Customer Capital and the Aggregate Effects of Short-Termism

Marco Errico
Bank of Italy

Alessandro Dario Lavia
University of Turin

Luigi Pollio*
UMBC

This Draft: August 28, 2025

Abstract

Managers face strong pressure to meet analysts' earnings forecasts, but the effects on firms and consumers are ambiguous. In the data, firms that just meet earnings forecasts raise markups by 1.3 percent and report weaker customer sentiment than those that just miss, consistent with short-term incentives distorting both short-run pricing decisions and long-run customer acquisition. We develop a dynamic general equilibrium model with heterogeneous firms and endogenous customer accumulation, where short-term incentives emerge endogenously as an optimal mechanism to discipline managers' private benefit. We estimate that short-termism leads the average firm to raise markups by 20 basis points and annual profits by 1.2 percent. Consumers experience a 7-basis-point annual increase in consumption and a 1.2 percent gain in lifetime utility, as income effects outweigh the welfare costs of higher prices.

JEL Codes: E20, G30
Keywords: Short-termism, Agency Conflict, Markup, Customer Capital, Firm Heterogeneity.

*Corresponding author: Luigi Pollio, lpollio1@umbc.edu. Contact: Marco Errico, marco.errico@esterni.bancaditalia.it. Alessandro Dario Lavia, alessandro.lavia@unito.it. We benefited from discussions with many including Ryan Chahrour, Stephen Terry, Susanto Basu, Fabio Schiantarelli, Peter Ireland, Rosen Valchev, Jaromir Nosal, Kyle Jurado, Jean-Paul L'Huillier, Chris Foote, Vaishali Garga, Chris Cotton, Omar Barbiero, Fabio Bagliano, the seminar participants at the 2023 GLMM (BC-BU), FED Boston, 2024 NASM and 19th Annual Dynare Conference. Part of the research was conducted while Alessandro Lavia was visiting the Federal Reserve Bank of Boston. The views expressed here do not necessarily reflect those of the Bank of Italy or the Euro-System.

1 Introduction

The model of corporate governance holds substantial influence over company operational choices, thereby potentially impacting the broader aggregate economy. The model of corporate governance common in the United States and the United Kingdom is often noted for encouraging efficient resource allocation, well-informed investment choices, and effective oversight through its promotion of market liquidity, dispersed ownership, transparent reporting, and managerial discipline (Shleifer and Vishny, 1997; Burkart et al., 1997; Dewatripont and Maskin, 1995). Nonetheless, in this model, firm performance is routinely scrutinized and benchmarked against analysts' earning forecasts, generating pressure on managers to meet short-term earnings targets.[1] This pressure can mitigate agency conflicts between managers and shareholders, increasing firm value and profits, but it may also distort firm decisions, with negative consequences for the aggregate economy (Terry, 2022; Fama, 1980; Demsetz, 1983).[2] The former may improve economic efficiency and overall welfare, while the latter can negatively affect shareholders and households.

In this paper, we study how short-term incentives to meet earnings forecasts affect firms' pricing and markup decisions in an environment with customer accumulation, and we quantify the resulting aggregate effects on consumers. Firms typically invest in pricing strategies and promotional discounts to attract and retain customers, sacrificing current markups to expand their customer base (Gourio and Rudanko, 2014; Hitsch et al., 2021). However, the pressure to meet short-term targets can push managers to raise prices in order to boost current earnings, thereby reducing investment in customer capital and long-run firm value. The implications for consumers are ambiguous. Higher markups reduce purchasing power and lower welfare, but higher firm profits increase shareholder returns and household income. Which force dominates is ultimately a quantitative matter. Using a structural model, we find that short-term incentives may boost real consumption by 8.7 basis points annually.

We begin by providing suggestive evidence that short-term incentives influence firms' pricing decisions at the expense of customer acquisition. Most firms report earning equal to or just above analyst forecasts, suggesting that managers may undertake operational changes to actively meet earning targets. Using Compustat data and a novel measure of

[1] A notable survey found that approximately 90% of U.S.-based managers report experiencing pressure to meet short-term profit targets (Graham et al., 2005).

[2] This model of corporate governance contrasts with other approaches, such as the one prevalent in Continental Europe or Japan, where ownership is more concentrated and less emphasis is placed on short-term financial goals (La Porta et al., 1999; Hoshi et al., 1991; Demsetz and Lehn, 1985).

CEOs' customer sentiment, we show that firms that just meet analysts' earnings forecasts exhibit markup growth about 1.3 percentage points higher than those that narrowly miss, an effect amounting to roughly 25 percent of the average growth rate. At the same time, CEOs of these firms report nearly a 10 percent stronger decline in sentiment about their future customer base two years after meeting the target. These findings are consistent with the idea that managers may react to short-term targets by raising or maintaining relatively higher prices to boost current earnings, even while recognizing potential risks to long-run customer capital and firm value. Because these results capture local discontinuities rather than causal effects, they should be viewed as motivating evidence, underscoring the need for a quantitative model to assess the broader implications of short-termism at both the micro and macro levels.

We qualitatively illustrate how short-termism affects firms' pricing decisions using a two-period, partial-equilibrium model with customer accumulation. Short-term incentives emerge as shareholders' optimal response to agency conflicts arising from empire-building motives. Managers' pricing choices influence customer accumulation through the trade-off between investing in future demand and harvesting the existing customer base. In the absence of short-term incentives, managers inefficiently underprice to expand the firm's customer base. Short-term incentives correct this inefficiency by increasing the marginal benefit of raising prices, leading managers to charge higher prices, boosting current profits but reducing future customer acquisition. The quantitative effect on consumers is therefore ambiguous: higher prices, but also higher income.

We develop a dynamic quantitative general equilibrium model with heterogeneous firms to quantify the impact of short-termism on firms' outcomes and consumers. The economy features a continuum of ex-ante identical households and heterogeneous firms. Households display consumption inertia: in each period, a fraction of consumers remains locked into their previous variety choice, while the rest re-optimize across available products (Bornstein, 2021). The presence of consumer frictions generates dynamic customer accumulation and forward-looking demand, so that firms' pricing decisions affect both current revenues and the size of their future customer base. Firms produce differentiated goods using labor, face idiosyncratic productivity and accounting shocks, and compete for customers over time. They are run by risk-neutral managers who observe shocks and choose prices and accrual manipulation to maximize their private utility, which depends on firm profits and non-pecuniary private benefits from empire-building motives. Analysts form earnings forecasts based on observable customer capital and pricing incentives but do not observe accounting shocks. Shareholders observe analysts' forecasts and impose penalties on managers when profits fall short, thereby introducing optimal short-term incentives tied to the probability of meeting analysts' forecasts (Terry, 2022).

Short-term incentives lead firms to raise markups when they are close to the forecast threshold, but encourage greater customer accumulation when they are far from it. Near the threshold, managers face strong pressure to boost reported profits and avoid short-term penalties, prompting both higher prices and accrual manipulation at the expense of future demand. By contrast, when firms are comfortably above or below the target, managers face less immediate pressure and instead lower markups to attract additional customers. By expanding their customer base, managers increase the pool of locked-in customers and, in turn, the marginal payoff of future price hikes, giving them greater flexibility to meet earnings targets in subsequent periods

We discipline the model by estimating eight parameters with Simulated Method of Moments (SMM), targeting twelve empirical moments from Compustat-IBES data spanning 2003-2019, the post-SOX period. Firm heterogeneity parameters are identified from correlations across markup, profit, and sales growth, while short-termism parameters and managers' private benefits are estimated from forecast errors, the distribution of firms around analyst forecasts, and the probability of narrowly meeting forecasts. We calibrate demand elasticity to match average markups. We estimate that missing analysts' forecasts costs the manager a loss equal to 0.185 percent of the firm's production profits.

We quantify the effects of short-termism in the estimated model. Short-term incentives lead the average firm to raise markups by about 20 basis points, increasing annual profits by 1.2%, of which only 0.23% comes from accrual manipulation. This translates into roughly \$5 million in additional reported profits per year and a \$13.7 million increase in the average firm's market value. The effect on consumers is ambiguous: prices rise by 8.7 basis points, reducing purchasing power, but higher profits increase household income. Based on our estimates, the income effect dominates, lifting real consumption by 7 basis points per year, equivalent to an additional \$12 billion of total consumer spending in 2018, and lifetime utility by 1.2%. The magnitude of these aggregate effects is comparable to the estimated cost of inflation or business cycles, and stands in contrast to prior work that finds welfare losses from reduced innovation, underscoring the importance of analyzing different channels of short-termism.

Finally, we further discuss the robustness of our quantitative framework. We show that, when the demand elasticity is higher, short-term incentives are stronger and induce more aggressive price increases and smaller income gains for consumers, making welfare losses more likely. We find empirical support for this prediction in the data using variation across 3-digit NAICS industries, providing external validation for our model. We also extend our baseline mode introducing marketing as additional margin that CEOs can use to meet earning forecasts. In this case, price and markup increases are modestly mitigated, resulting in stronger consumption gains for consumers in the presence of short-term incentives.

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 (Zhang and Gimeno, 2016, 2010; Bhojraj et al., 2009; Roychowdhury, 2006), and delaying or reducing research and development expenditures (Terry, 2022; Corredoira et al., 2021; Bebchuk and Stole, 1993). Relative to this literature, we provide novel evidence consistent with markup manipulation in a context of customer accumulation 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 a different margin, namely how the presence of short-termism affects pricing decisions, customer accumulation, average markups and, ultimately, consumer welfare.[3]

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 incentives to explore the effects of short-termism on pricing behavior and welfare. On one hand, our model micro-found customer capital accumulation process as in Bornstein (2021), which have been used in business cycle models (Gourio and Rudanko, 2014; Ravn et al., 2008), models of firms' dynamics and business dynamism (Moreira, 2016; Foster et al., 2016), or 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

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

its long-term effects. Our model differs from theirs due to the inclusion of an endogenous markups and customer capital accumulation.

The remainder of the paper is organized as follows. Section 2 present empirical evidence on the relationship between short-termism and opportunistic pricing and markup manipulation. Section 3 presents the key theoretical intuition on short-term incentives. Section 4 introduces our quantitative model. Section 5 estimates the impact of short-termism. Section 6 concludes.

