix D.5 reports the results of the model and estimated parameters

[40] 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.

[41] 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.

Figure 5: 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.

under the CES assumption.[42] 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

[42]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.

customers.

Lastly, while the results align qualitatively with our benchmark model, incorporating customer capital accumulation within our framework improves dramatically the quantitative performance in terms of key moment matching. 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 per year 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.

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Appendix

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:

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

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

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

Figure 6 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:

$$\mathbf{Q}_{it} = \mathbf{Q}_{it}(\mathbf{K}_{it}, \bar{K}_{it}, \gamma_{it}), \tag{22}$$

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:

$$\mathcal{L}(\mathbf{K}_{it}, \bar{K}_{it}, \gamma_{it}) = \mathbf{R}_{it}\mathbf{K}_{it} + r\bar{K} + F_{it} - \lambda(\mathbf{Q}(.) - \bar{\mathbf{Q}}_{it}), \tag{23}$$

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:

$$\mu_{it} = \theta_{it}^{\mathbf{K}} \frac{P_{it} Q_{it}}{R_{it}^{\mathbf{K}} \mathbf{K}_{it}}, \tag{24}$$

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:

$$\mu_{it} = \widehat{\theta}_{it} \frac{\text{Sales}_{it}}{\text{Cost of goods sold}_{it}} = \widehat{\theta}_{it} \frac{\text{saleq}}{\text{cogsq}}, \tag{25}$$

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:

$$\mu_{it} = \theta_{it} \frac{\text{Sales}_{it}}{\text{Costs of goods sold + Overhead costs}_{it}} = \theta_{it} \frac{\text{saleq}}{\text{cogsq + xsgaq}}, \tag{26}$$

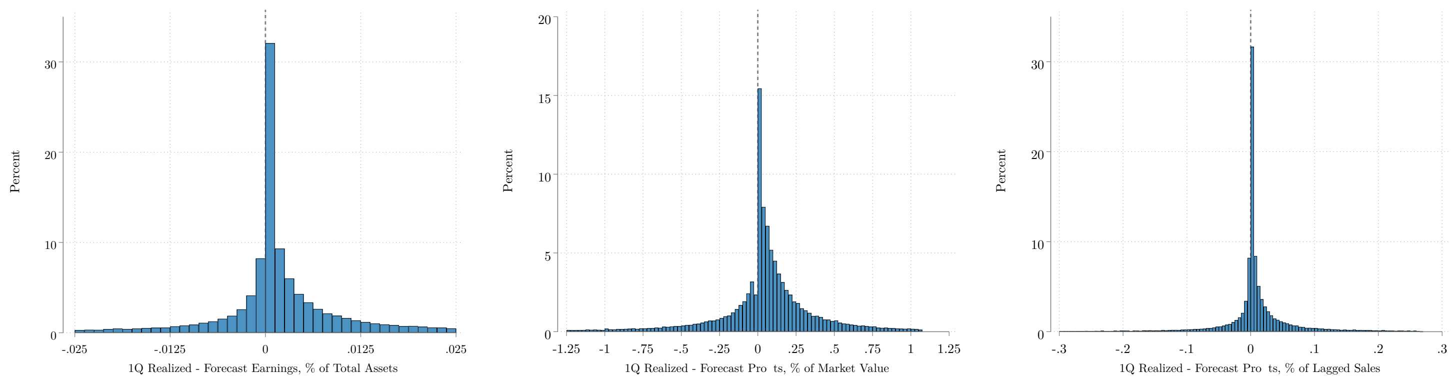
where $\widehat{\theta}_{it}$ is also estimated including selling and general expenses in the definition of variable input.

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

$$\mu_{it} = 1 - \frac{\text{Costs of goods sold}_{it}}{\text{Sales}_{it}} = 1 - \frac{\text{cogsq}}{\text{saleq}}. \tag{27}$$

A.5 Distribution of forecast errors from IBES

Figure 6: 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 4: 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 A for additional information on variables construction.

Table 5: 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 A for additional information on variables construction.

B.2 Additional Controls

Table 6: 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 A for additional information on variables construction.

Table 7: 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 A for additional information on variables construction.

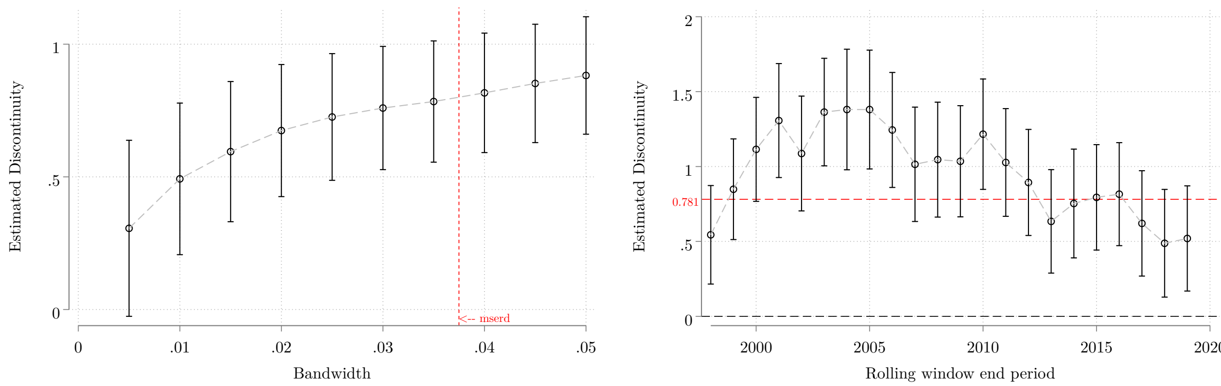
Table 8: Diversification

	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 A for additional information on variables construction.

B.3 Optimal Bandwidth and Discontinuity Over Time

Figure 7: 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 A for additional information on variables construction.

B.4 Sales vs Costs

Table 9: 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

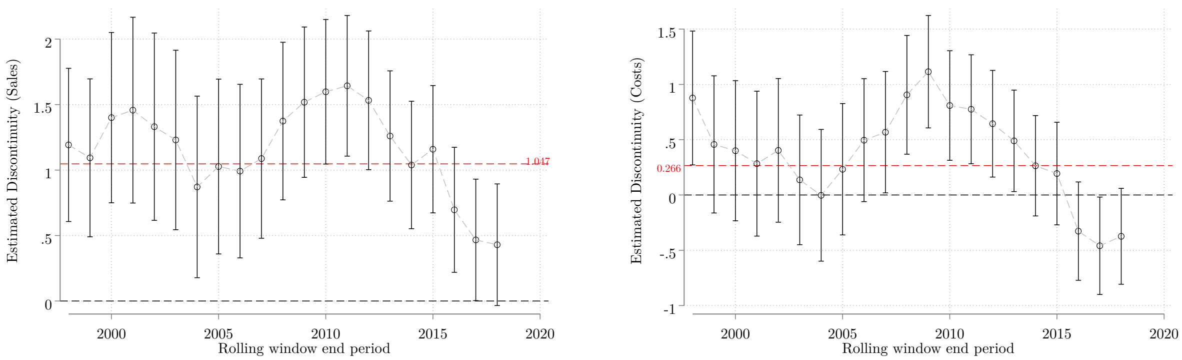
Notes: The Table reports the estimated discontinuity in sales and costs growth (in p.p.) for firms just hitting analysts' forecasts. We estimate Equation (3) using a local linear regression discontinuity with triangular kernel and optimal bandwidth (Calonico et al., 2020). In Columns (1) and (3) (Columns (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 A for additional information on variables construction.

Table 10: 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 A for additional information on variables construction.

Figure 8: 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 A for additional information on variables construction.

B.5 Boom vs Recession

Table 11: 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 A for additional information on variables construction.