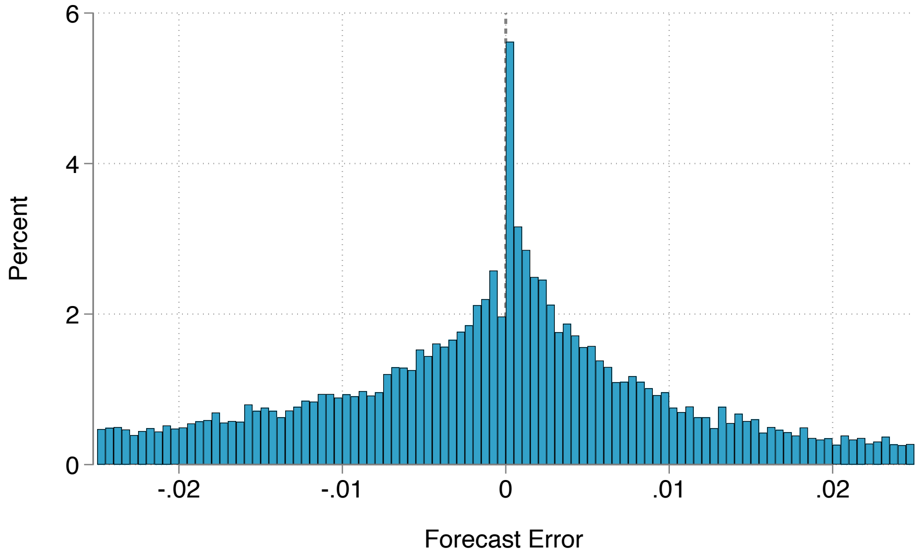
2 Motivating Evidence

We provide evidence consistent with short-termism inducing firms to raise markups in order to meet analyst earnings forecasts at the expenses of future customer base. To this end, we merge annual Compustat data, which provides detailed information on firm-level characteristics allowing to measure markups following De Loecker et al. (2020), with analyst earnings forecasts and realized "Street" earnings from the Institutional Brokers' Estimate System (IBES).[4] We complement these data with earnings call text analytics from NL Analytics, which provides sentence-level classifications of transcripts by topic and sentiment. For each call, the platform reports topic-conditioned positive and negative sentence counts based on a customer base-related dictionary. This information allows us to construct a measure of CEO sentiment regarding future customer base dynamics. Our final dataset comprises approximately 2,200 U.S. based non-financial public firms observed annually from 1990 to 2019. Appendix A contains additional details regarding data sources, sample construction and cleaning, and descriptive statistics.

Figure 1 provides evidence consistent with managerial incentives to meet earnings forecasts. We define the forecast error as the IBES realized earnings minus the median one-year-ahead analyst forecast, scaled by the firm's total assets (Terry, 2022). We plot the distribution of forecast errors and observe significant bunching of realized earnings at or just above analysts' forecasts, with relatively fewer firms narrowly missing them. Quantitatively, about 6 percent of firm-year observations exhibit forecast errors between 0 and 0.05 percent, whereas fewer than 2 percent fall just below forecasts by the same margin. This pattern suggests that managers are concerned with meeting analysts' forecasts and may take oper-

[4] We use annual rather than quarterly data to mitigate concerns arising from intra-year earnings management that could confound the measurement of short-termism. Nevertheless, results are robust at quarterly frequency.

Figure 1: Forecast Error Distribution



Notes: The Figure plots the histogram of forecast errors based on a 1990 - 2019 sample of 2,200 U.S.-based public, non-financial firms, totaling 27,274 firm-year observations. Forecast errors are calculated as the difference between realized earnings and earnings forecasts, expressed as a percentage of total assets. Realized earnings refer to Street annual earnings in U.S. dollars, while the earnings forecast corresponds to the median one-year-ahead analyst forecast. Earnings and analyst forecasts are sourced from IBES, and total assets are from Compustat. See Appendix A for additional details on data sources and the construction of the measures.

ational actions, such as reducing costs or raising prices, to avoid small negative shortfalls.[5] Accordingly, such behavior can be empirically detected by comparing firm-level outcomes across firms with forecast errors around zero.

To empirically test the hypothesis that managers adjust markups in response to meet earnings forecasts, we investigate whether firms narrowly meeting analyst forecasts systematically differ from those narrowly missing them in terms markup dynamics. Specifically, we estimate a discontinuity in markup growth at the zero forecast-error threshold, employing the following regression discontinuity design:

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

where ΔX_{it} is the annual growth rate of the outcome for firm i in year t, and fe_{it} is the

[5]Bunching behavior around analyst forecasts has been widely documented in the corporate finance literature and is robust across different measures and contexts. See Terry (2022) for a recent overview.

Table 1: Discontinuity in Markup and CEO Sentiment

	(1) Markup	(2) CEO Sentiment
Mean Change at $fe_{it} = 0$	1.356	-9.745
	(0.630)	(3.907)
Standardized (p.p.)	9.633	-38.732
Firm, Year FEs	Yes	Yes
Mean (p.p.)	5.309	20.608
Median (p.p.)	2.249	14.200
Observations	14,956	1,770

Notes: The Table reports estimated discontinuities in the growth rate of markup (column 1) and CEO sentiment (column 2), with forecast errors as running variable. We estimate Equation (1) using a local linear regression discontinuity with a triangular kernel and optimal bandwidth (Calonico et al., 2020). Markup is measured using De Loecker et al. (2020) and Compustat data. CEO sentiment is measured using NL Analytics. We use the two-year annual growth rate in CEO sentiment. Forecast error is the difference between realized earnings and the median IBES analyst forecast, scaled by total assets. All regressions include firm and year fixed effects. Standardized estimates are also reported. "Mean" and "Median" refer to the average and median of the absolute markup growth rates. Standard errors, clustered at the firm level, are reported in parentheses. See Appendix A for additional information on variables construction.

forecast error. We demean the outcome variable by firm and year to control for fixed effects. The coefficient of interest, δ, captures the local difference in growth outcomes at the forecast error cutoff.

Table 1 provides evidence consistent with upward markup adjustments aimed at boosting earnings to meet analysts' forecasts. Specifically, we find that firms that narrowly meet forecasts experience 1.36 percentage points higher markup growth compared to those that narrowly miss.[6] We also find that upward markup adjustments come at the cost of worsening CEO sentiment about the customer base. Specifically, CEOs at firms that just meet expectations experience an almost 10 percent decline in customer sentiment after two years compared to those that narrowly miss, suggesting heightened managerial concern about customer retention and expansion. This evidence is consistent with higher prices and markups hindering both current and future customer retention and acquisition. All effects are eco-

[6]These findings are consistent with various pricing strategies firms may use to enhance short-term profitability, including raising list prices, reducing promotional discounts, or shifting sales toward higher-margin products. Our data, however, do not allow us to identify which specific mechanism dominates.

nomically meaningful, amounting to roughly 25 to 50 percent of the average variation in the outcome variables.[7]

Two main caveats apply to our motivating evidence. First, the discontinuities around the threshold may partly reflect accrual manipulation or other accounting practices that artificially boost reported profits through sales or costs (Zhang and Gimeno, 2016, 2010; Roychowdhury, 2006; Laverty, 1996). Second, these empirical discontinuities represent local reduced-form estimates, reflecting an endogenous detection mechanism rather than causal, general-equilibrium effects of short-termism (Terry, 2022). To explicitly address these limitations, the next section develop a quantitative model that separately model operational responses and accrual manipulation, and quantifies their distinct contributions to firm-level and aggregate outcomes.

3 A Simple Two-Periods Model

We qualitatively study the implications of short-termism for firms' pricing decisions through the lens of a two-period, partial equilibrium model with customer accumulation and short-term incentives. We assume that short-term incentives emerge endogenously as shareholders' optimal response to managers' agency conflicts (Terry, 2022), and we follow the literature in assuming that pricing decisions influence customer accumulation through investing and harvesting motives (Foster et al., 2016; Gilchrist et al., 2017; Moreira, 2016).

3.1 Environment

Consider a single firm operating over two periods, t (today) and $t+1$ (tomorrow), producing a differentiated product using a linear technology with constant marginal cost c. The firm earns profits by selling its output to consumers in an imperfectly competitive market.

The quantity of output sold today, y_t, depends on the stock of existing customers b_t, predetermined at time t, and the price p_t, set by the firm's manager:

$$y_t = f(b_t, p_t), \tag{2}$$

where $f(\cdot)$ is a twice continuously differentiable function with $\frac{\partial f}{\partial b_t} > 0$, $\frac{\partial f}{\partial p_t} < 0$. These

[7] Appendix A shows that the results are quantitatively robust to the definition and horizon of markup and CEO sentiment growth. Moreover, the results are robust to the econometric strategy and the dimension of the bandwidth of the regression discontinuity design.

assumptions imply that demand is increasing in the customer base and decreasing in price.

Tomorrow, the firm sells output y_{t+1} at the price p_{t+1}. Without loss of generality, we assume that the demand function exhibits constant price elasticity, that is, $\varepsilon(p_t) \equiv -\frac{\partial f}{\partial p_t} \cdot \frac{p_t}{f} = \varepsilon > 1$. Hence, the optimal price tomorrow is equal to a constant markup over the marginal cost c, $\bar{p} = \frac{\varepsilon}{\varepsilon - 1} c$, and future profits depend solely on the customer base b_{t+1}, which is determined by both retained and newly acquired customers based on today's pricing decision:

$$b_{t+1} = g(b_t, p_t), \tag{3}$$

with $g(\cdot)$ is a twice continuously differentiable function with $\frac{\partial g}{\partial b_t} > 0$ and$\frac{\partial g}{\partial p_t} < 0$. The latter captures the investing motive: lower prices today expand the future customer base.

Given the firm' discount factor β, firm value $V(p_t)$ is the sum of current and discounted future profits:

$$V\left(p_t\right) = (p_t - c) f(b_t, p_t) + \beta(\bar{p} - c) f(g(b_t, p_t), \bar{p}).. \tag{4}$$

The firm's price influences both current revenues and the future customer base b_{t+1}. The optimal pricing decision trades off charging a higher price today to extract rents from the inelastic portion of demand (harvesting motive) against lowering the price to attract more customers and expand future revenues (investing motive).

Today's profits are observed with accounting noise, ν_t:

$$\Pi_t = (p_t - c) f(b_t, p_t) + \nu_t, \quad \nu_t \sim N(0, \sigma_\nu^2), \tag{5}$$

where noise ν_t, with CDF F_ν and PDF f_ν, is unobservable when prices are chosen. Market analysts observe the stock of firms' customers b_t and generate profit forecast Π_t^f under imperfect information.

Short-term incentives are introduced by the board of directors to mitigate the agency conflict between the manager and shareholders. A risk-neutral manager sets the price p_t to maximize a utility function that combines the firm's value with a non-pecuniary private benefit $h\left(b_{t+1}\right)$ from expanding firm size, reflecting empire-building motives. Aware of this motives, the board imposes a cost $\theta_\pi > 0$ that penalizes the manager when profits Π_t fall short of analysts forecast Π_t^f. Because of the uncertainty over profits due to accounting noise, the manager cannot control outcomes precisely and therefore considers the probability of missing analysts' forecast when choosing price. Thus, given analysts' forecast and board incentives, the manager's objective solves:

$$V^M\left(p_t \mid \Pi_t^f, \theta_\pi\right) = (p_t - c)f(b_t, p_t) + h\left(b_{t+1}\right) - \theta_\pi \mathbb{P}\left(\Pi_t < \Pi_t^f\right) + \beta(\bar{p} - c)f(b_{t+1}, \bar{p}), \quad (6)$$

where b_{t+1} is from Equation (3), the term $\theta_\pi \mathbb{P}\left(\Pi_t < \Pi_t^f\right)$ captures the short-term incentives introduced to discipline managerial behavior, and $h\left(b_{t+1}\right)$ captures the private benefit from expanding firm size (i.e. $\frac{\partial h}{\partial b_{t+1}} > 0$).

An equilibrium with rational expectations and optimal short-term incentives in this simple model requires that: the manager determines price to maximize his utility conditional to the analysts' forecasts and short-term incentives; analysts' forecast are rational given the analysts' information set; the board of director sets the optimal short-term incentives to maximize firm value given manager's decision.

3.2 Effect of Short-term Incentives on Pricing

Optimal managers' pricing decisions and short-term incentives are pinned down by the first-order condition with respect to p_t and θ_π. Given analysts' 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:

$$\begin{aligned} &\underbrace{f(b_t, p_t) + (p_t - c)\frac{\partial f(b_t, p_t)}{\partial p_t}}_{\text{Harvesting}} + \underbrace{\frac{\partial h(b_{t+1})}{\partial b_{t+1}} \frac{\partial g(b_t, p_t)}{\partial p_t}}_{\text{Empire-building}} + \underbrace{\theta_\pi f_\nu \frac{\partial \Pi}{\partial p_t}}_{\text{Short-term}} = \qquad (7) \\ &- \underbrace{\beta(\bar{p} - c)\frac{\partial f(b_{t+1}, \bar{p})}{\partial b} \cdot \frac{\partial g(b_t, p_t)}{\partial p_t}}_{\text{Investing}}. \end{aligned}$$

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 tomorrow, thereby reducing next period's profits (Investing term). 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 (Harvesting term). The second term is the marginal private benefit received by the manager from increasing the price today (Empire-building term). Under the functional form assumptions, this term is negative, reducing the marginal benefit of increasing the current price and prompting the manager to lower prices. Finally, the last term represents the marginal benefit obtained from meeting analysts' forecasts (Short-term term).

The board of directors sets the optimal level of short-term costs, θ_π^*, to maximize firm value and restore the firm's optimal pricing decision:

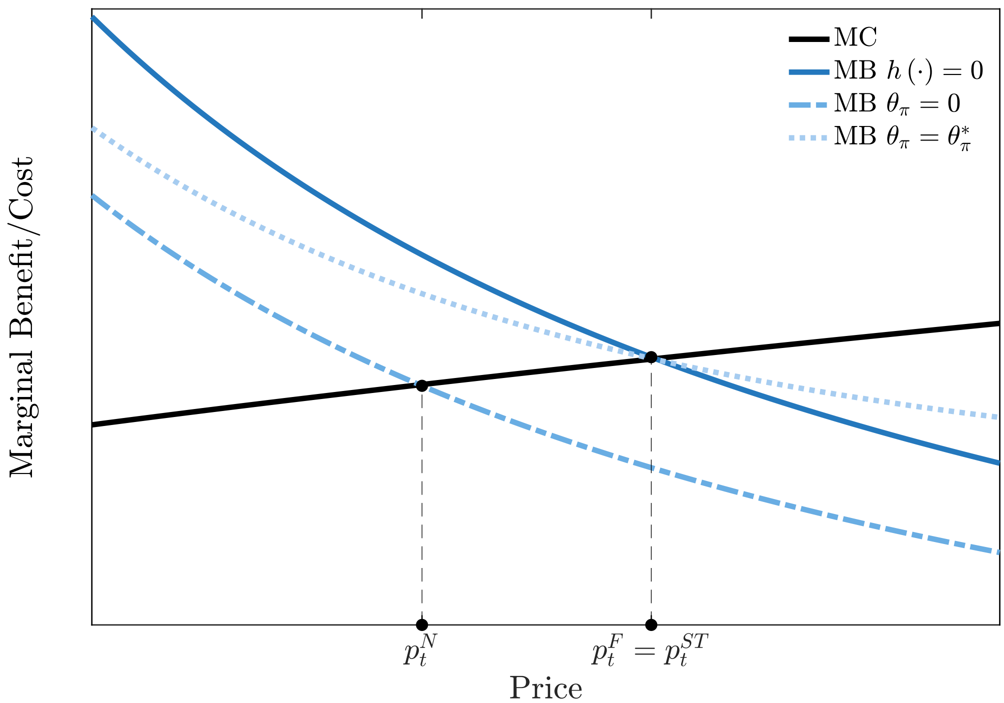
$$\theta_\pi^* = \max\left\{0, -\frac{\partial h(b_{t+1})}{\partial b_{t+1}}\frac{\partial g(b_t, p_t)}{\partial p_t}\left[f_\nu \frac{\partial \Pi}{\partial p_t}\right]^{-1}\right\}. \tag{8}$$

The optimal level of short-term incentives depends on two key forces. First, a stronger private benefit increases the manager's incentive to expand firm size at the expense of profits, calling for stronger disciplinary pressure to realign managers' incentives to firm's maximizing choices. Second, the sensitivity of the probability of not meeting analysts' forecasts to price—captured by the term $f_\nu \cdot \frac{\partial \Pi}{\partial p_t}$ – determines how effective price adjustments are in reducing the risk of falling short. When this sensitivity is high (i.e., the denominator is large), even small price changes substantially affect the likelihood of meeting analysts' forecasts, allowing the board to impose relatively smaller incentives to discipline the manager.

Short-term incentives push managers to raise prices when, due to empire-building motives, they would otherwise set them inefficiently low. Figure 2 plots the optimal pricing decision in the presence of and abstracting from short-term incentives for an illustrative case consistent with the functional forms of the model. In the absence of short-term incentives ($\theta_\pi = 0$), managers choose a price level (p_t^N) lower than the one maximizing the firm's value (p_t^F). This occurs because the 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, managers' private benefits are offset when the board of directors is allowed to introduce short-term incentives ($\theta_\pi > 0$), resulting in the manager setting higher prices ($p_t^{ST} > p_t^N$) and increasing firm value. Higher prices increase profits and, thus, the probability of meeting analysts' forecasts. In equilibrium with optimal short-term incentives ($\theta_\pi = \theta_\pi^*$), managers pricing decisions match the value-maximizing decision ($p_t^{ST} = p_t^F$).

While the model illustrates how short-term incentives may influence firms' pricing decisions, it does not account for general equilibrium effects and, therefore, is not suitable for quantification. In general equilibrium, short-term incentives create a trade-off for consumers between an *income effect* – higher real consumption driven by increased firm profits – and a *price effect* – lower real consumption as elevated prices erode consumers' purchasing power. Therefore, we present a general equilibrium model that incorporates other relevant features such as persistent heterogeneity in firm productivity, rich substitutability patterns across

Figure 2: Optimal pricing decisions



Notes: The Figure plots the marginal cost (black line) and the marginal benefit (blue lines) from Equation (7) without agency conflict (dark blue line), with agency conflict but without short-term incentives (medium blue line), and with agency conflict and short-term incentives (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 incentives; p_t^{ST} is the price that maximize manager value facing short-term incentives.

firms, private managerial information, and accrual-based tools for profit manipulation.

4 Quantitative Model

We study the quantitative implications of short-termism, as outlined in the previous section, using a discrete-time, infinite-horizon, dynamic general equilibrium model with customer accumulation, endogenous markups, and heterogeneity in firm-level idiosyncratic productivity. We model customer accumulation by introducing consumer inertia in firm-level demand a la' Bornstein (2021), and follow (Terry, 2022) in modelling short-term incentives.

4.1 Households

The economy is populated by a continuum of ex-ante identical households in the economy, indexed by i. Each household supplies one unit of labor inelastically at the wage W, and owns an equal share of all firms in the economy. Households maximize their discounted lifetime utility given by:

$$U_i = \sum_t \beta^t \log(C_{i,t}), \tag{9}$$

where $C_{i,t}$ is the aggregate consumption bundle chosen by household i in period t.

Each household chooses how to allocate its spending across a set of differentiated consumption goods to maximize their utility. There is a continuum of product types of unit mass. Within each type, there is a continuum of mass one of varieties produced by different firms. Let j_m denote variety j within product type m. Households consume c_{j_m} units of a single variety j_m in each product type m. The household's consumption bundle C_i aggregates the consumption goods across product types according to:

$$C_i = \left\{ \int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \varepsilon_{j_m} \right) c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}}, \tag{10}$$

where σ governs the elasticity of substitution across varieties within products, η captures the elasticity of substitution between products, and ε_{j_m} is a variety-specific Gumbel-distributed taste shock that is independent across households, products, and varieties.[8]

Households experience consumer inertia within product types. At the beginning of each period, a household remains locked into its previous variety choice j_m within product type m with probability $1 - \theta$; with probability θ, the household can re-optimize and select a new variety. The optimal product variety j_m chosen by household i for product type m in a given period is:

$$j_m^* = \begin{cases} \arg\max_{j_m} \left\{ \dfrac{1}{\sigma - 1} \varepsilon_{j_m} - \log p_{j_m} \right\}, & \text{if re-optimizing} \\ j_{m,-1}. & \text{if locked-in} \end{cases} \tag{11}$$

[8] In Section 5.3, we introduce variety-specific appeal shifters that depend on firms' marketing choices.

Thus, the household problem is given by:

$$\max_{\{j_m, c_{j_m}\}_{m\in(0,1)}} \sum_{t=0}^{\infty} \beta^t \log\left(\left\{\int_0^1 \left[\exp\left(\frac{1}{\sigma-1}\varepsilon_{j_m}\right) c_{j_m}\right]^{\frac{\eta-1}{\eta}} dm\right\}^{\frac{\eta}{\eta-1}}\right), \tag{12}$$

$$\text{s.t.} \quad \int_0^1 p_{j_m} c_{j_m} = W + \Pi \qquad \forall t, \tag{13}$$

$$j_m = j^*_{m,-1} \quad \text{if } \xi_m = 0, \tag{14}$$

where the maximization of the households' discounted lifetime utility is constrainted by the budget constraint in Equation (13) and the consumer inertia constraint in Equation (14). The indicator variable ξ_m denotes whether the household can reoptimize its choice for product m at time t or not according to Equation (11).

Customer base and demand When a household has the opportunity to re-optimize, the probability that a particular variety within a product type is selected depends on the current relative attractiveness–based on price and taste–of that variety, without internalizing the possibility of being locked in (Bornstein, 2021). Under the assumption that idiosyncratic taste shocks follow a Gumbel distribution, the household's consumption choice over product varieties can be represented as a multinomial logit discrete choice problem. Thus, in each period, the probability that a re-optimizing household i becomes new customer of firm j^* in product type m is:

$$\text{Prob}(j_m = j^*) = \left(\frac{p_{j^*}}{P_m}\right)^{1-\sigma} \quad \text{where} \quad P_m = \left[\int_0^1 p_{j_m}^{1-\sigma} dj_m\right]^{\frac{1}{1-\sigma}}, \tag{15}$$

where P_m is the price index for product m.