Table 12: Sales vs Costs - Boom vs Recession

	$\Delta \log$ Sales		$\Delta \log$ Costs		Alternative $\Delta \log$ 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 A 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:

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

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 $V^M_0(a, \varepsilon, b)$;

      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 $V^M_1(a, \varepsilon, b)$;

      iv) Update the value function and iterate until $\max ||V^M_1 - V^M_0||$ 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.

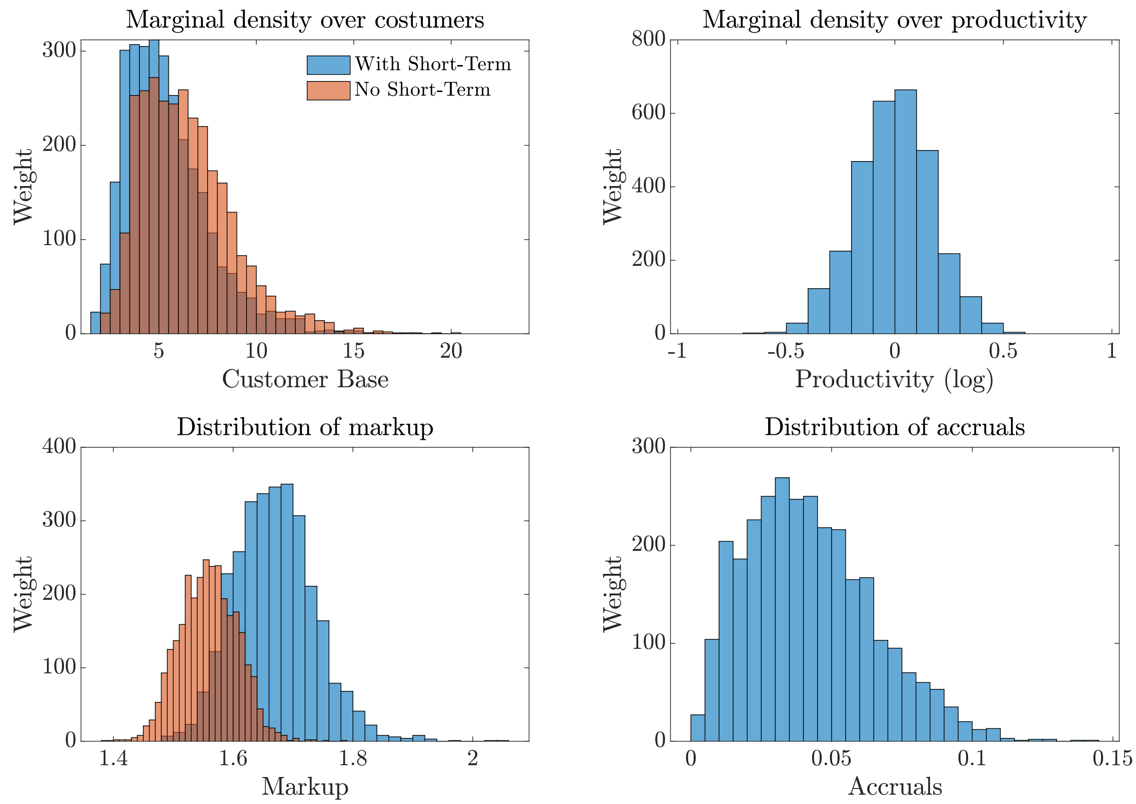
4. Given a solution for b', m calculate the distribution Γ of firms over (a, ε, b) in the stationary equilibrium using Young (2010).