The presence of consumer inertia gives rise to a slow moving customer base and forward-looking demand. The customer base of a firm producing variety j_m in a given period evolves as follows:

$$b'_{j_m} = (1-\theta) b_{j_m} + \theta \left(\frac{p_{j_m}}{P_m}\right)^{1-\sigma}, \qquad 0 < \theta < 1, \tag{16}$$

where the first term captures the locked-in households inherited from the previous period due to consumer inertia, and the second term represents newly re-optimizing households attracted by the firm's pricing decision. Since re-optimizing households choose based on relative prices, pricing becomes the firm's primary tool for acquiring new customers and shaping both current and future demand. Higher prices may increase current profits but reduce future customer acquisition, introducing a trade-off between short-term profit maximization and long-term growth in customer base (investing vs harvesting motives).

The demand function faced by each firm is:

$$y_{j_m} = \left[(1-\theta)\frac{b_{j_m}}{p_{j_m}^{\eta}} + \theta\left(\frac{p_{j_m}}{P_m^{\eta}}\right)^{-\sigma}\right]\frac{W+\Pi}{\theta P_m^{1-\eta} + (1-\theta)P_b^{1-\eta}}, \tag{17}$$

where $(W+\Pi)$ represents total household income, P_m is the price index of product m as in Equation 15, and P_b is the customer base-weighted price index, $P_b = \left[\int b_{j_m} p_{j_m}^{1-\eta} dj_m\right]^{\frac{1}{1-\eta}}$. Firm pricing decisions, relative to their competitors, affect the size of their customer base, the attractiveness to reoptimizing household, and the households' expenditure share allocated to their products.

4.2 Firms, Managers, and Board of Directors

Within each product type, each variety is produced by a firm j managed by a risk-neutral manager under the guidance of a board of directors. Firms take aggregate demand conditions as given, though they recognize that current pricing decision influence their customer base over time.

Technology and profits. Each firm produces a single variety j using a linear technology with labor l as the sole input. Firms hire labor from the market at a predetermined wage W. The production function for each firm is:

$$y_{j_m} = a_{j_m} l_{j_m}, \tag{18}$$

where a is an idiosyncratic productivity shock and l the labor used in production. Productivity follows a discrete-time, first-order, stationary Markov process in logs, which is common knowledge in the economy:

$$\log a'_{j_m} = \rho_a \log a_{j_m} + \sigma_a \omega_{j_m}, \qquad \omega_{j_m} \sim N(0,1). \tag{19}$$

Firm's profits are production profits adjusted for accruals manipulation, m_{j_m}, chosen by the manager, and accounting noise, z_{j_m}, which captures timing issues, accounting errors, or other non-strategic factors (Terry et al., 2023; Terry, 2022):

$$\Pi_{j_m} = \left(p_{j_m} y_{j_m} - \frac{W}{a_{j_m}} y_{j_m} \right) (1 + z_{j_m}) + m_{j_m}. \tag{20}$$

Π_{j_m} represents the profits reported outside the firm, while the production profits $(p_{j_m} - \frac{W}{a_{j_m}})y_{j_m}$ represent the actual firm earnings. Importantly, the transitory shock z_{j_m} is modeled as the sum of two independent components:

$$z_{j_m} = \varepsilon_{j_m} + \nu_{j_m}, \qquad \varepsilon_j \sim N(0, \sigma_\varepsilon^2), \qquad \nu_{j_m} \sim N(0, \sigma_\nu^2), \tag{21}$$

where ε_{j_m} is observed only by the manager when making decisions, while ν_{j_m} is unobservable to the manager. On the contrary, the realization of z_{j_m} is unobserved by stakeholders. The presence of information asymmetry implies that stakeholders cannot perfectly predict firm profits, creating uncertainty in their forecasts.

Manager. Each firm is operated by a risk-neutral manager who maximizes his private utility choosing variety's pricing and accounting manipulation, $\{p_{j_m}, m_{j_m}\}$, subject to short-term incentives from the shareholders. The manager's utility reflects two components: a pecuniary benefit tied to firm value and a non-pecuniary, private incentive related to the empire building motive. The pecuniary benefit determined by the board includes a share θ_e of the firm production profits, reduced by θ_π units if profits Π_{j_m} falls below analysts' profit forecast $\Pi^f_{j_m}$. We normalize θ_e, which measures how much managers' incentives align with those of the board of directors, to one without loss of generality. The non-pecuniary private benefits are proportional to firm's production profits with parameter $\phi_e > 0$. Moreover, managers bear quadratic cost of accrual manipulation with intensity parameter $\phi_m > 0$, which gives the manager an incentive to avoid high volatility in reported profits. We assume that the cost increases not only in the magnitude of manipulation, but also in the size of the firm's profits, capturing the idea that larger firms face greater scrutiny and reputational risks when engaging in earnings management.[9]

The manager chooses the price of the differentiated variety and the level of accrual

[9]This is consistent with the empirical findings of Dechow and Skinner (2000).

manipulation to solve the following dynamic problem:

$$V^M\left(a_{j_m}, \varepsilon_{j_m}, b_{j_m} | \theta_\pi, \Pi^f_{j_m}\right) = \max_{\{p_{j_m}, m_{j_m}\}} \Bigg\{ \theta_e \left(p_{j_m} y_{j_m} - \frac{W}{a_{j_m}} y_{j_m}\right) - \theta_\pi \mathbb{P}\left(\Pi_{j_m} < \Pi^f_{j_m}\right) \tag{22}$$
$$+\phi_e p_{j_m} y_{j_m} - \phi_m \left(\frac{m}{\Pi}\right)^2_{j_m} \Pi_{j_m} + \beta \mathbb{E}_t V^M\left(a'_{j_m}, \varepsilon'_{j_m}, b'_{j_m} | \theta_\pi, \Pi^f_{j_m}\right) \Bigg\},$$

where the first two terms are the share of firm production profits and the short-term compensation, respectively; the third term represents the private payoff; and the last term represents the continuation value of the firm. The presence of private benefits creates an agency conflict due to the misalignment between the manager and board of directors' profit-maximizing objectives.

Analyst. Analysts are rational and seek to maximize their expected utility by accurately forecasting firm-specific profits. The optimal forecast for firm j in a given period, denoted by $\Pi^f_{j_m}$, is determined based on the information available at the beginning of each period. Analysts observe the firm's customer base, b_{j_m}, but do not have access to the firm's idiosyncratic profit, z_{j_m}, or productivity, a_{j_m}, for the current period. We assume that profit forecasts are the solution to the following problem:

$$\Pi^f_{j_m} = \arg\min_{\Pi^f_{j_m}} \mathbb{E}\left[\left(\Pi_{j_m} - \Pi^f_{j_m}\right)^2 | b_{j_m}\right] = \mathbb{E}\left[\Pi_{j_m} | b_{j_m}\right], \tag{23}$$

where analysts' payoff is decreasing in the mean squared prediction error.

Board of directors. Given the manager's policies of prices, $p^*_{j_m}$, and accounting manipulation, $m^*_{j_m}$, the board of directors optimally sets the short-term cost, θ_π, to discipline the manager's behavior and align it with the firm's interests. Conditional on the manager's choices, the value of the firm is given by:

$$V^F\left(a_{j_m}, \varepsilon_{j_m}, b_{j_m}\right) = \left[p^*_{j_m} y^*_{j_m} - \frac{W}{a_{j_m}} y^*_{j_m} + \beta \mathbb{E} V^F\left(a'_{j_m}, \varepsilon'_{j_m}, b'^{,*}_{j_m}\right)\right]. \tag{24}$$

The board of directors commits to an optimal level of short-term incentives, θ^*_π, to maximize the mean firm value conditional on the customer base in the long-run. Formally, let Γ be the erogdic distribution of firms over idiosyncratic productivity, a_{j_m}, profit shock, ϵ_{j_m}, and customer base, b_{j_m}. The board of directors of each firm sets θ_π to solve the following problem:

$$\theta_\pi^* = \arg\max_{\theta_\pi} \int V^F \left(a_{j_m}, \varepsilon_{j_m}, b_{j_m}\right) d\Gamma \left(_{j_m}, \varepsilon_{j_m}, b_{j_m}\right). \tag{25}$$

Thus, the optimal level of short-term incentives emerges from a constrained maximization problem designed to restore the average unconditional maximum firm value. Notice that in the case there is no manager's private benefit ($\phi_e = 0$), the manager problem in Equation (22) collapses to the firm's problem. In this case, the optimal level of short-term incentives is $\theta_\pi^* = 0$, and managers do not have incentives to manipulate profits.

4.3 Equilibrium and Solution

We restrict our attention to a symmetric equilibrium where all product types are identical. We omit the subscript j_m in the definition of equilibrium for notational simplicity.

A stationary Markov-perfect equilibrium of the model with rational expectations and optimal short-term incentives consists of a set of aggregate prices and profits $\{P_m, P_b, \Pi\}$; 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 cost, 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 (22), given the analyst's forecasts, short-term incentives, and aggregate prices and profits;

ii) The analyst forms forecasts $\Pi_t^f(\theta_\pi)$ by solving Equation (23), conditional on the manager's optimal policies and aggregate prices and profits;

iii) The board of directors chooses the optimal short-term incentive θ_π^* by solving Equation (24), given the manager's optimal policies, the analyst's forecasts, and aggregate quantities;

iv) The firm distribution $\Gamma(a, \varepsilon, b)$ is consistent with the idiosyncratic stochastic processes and the manager's policy functions;

v) Aggregate prices and profits $\{P_m, P_b, \Pi\}$ are consistent with managers' decisions, analysts' forecasts, the board's incentives, and market-clearing conditions.

We solve the model numerically. Further details on the algorithm used in Appendix B.3.

4.4 Manager Policies

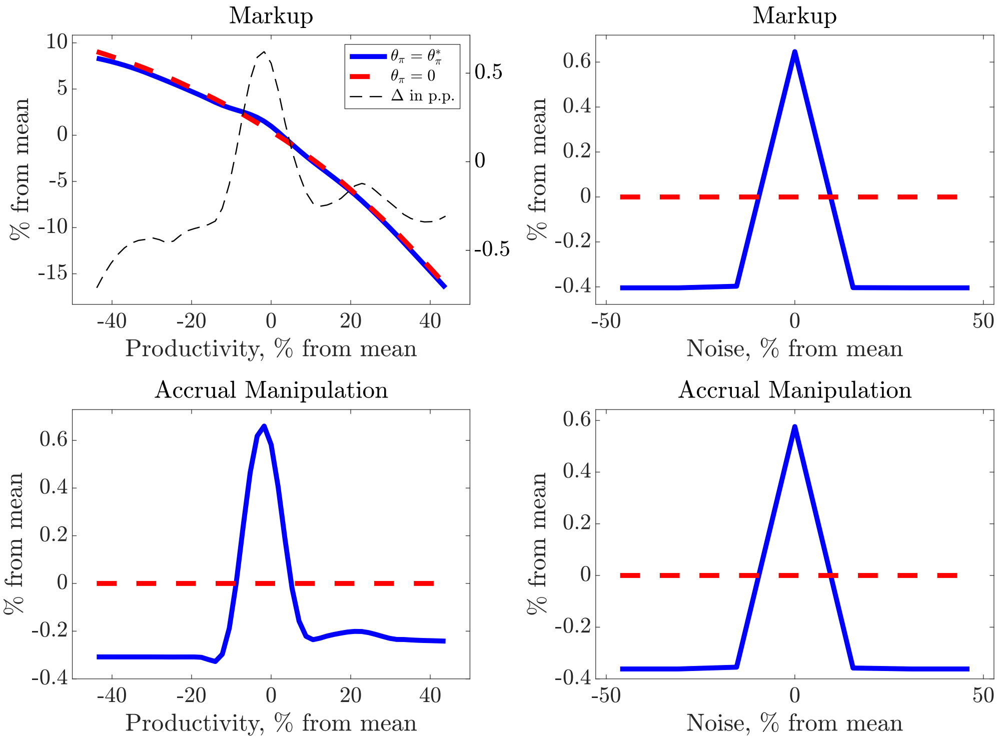
Figure 3 shows the managers' policy function for markup (top row) and accrual manipulation (bottom row) across idiosyncratic productivity (left column) and accounting noise (right column) to highlight the impact of short-termism on pricing and manipulation decisions. We compare optimal managers' decisions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

In a model without short-termism (red dashed line), managers do not face incentives to manipulate profits, resulting in a pricing policy that aligns with standard models of dynamic customer accumulation and in the absence of accrual manipulation. In high productivity states, the marginal benefit of raising prices is relatively low, leading firms to lower their prices and markups below average and invest more aggressively in acquiring new customers. Conversely, in low productivity states, investing in customer acquisition becomes relatively more costly. Firms therefore postpone customer investment and push prices and markups above average. Accounting shocks, by contrast, affect only reported profits without impacting customer accumulation or firm fundamentals. Thus, in the absence of short-term incentives, managers have no reason to respond to accounting shocks, and pricing, markup, and customer acquisition strategies remain unaffected.

In a model with short-termism (blue solid line), managers face pressure to opportunistically adjust accruals and markups when close to meeting analysts' forecasts, causing prices to rise and misreporting of earnings. As productivity shocks approach zero from the left, firms seize the opportunity to strategically raise markups and increase accrual manipulation to enhance current profits and reduce the costs associated with not meeting analysts' forecasts. Figure 3 shows a spike in accrual manipulation and markup values just around zero productivity. This strategy is inherently short-term in nature, as it sacrifices long-term growth and customer acquisition opportunities to boost current profits. Moreover, short-termism causes excess sensitivity of markups to noise: in response to negative accounting shocks, firms have incentives to both inflate reported profits relative to production profits and strategically raise markups to boost reported profits, reducing the risk of not meeting analysts' forecasts but undermining the firm's potential for future growth.

Conversely, when firms are far from meeting analysts' forecasts–either clearly above or below–managers have incentives to expand their customer base by lowering markups relative to those in an economy without short-term incentives. The reason is that, when firms are far from their profit targets today, it becomes optimal to lower prices and expand the customer

Figure 3: Manager policies over shocks



Notes: The Figure plots the manager's policy functions with and without short-term incentives. The dashed 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 conditional stationary distribution. The top row shows the mean markup policies, and the bottom row shows manager accruals manipulation policies. The left column depicts the policies over the idiosyncratic productivity grid as a percentage deviation from the mean, and the right column shows mean policies over the idiosyncratic noise grid. In the top-right panel, the dashed black line reports the difference between the policy function with and without short-term incentives, with a secondary y-axis on the right. Policies are computed using the parameterization in Table 2 and are smoothed before plotting.

base to gain more flexibility in the future in case a price hike becomes necessary to meet earnings expectations. This intuition can be grasped by noting that the marginal profit from a price increase rises with the size of the customer base:

$$\frac{\partial^2 \Pi_t}{\partial b_t \partial p_t} \approxeq \frac{(1-\theta)}{p_t^\eta} \frac{W}{a_t p_t} > 0. \tag{26}$$

With more locked-in customers, a price increase yields a proportionally larger increase in current profits, giving managers greater flexibility to manage earnings expectations. This precautionary investment motive in building a customer base under short-term incentives is unique to lifetime-horizon dynamic models and parallels similar mechanisms in corporate finance models with costly external financing.[10]

Lastly, short-termism affect the steady state distribution of firms' markup, prices and customer bases. Figure 8 in Appendix B displays the distribution of managers' policy functions, computed over 3,000 firms simulated for 50 periods and average them over time. In the model with short-term incentives, managers, on average, charge higher prices to their customers compared to the scenario without them (bottom left) because of higher markups. As a consequence, in the absence of short-termism, firms are relatively larger due to their larger customer base (top left).

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' outcomes and aggregate. Section 5.3 discusses the effects of changes in the structural parameters on the aggregate implications.

5.1 Estimating the Model

We calibrate a set of parameters following previous works in the literature. We set the parameter $\theta = 0.25$, implying that 75% of a firm's existing customers are locked-in with the firm each year without reconsidering alternative product varieties (Ravn et al., 2006; Moreira, 2016; Bornstein, 2021). We normalize the equilibrium wage to one, and set the annual discount factor $\beta = 0.96$ which implies a roughly 4% interest rate in the long-run.

Simulated Method of Moments. We estimate the remaining 8 parameters in Table 2 using the Simulated Method of Moments (SMM). 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. We target a set of 11 empirical moments computed from annual Compustat and IBES datasets, selected based on prior studies in the literature. These moments are computed using data spanning from 2003 to 2019, which corresponds to the period following the implementation of the Sarbanes-Oxley (SOX) Act (Terry, 2022). The dataset consists of 9,319 firm-years of data from around

[10] See Strebulaev et al. (2012) for a discussion.

2,520 firms. Our targeted moments include the correlation matrix between sales growth, profit growth, markup growth, and forecast error. These moments are informative about the productivity process and the accounting noise shocks. We also include the probability of meeting analysts' forecasts, defined as the percentage of firms that outperform analysts in the simulated data, and the probability of just meeting forecasts, defined as the ratio between the fraction of firms exceeding forecasts by at most 10% and the mass of firms that not meeting forecasts by at most 10%. These moments are informative about the observed jump in forecast errors at zero. Finally, we also target the average markup in the model to estimate the elasticity of substitution within and between product types.

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:

$$\hat{\Theta}_{\text{SMM}} = \Theta : \min_{\Theta} \quad \Big(m(\tilde{x} \mid \Theta) - m(\tilde{x})\Big) W \Big(m(\tilde{x} \mid \Theta) - m(\tilde{x})\Big)', \tag{27}$$

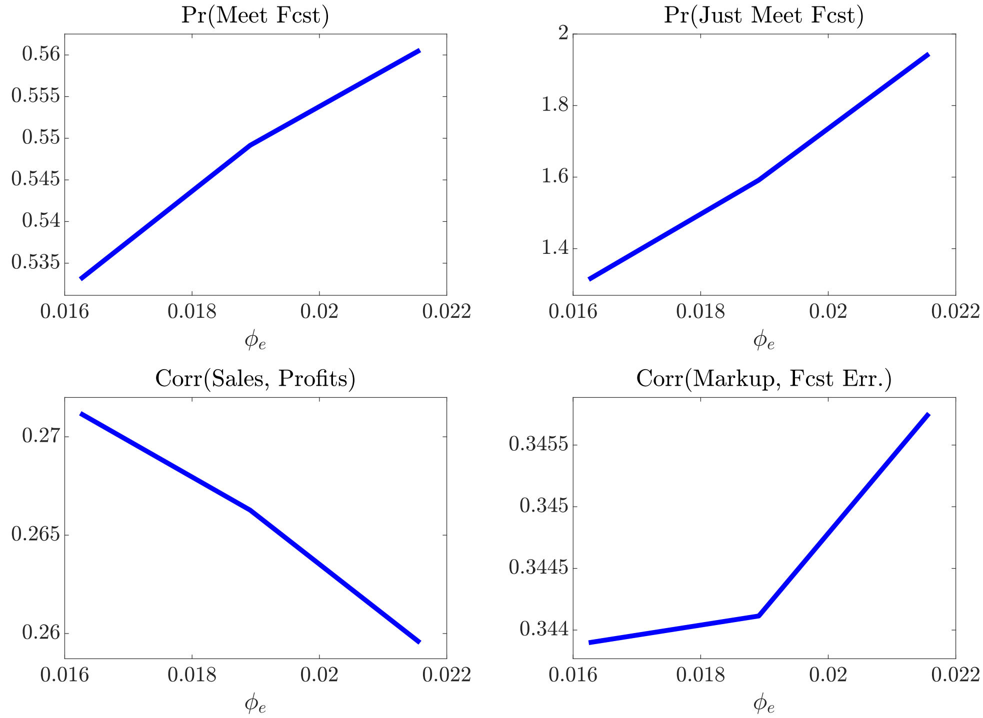
where $m(\tilde{x})$ is the data moment vector and $m(\tilde{x} \mid \Theta)$ is the vector of model simulated moments. We use the asymptotically efficient weighting matrix W, cluster standard errors by firm with the asymptotic formulas in Hansen and Lee (2019). We generate simulated data on 3,000 firms 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 (27), we use the particle swarm stochastic search algorithm.

Identification. Figure 4 shows how selected moments contribute to the identification of the agency conflict parameter ϕ_e, which in turn directly influences the identification of short-term cost, θ_{pi}, in the model. First, as boards impose greater penalties for missing targets, managers are more inclined to engage in accrual manipulation or price adjustments to narrowly meet analysts' forecasts. Consequently, a higher agency conflict parameter is associated with a greater probability of meeting forecasts (upper right) and increased bunching just above the zero forecast error threshold (upper left). Second, greater short-term incentives induce more aggressive manipulation in both accruals and pricing. As a result, sales growth becomes increasingly disconnected from profit growth (bottom right), while the correlation between markup growth and forecast error increases (bottom left).[11]

Figure 10 in Appendix B plots the relationship between the estimated parameters and

[11] The increase in the correlation between markup growth and forecast error is small because most of the pricing response to short-term incentives occurs locally around zero forecast error.