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

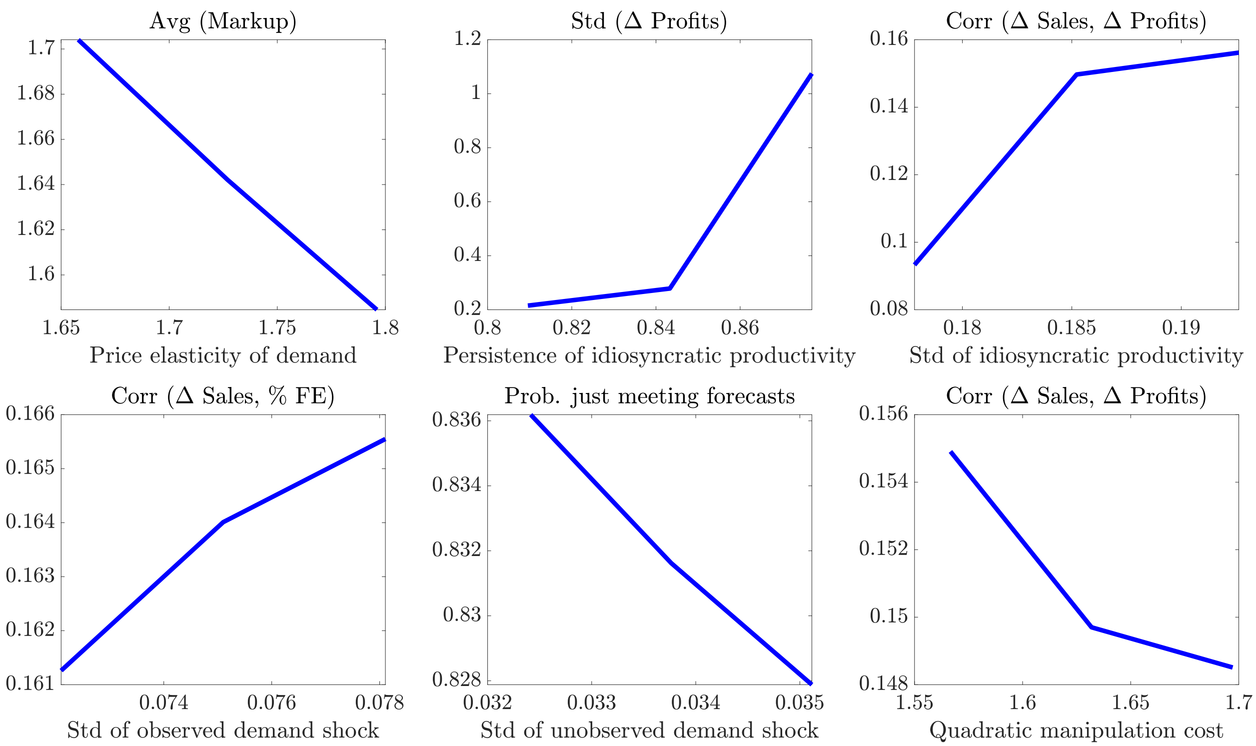
Figure 9: Density and Manager Policy



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

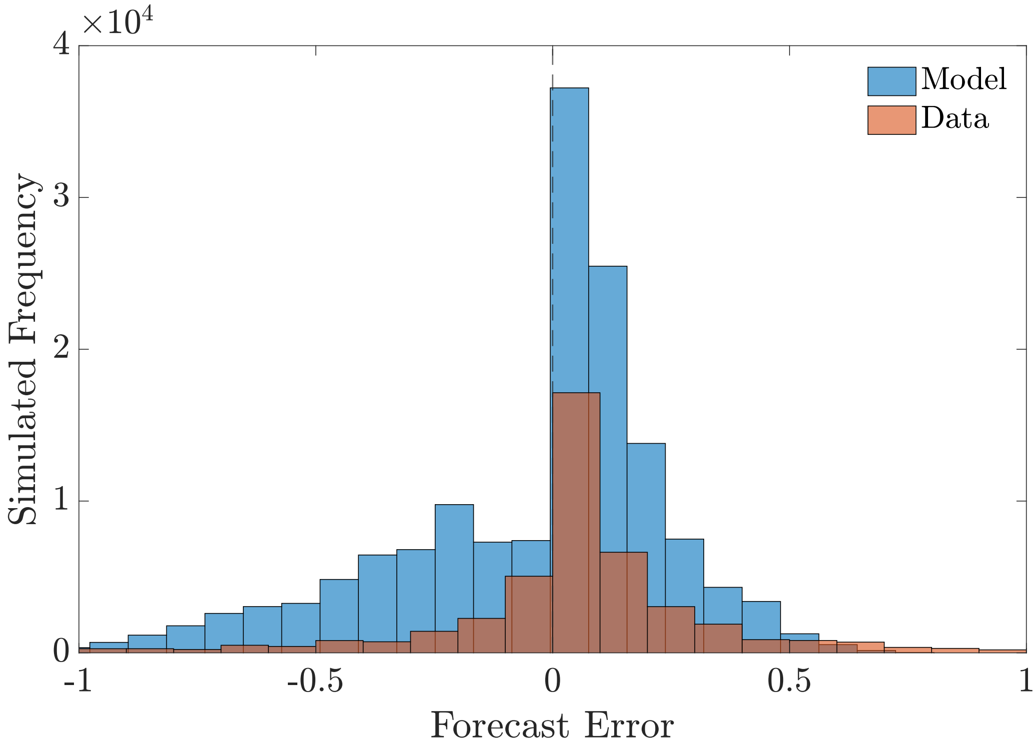
Figure 10: Identification of the other parameters