Figure 4: Identification of the short-termism parameter



Notes: The Figure plots selected simulated target moments as a function of the agency conflict parameter ϕ_e, varying its value by $\pm 1\%$ standard deviation around the baseline estimate reported in Panel A of Table 2.

selected target moments that are important for identification. The correlation between sales and profit growth helps separate the within- and across-product elasticities, σ and η. A higher σ weakens firms' market power, limiting their ability to convert sales into profits and thereby reducing the correlation. In contrast, a higher η intensifies cross-product competition, prompting firms to align pricing more closely with profitability and thus strengthening the correlation. Greater persistence in idiosyncratic productivity, ρ_a, makes profits more predictable over time, resulting in a weaker correlation between profit growth and forecast errors. Higher volatility in idiosyncratic productivity, σ_a, amplifies fluctuations in firms' marginal costs, decreasing the correlation between profit growth and markup growth. An increase in the variance of observable accounting shocks, σ_ε, directly raises firms' reported profits. Once that is pinned down, greater volatility of the unobservable accounting shock, σ_ν, lowers the probability that firms just meet profit targets, since greater noise makes reported earnings less predictable and reduces the effectiveness of profits' manipulation. Finally, an increase in the cost of accrual manipulation, ϕ_a, makes manipulation more expensive, thereby reducing

Table 2: Estimated parameters and moments

A. Estimated parameters	Symbol	Estimate	Std. Error
Elasticity of substitution within products	σ	3.7389	0.1279
Elasticity of substitution across variaties	η	3.2387	0.1228
Persistence of idiosyncratic productivity	ρ_a	0.9336	0.0042
Std of idiosyncratic productivity	σ_a	0.0524	0.0019
Std of observed accounting noise shock	σ_e	0.1544	0.0077
Std of unobserved accounting noise shock	σ_u	0.0390	0.0197
Quadratic manipulation cost	ϕ_m	3.2543	0.4411
Private benefit manager	ϕ_e	0.0189	0.0027
B. Targeted moments	**Data**	**Std. Error**	**Model**
Std. deviation of sales growth	0.1689	0.0036	0.1723
Correlation of sales growth, profits growth	0.6530	0.0118	0.5046
Correlation of sales growth, forecast error	0.2162	0.0149	0.2663
Std. deviation of profits growth	0.3441	0.0059	0.2667
Correlation of profits growth, markup growth	0.6685	0.0111	0.7595
Correlation of profits growth, forecast error	0.3556	0.0157	0.4763
Std. deviation of markup growth	0.0670	0.0023	0.0513
Correlation of markup growth, forecast error	0.2561	0.0154	0.3441
Std. deviation of forecast error	0.3862	0.0076	0.3069
Probability of meeting forecasts	0.5439	0.0035	0.5491
Probability of just meeting forecasts	1.5109	0.0558	1.5917
Average markup	1.2029	0.0051	1.2241

Notes: Panel A reports the SMM parameter estimates obtained using efficient moment weighting. Panel B reports the data moments constructing from a panel of 2,522 firms for 9,319 firm-years using Compustat and IBES data from 2003 to 2019. Model moments use a 25-year simulated panel of 3,000 firms. Moment units are proportional (0.01 = 1%). Standard errors are clustered at the firm level.

the probability of meeting the profit target.

Baseline Estimates. The estimation procedure yields a set of parameter estimates that are broadly consistent with previous studies. The elasticities of substitution within and between product types, σ and η, are estimated at 3.7 and 3.2, respectively, in line with standard values found in the macroeconomic and industrial organization literature. The idiosyncratic productivity exhibits a high level of persistence, with ρ_a estimated to be 0.933, while the standard deviation, σ_a, is estimated to be 5.2 percent. These estimates are comparable to those found in the firm dynamics literature. The standard deviations of the observed and unobserved noise shock, σ_e and σ_u, are estimated at 15.4 and 3.9 percent, respectively, implying a ratio of roughly 3.5, suggesting strong asymmetric information in line with Terry (2022). The quadratic cost of accrual manipulation, ϕ_m, is estimated at 3.254, indicating that managers bear large private costs when boosting reported profits. The degree of private benefit for managers is estimated at $\phi_e = 0.0189$, indicating that managers perceive the marginal benefit of higher revenues to be 2 percent higher than its fundamental, due to their private benefit. The optimal short-term cost parameter chosen by the board is $\theta_\pi = 0.185$, indicating that missing analysts' forecasts costs the manager a loss equal to 0.185% of the firm's production profits.[12] Panel A of Table 2 summarizes the estimated parameters and their standard errors.

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 probability of just meeting forecasts, the probability of meeting forecasts, and the correlation between profit growth and markup growth. Similarly, the average markup and the volatility of forecast errors in the model also closely to the corresponding moment in the data. Secondly, in the simulation, we assume that unobserved noise shocks affect reported profits, introducing measurement error in profit growth. As a result, the cross-correlation between sales growth and profit growth in the model is smaller than in the data. Lastly, Figure 9 in Appendix B illustrates that the distribution of forecast errors generated by the model closely aligns with the data, even though we only target the probability of just meeting forecasts.

5.2 The Impact of Short-Termism

We estimate the impact of short-termism at both the micro and macro levels using the estimated model. We simulate a panel of 3,000 firms over 50 periods under optimal short-term incentives (θ_π^*) and compare it to a scenario without short-term incentives ($\theta_\pi = 0$). We estimate the impact of short-termism at micro level by taking the ratio of outcomes under short-termism to those without, and then averaging across firms and time. The results

[12] The relative importance of the two mechanisms –private benefit and board choice– is consistent with the previous literature (Terry, 2022; Terry et al., 2023; Celik and Tian, 2022). However, the individual estimates need not align with earlier work, as we focus on different margins, namely customer accumulation.

Table 3: The impact of short-termism

Panel A. Firm-level outcomes	%Δ from $\theta_\pi = 0$
Average markup	0.191
Annual reported profits	1.191
Accrual-based manipulation	0.232
Firm market value	0.884
Panel B. Aggregate outcomes	
Aggregate price level	0.087
Annual aggregate income	0.157
Annual real consumption	0.070
Lifetime utility	1.233

Notes: The Table presents the main results of the baseline model. We estimate the impact of short-termism by comparing the average moments in the baseline model with short-term incentives (θ_π^*) to the moments in a counterfactual model without short-term incentives ($\theta_\pi = 0$). The quantitative impacts are calculated based on model moments computed over a 50-quarter simulated panel of 3,000 firms, with a burn-in period of 100 periods. Panel A reports firm-level outcomes, and Panel B reports aggregate outcomes. Changes in the last column are expressed in percentage points (1 = 1%).

captures how the average firm behaves differently in the presence of short-term incentives. Instead, we quantify the aggregate effect by comparing general equilibrium outcomes across the two model specifications, constructing aggregate outcomes from simulated data rather than from policy functions and ergodic distributions. Table 3 reports the results.

Short-term incentives significantly affect the average firm's pricing behavior, prompting managers to raise markups and inflate current reported profits at the expense of future customer accumulation (Panel A of Table 3). In steady state, short-term incentives leads the average firm to increase its markup by approximately 20 b.p.. This translates into a 1.20% increase in annual profits, of which only 0.23% stems from accrual manipulation. By disciplining managerial behavior, the presence of short-termism results in a 0.88% increase in the average firm's market value and higher income for shareholders and households.

These effects are economically meaningful. Relative to the average annual operating profits, defined as sales minus cost of goods sold and SG&A, of $417 million per firm in Compustat over the period 2003–2019, short-termism yields an additional $5 million in reported profits. Similarly, given the average market capitalization of $1.561 billion per firm, short-termism accounts for an estimated $13.74 million increase in firm value. The 0.20% rise in markups is also notable when compared to the 8% economy-wide increase observed between 2000 and 2015 (De Loecker et al., 2020). These findings underscore how even modest shifts in managerial incentives alter firm-level pricing decisions and performance.

While short-term incentives benefit shareholders by prompting firms to raise prices, their general equilibrium effects on consumption and welfare are, in fact, ex-ante ambiguous. Panel B of Table 3 shows that, on one hand, short-term incentives raise the aggregate price level by 8.7 basis points, reducing consumers' purchasing power. On the other hand, higher firm profits translate into increased household income through equity ownership. In our estimated model, this positive income effect dominates: real consumption increases by 7 basis points per year, equivalent to \$12 billion of total consumer spending in 2018, resulting in an overall gain in lifetime utility of approximately 1.2%.

The magnitude of our aggregate estimates on consumer welfare is comparable to the estimated cost of inflation at around 1 percent (Lucas, 2000) or of business cycles at around 2 percent (Krusell et al., 2009). Our quantification is qualitatively in contrast with previous work on the aggregate effects of short-termism. Terry (2022) and Celik and Tian (2022) find that short-termism generate welfare losses of approximately 1.1% and 1.5%, respectively, due to its negative impact on R&D and innovation. In contrast, our model produces a modest welfare gain driven by improved managerial discipline and higher household income through general equilibrium effects. This indicates the importance of analysing the consequences of short-term incentives on different firms' margins.

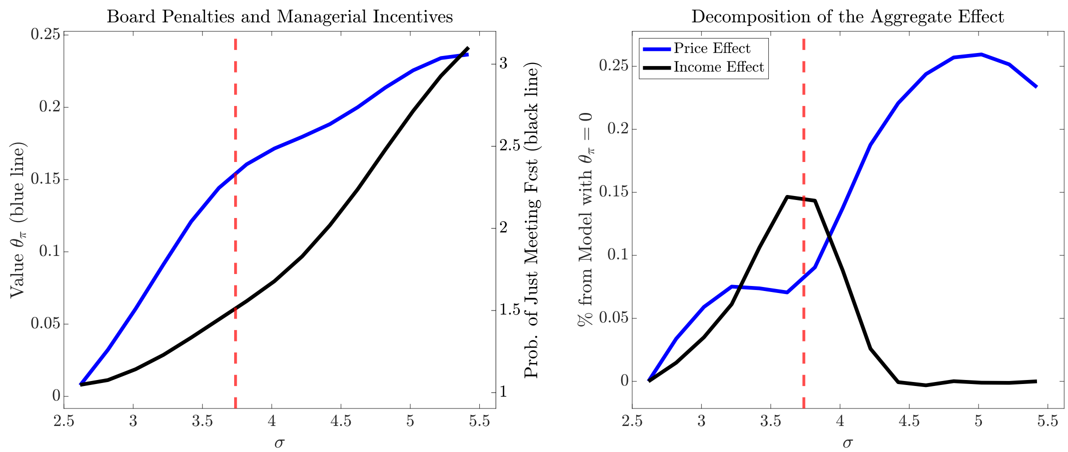
5.3 Discussion and Robustness

The section presents additional discussions and robustness on specific elements and functional specifications of the theoretical framework. Additional details are presented in the corresponding Appendices.

Market competition and short-term incentives. The impact of short-termism depends on the sensitivity of markups and, ultimately, on the demand elasticity in the markets where firms operate. We perform a sensitivity analysis by varying the elasticity of substitution within products variety, σ while keeping the difference between σ and η constant. Figure 5 plots how the optimal short-term incentives (θ_π), the probability of "just" meeting earning forecasts, and the welfare effects of short-term incentives change as functions of σ.

When the elasticity of demand increases, the board imposes stronger penalties on managers for missing targets, and the local effects of short-termism become more pronounced (left panel). In markets with more elastic demand, the optimal θ_π rises because, on one

Figure 5: Sensitivity analysis of short-termism to demand elasticity

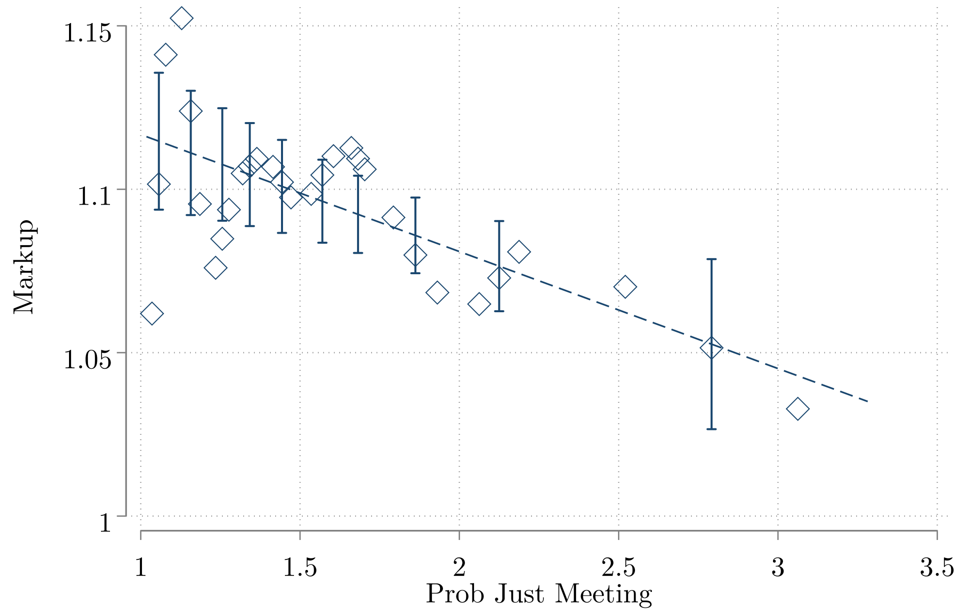


Notes: This Figure presents the results of a sensitivity analysis with respect to the elasticity of substitution in demand, σ. We vary σ and keep the difference $\sigma - \eta$ constant. For each value, we compute the optimal short-term incentive cost, θ_π^*, the probability of just meeting forecasts (right panel), and the aggregate effect on consumers, decomposed into price and income effects (left panel). The variation in real consumption relative to a counterfactual model without short-term pressure corresponds to the difference between the black and blue lines in the left panel. Values on the y-axes are expressed as percentage deviations from the counterfactual ($\theta_\pi = 0$). The red dotted lines represent the estimated benchmark case. Values in the right panel are spline-interpolated for presentation purposes.

hand, managers' private benefits are stronger and, on the other hand, a given price change has a smaller impact on current profits, as shown in Equation (8). Since meeting earnings forecasts requires larger price increases when demand elasticity is higher, only firms already close to analysts' forecasts pursue such adjustments. As a result, economies with greater elasticity display more clustering of firms just above profit targets and larger local pricing distortions.

At the aggregate level, as the elasticity of demand increases, the welfare effects of short-term incentives shift from positive to negative (left panel). The welfare loss from higher prices grows monotonically, while the aggregate income gain follows an inverted-U pattern. Intuitively, managers must raise prices and markups more aggressively to achieve a given improvement in reported profits as elasticity rises. Yet in more elastic markets, such price increases trigger larger drops in quantity sold, making it harder to sustain profit growth. Consequently, economies with higher demand elasticity experience larger aggregate price increases but smaller income gains, and thus a greater likelihood of welfare losses from short-termism. For low levels of demand elasticity, both price and income effects are small and quantitatively similar because θ_π is small. At intermediate levels, including the baseline

Figure 6: Short-term pressure and demand elasticity



Notes: This Figure plots the relationship between industry-level markups and the short-term incentives across industries. The latter is proxied by the ratio between the probability of firms narrowly meeting analysts' earnings forecasts and the probability of firms narrowly missing them (within 10% of forecast errors, as in the model) within an industry. Industry-level markup are computed as the average across all firm-year observation. Firm-level markups are measured as in the quantitative model (see Appendix A).

calibration, the income effect dominates the price effect, so short-termism improves welfare. As demand elasticity continues to rise, the income effect declines, and the welfare impact of short-term incentives turns negative.

We test the hypothesis that the relationship between demand elasticities and short-term incentives holds using variation across US industries. To do so, we estimate the average short-term incentives faced by managers within each 3-digit NAICS industry by calculating the "jump" at zero forecast error–defined as the ratio of the probability of firms narrowly meeting versus narrowly missing analysts' forecasts (within $\pm$ 10%). We then correlate this measure with the average markup in the same 3-digit NAICS industry, an inverse proxy for the demand elasticity in the industry. Figure 6 shows that industries with lower markups (or higher demand elasticity) display a larger jump at zero forecast error, indicating stronger managerial incentives to meet short-term targets. This result both provides external validation for our theoretical mechanism and highlight important policy implications as short-termism is less of a concern in less competitive markets, where stronger income effects offset the distortions from pricing and markup decisions.[13]

Sensitivity to other parameters. Table 6 in Appendix C shows that our main results are robust to a variation of one standard deviation around the benchmark estimated parameters. Notably, the magnitude of the price effect is very close to the benchmark values in all the experiments we conduct, which reflects the partial equilibrium loss to consumers from higher prices alone, whereas most of the differences arises from the size of the income effect. The overall effect on welfare, however, remains positive.

Accounting for marketing. We extend the baseline model by allowing firms to accumulate customers not only through competitive pricing, but also through marketing activities that enhance the attractiveness of their product variety. Marketing enters the model as a firm-level variable that amplifies the perceived quality of the good, increasing its attractiveness to consumers. Specifically, we assume that households derive utility from a variety-adjusted quantity of consumption, where marketing effort h_{j_m} scales the effective consumption of a good. As a result, consumers respond not to absolute prices, but to the marketing-adjusted price $\tilde{p}_{j_m} = \frac{p_{j_m}}{h_{j_m}}$, which captures both pricing and marketing effort.

The law of motion for the firm's customer base b', incorporating marketing, becomes:

$$b'_{j_m} = (1-\theta)b_{j_m} + \theta \left(\frac{\tilde{p}_{j_m}}{\tilde{P}_m}\right)^{1-\sigma}, \qquad 0 < \theta < 1, \tag{28}$$

where $\tilde{P}_m$ is the price index across product varieties of type m, also adjusted for marketing. Firms therefore acquire new customers by offering either lower prices or higher marketing. Derivation is in Appendix C. Given the accumulation of customer capital, the quantity demanded from firm j_m becomes:

$$h_{j_m} y_{j_m} = \left[(1-\theta) \cdot \frac{b_{j_m}}{\tilde{p}^{\eta}_{j_m}} + \theta \cdot \left(\frac{\tilde{p}_{j_m}}{\tilde{P}^{\eta}_m}\right)^{-\sigma}\right] \cdot \frac{W + \Pi}{(1-\theta)\tilde{P}_b^{1-\eta} + \theta \tilde{P}_m^{1-\eta}}, \tag{29}$$

where $h_{j_m} y_{j_m}$ denotes the quantity of utility-relevant consumption, and $\tilde{P}_b$ is the weighted marketing-adjusted price index across customer types.

[13] Overall, these results suggest that while the aggregate effect of short-term pressure may appear modestly beneficial, it masks significant heterogeneity. A quantitative model accountinf for sectoral heterogeneity and input-output linkages is a promising venue for future research.

We assume that marketing effort h_{j_m} depreciates immediately, rather than being accumulated as a stock. Thus, firms invest in marketing in each period. Thus, the production profits of firm j_m in a given period are:

$$\Pi_{j_m} = \left(\tilde{p}_{j_m} - \frac{W}{a_{j_m} h_{j_m}} - \frac{\xi}{2} \frac{\left(h_{j_m} - 1\right)^2}{h_{j_m}} \right) y_{j_m}, \qquad \xi > 0 \tag{30}$$

where the cost of marketing is increasing and convex in effort h_{j_m}, parameterized by ξ. The firm first chooses the effective price $\tilde{p}$ to determine demand, then selects the cost-minimizing combination of price and marketing to implement it. Note that as ξ tends to infinity, the optimal h_{j_m} converges to 1, causing the model to collapse to the baseline specification.

We estimate the impact of short-termism on firm-level and aggregate outcomes leaving all other model components, including firm dynamics and aggregation, as in the benchmark specification. To estimate the parameter ξ, we include the average marketing intensity, defined as, as an additional moment in the estimation step. The marketing intensity is computed using Compustat information on S&GA expenditure (Morlacco and Zeke, 2021).

Table 7 in Appendix C presents the results of the extended model and its estimated parameters. Both the micro- and macro-level effects of short-termism are consistent with our baseline estimates. The presence of short-termism increases markups by about 0.17% relative to the counterfactual model, which in turn raises reported profits and firm value by roughly 1% for the average firm. Thus, the presence of marketing only moderately attenuates the effects of short-term incentives on markups and prices. At the aggregate level, the lower increase in prices relative to the benchmark case translates into a slightly higher increase in real consumption relative to the baseline case (8.9 basis points per year, compared with 8.7 basis points in the baseline), indicating that our quantification likely represents a lower bound.

CES demand. We contrast our model specification with a standard static CES framework that does not incorporate customer capital, thereby eliminating the investment motive. While the absence of such a motive may appear inconsistent with the definition of short-termism itself, it is worth noting that short-termism still generate similar qualitative effects on pricing and markup in a CES framework without dynamic demand accumulation, since empire-building motives alone still lead to underpricing inefficiencies from the shareholders' perspective. Table 8 in Appendix C reports the results of the model and the estimated parameters under the CES assumption, that corresponds to the case with $\theta = 1$ and $\sigma = \eta$

in our baseline model.

The data reject this specification. The model produces a correlation between sales, profits, and markup growth close to one, whereas the correlation in the data is much smaller. To reconcile this discrepancy, the model relies on an unrealistically large amount of noise rather than on fundamental shocks. This result connects to a substantial body of recent empirical literature on the relationship between markups, customer capital, and firm dynamics (Foster et al., 2016), and underscores the importance of customer capital in quantifying the impact of short-termism on both micro and macroeconomic variables.

6 Conclusions

The model of corporate governance adapted by firms can have a significant impact on the aggregate economy. This paper examines how short-term incentives impacts impact firms' pricing decisions in a framework with customer capital and quantify its implication for consumers.