Notes: Figure 10 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.

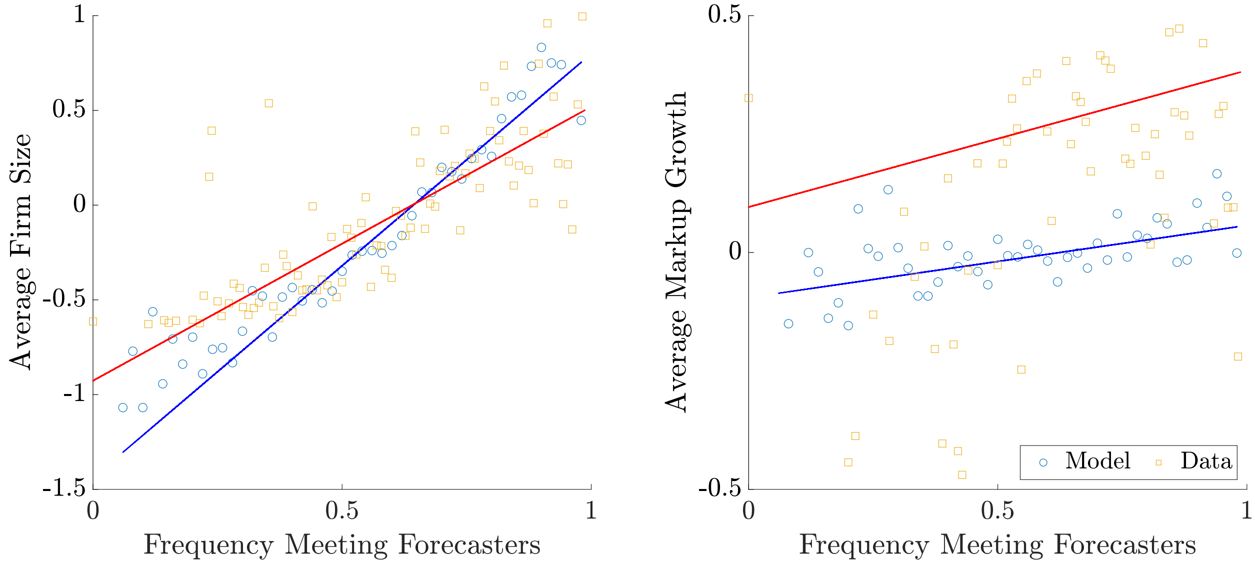
D.4 Model Fit and Untargeted Moments

Figure 11: Forecast Error Distributions



Notes: Figure 11 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 12: Untargeted Moments



Notes: Figure 12 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 13: Discontinuity in markup growth in the model

	Model	Model	Data	Data
	(1)	(2)	(3)	(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 14: 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 15: 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 16: 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 ($0.01 = 1\%$).