Firm performance is routinely scrutinized and compared to market expectations, generating pressure on managers to meet short-term analysts' forecast. Using micro-level data from Compustat-IBES, we provide evidence that short-term incentives may results in opportunistic markup manipulation to meet analysts' forecast. Managers may have incentives to raise their markups to meet short-term analysts' forecast 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 incentives and endogenous markups due to customer accumulation. Our study reveals that short-termism causes firms to increase their markups by around 20 basis points, which translates into approximately $5 millions of additional annual profits for the average firm over the period 2003-2019. Differently from previous work, we find that, at the aggregate, short-term incentives increase lifetime utility by 1.2 percent as the positive income effect driven by the increase in firms' value more than offset the increase in markups and prices. Our results indicate the importance of analysing the consequences of short-term incentives on different firms' margins.

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Appendix

A Data Construction

Compustat data and firm-level markup. We construct firm-level variables from annual Compustat following standard practice. Firm size is measured as the logarithm of total assets, $\log(at_{it})$. Nominal sales, cost of goods sold, and selling, general, and administrative (overhead) expenses are $sale_{it}$, $cogs_{it}$, and $xsga_{it}$, respectively. Market value is $mkvalt_{it}$, Compustat's market capitalization at the end of fiscal year. Capital stock is constructed using a perpetual-inventory approach: the initial stock is set to the earliest available gross property, plant, and equipment ($ppegt_{it}$), and updated iteratively with changes in net property, plant, and equipment ($ppent_{it}$) to obtain a consistent book-value series. 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, so that all series are expressed in real terms. All variables are measured annually at the fiscal-year frequency. The sample spans from 1990 to 2019. We keep U.S. incorporated firms; exclude regulated utilities and financials with 4-digit SIC in $[4900, 5000)$ or $[6000, 7000)$; drop firm-years with $acq_{it} > 0.05 \times at_{it}$; drop firm-years with missing or negative at_{it}, $sale_{it}$, $ppent_{it}$, che_{it}, $dlc_{i,t}$, $dltt_{it}$, or $invt_{it}$; drop firm-years prior to the firm's first observation of $ppegt_{it}$ to ensure a well-initialized capital series; drop firms with total assets above the 97.5 percentile of the distribution.

We rely on De Loecker et al. (2020) to construct firm-level measures of markup using Compustat data. Under the assumption of CRS Cobb-Douglas production function and cost minimization (De Loecker and Warzynski, 2012), we can define the markup for firm i at time t as follows:

$$\mu_{it} = \widehat{\theta}_{it}^{V} \frac{P_{it}Q_{it}}{P_{it}^{V}Q_{it}^{V}}, \tag{31}$$

where $\widehat{\theta}_{it}^{V}$ is the output elasticity of variable input V, and $\frac{P_{it}Q_{it}}{P_{it}^{V}Q_{it}^{V}}$ is the revenue share of variable input V of firm i at time t. We adopt the methodology proposed by De Loecker et al. (2020) to estimate production function and output elasticity using Compustat data. Specifically, we use the cost of goods sold ($cogs_{it}$ in Compustat) as variable input and measure revenues with total quarterly sales ($sale_{it}$ in Compustat). In the baseline specification we estimate production function using a 5-year rolling window at the 2-digit NAICS industry, treating overhead expenses as factor of production. As alternative, we estimate production function and output elasticities without overhead expenses as factor of production. As additional robustness, we calibrate the output elasticity to be equal to 0.85 and common across firms and years. We trim the tails of markups at 1.5 percent on each side. For the empirical analysis, we compute annual growth rates using the Davis-Haltiwanger-Schuh formula.

IBES dataset and analysts' forecast error. We extract annual earning forecasts and "Street" actual earnings from the Institutional Broker's Estimate System (IBES) to construct our measures of earnings' forecast error.[14] We follow the cleaning methodology provided by WRDS to construct our final dataset and measure forecast errors. We start from the unadjusted dataset and extract annual forecasts, and collect yearly horizon forecasts only. Specifically, we restrict the analysis to the forecasts issued between 270 and 370 days before the fiscal period end date, following Joshua Livnat (2006). The presence of stock splits and rounding in the adjusted detail history of IBES generate misclassified observations and rounding issues (Payne and Thomas, 2003). We adjust the data by downloading the historical stock-split adjustment factors from CRSP, putting estimates on the same per-share basis as reported earnings. Finally, we define the consensus forecast as the median of analyst forecasts at the firm - fiscal period end data level. We link IBES and Compustat via *iclink* (IBES *ticker* to Compustat *gvkey*), using link-date ranges provided by WRDS.

Let $\texttt{acty\_usd}_{it}$ be realized dollar value annual earning for firm i in fiscal year t, and $\texttt{medfcst\_usd}_{it}$ denote the consensus forecast for the same fiscal period. We construct the measure of forecast error as follow:

$$fe_{it} = \frac{\texttt{acty\_usd}_{it} - \texttt{medfcst\_usd}_{it}}{\texttt{total\_assets}_{it}}, \tag{32}$$

where the difference between realized annual earning and consensus forecast are rescaled by firms' total assets are measured from Compustat. In the empirical analysis, we trim forecast errors that are above 0.025 in absolute value.

For the quantitative model, given the absence of a counterpart for total assets in our theoretical framework, we use the Davis-Haltiwanger-Schuh formula to express the forecast error fe_{it} in percentage terms as follows:

$$fe_{it} = 2 \cdot \frac{\texttt{acty\_usd}_{it} - \texttt{medfcst\_usd}_{it}}{|\texttt{acty\_usd}_{it}| + |\texttt{medfcst\_usd}_{it}|}. \tag{33}$$

[14]IBES actual earnings reflect Street earnings, which is the standard benchmark used by managers and analysts whereas Compustat reports GAAP earnings, which include transitory items and are less aligned with forecast targets (Bradshaw and Sloan, 2002).

Empirical results are robust to this definition of forecast error.

NL Analytics data and construction of sentiment variables We use NL Analytics' earnings call data to build a CEO sentiment index at the firm-year level. The platform provides a textual analysis tool that allows to quantify firms' and CEOs' sentiment associated to a specific topic. We rely on it to measure CEOs' sentiment on a customer base-related dictionary including the following words: `customer, client, user base, business relationship, loyalty program, loyalty programs, loyalty members, loyalty platform, membership program, loyalty customers`. The algorithm allows to count the number of sentences that contain at least one keyword from the query and also a positive or negative keyword (e.g. gain vs loss). The overall CEOs' sentiment is compute as the difference between the two. We rescale this measure by the number of total unconditionally positive or negative sentences reported in the earning calls. We aggregate this information at the firm-year level, across all earning calls of a fiscal year. We map the firm-year level measure to Compustat data using a crosswalk between `earningscallid` and `gvkey`. Formally, our baseline annual measure of sentiment is:

$$\texttt{sent\_unc\_an}_{it} = \frac{\sum_{c\in(i,t)} \texttt{sentiment}_c}{\sum_{c\in(i,t)} \left(\texttt{overall\_pos}_c + \texttt{overall\_neg}_c\right)}, \tag{34}$$

where c indicates an earning call for firm i in year t and $\texttt{sentiment}_c$ is the difference between the number of sentences that contain at least one keyword from the query and also a positive keyword and the number of sentences that contain at least one keyword from the query and also a negative keyword.

For the main specification in the empirical analysis, we compute the 2-year ahead growth rates, trimming all observations above ± 75 percent:

$$\texttt{d\_sent\_unc\_an}_{it} = 100 \times \frac{\texttt{sent\_unc\_an}_{i,t+2} - \texttt{sent\_unc\_an}_{i,t-1}}{\texttt{sent\_unc\_an}_{i,t-1}}. \tag{35}$$

As robustness, we compute also compute the 1-year growth rate or normalize CEOs' sentiment by the total number of sentences reported in the earning calls.

A.1 Additional Empirical Results

Optimal Bandwidth. Our baseline regression discontinuity design estimates rely on the optimal bandwidth selected by the `rdrobust` command. This choice, based on the methodology of Calonico et al. (2020), is designed to minimize the mean squared error by balancing the reduction in bias from using a smaller bandwidth against the loss in precision that comes from including fewer observations. In practice, the procedure selects the range of data around the cutoff that provides the best compromise between local identification and statistical power.

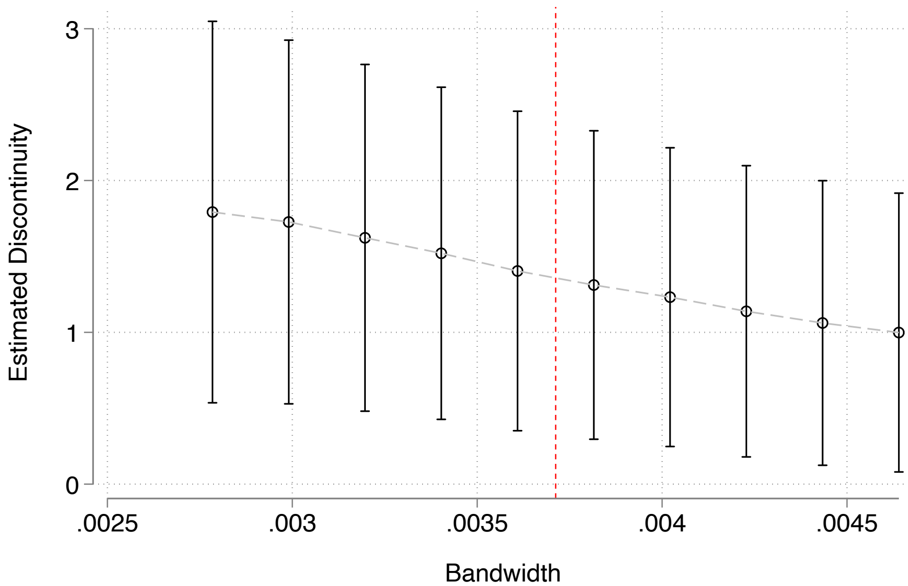
In our application, the running variable, the forecast error, has a smooth distribution, and the potential outcomes may change gradually as we move away from the cutoff. This makes the choice of bandwidth particularly important as too wide a bandwidth risks including firms whose behavior is driven by factors unrelated to narrowly meeting analysts' forecasts, while too narrow a bandwidth increases sampling variability and reduces statistical precision.

Figure 7 illustrates how the estimated discontinuity in markup growth varies with the bandwidth choice. The figure shows that the estimated discontinuity is relatively stable in a $\pm$ 25 percent neighborhood from the optimal bandwidth, approximately 0.0035. This stability gives us confidence that our results are not an artifact of the specific bandwidth choice but instead reflect a genuine local effect at the cutoff. The optimal bandwidth also keeps the analysis tightly focused on firms with nearly identical forecast errors, which supports the validity of the local comparison central to the RDD design.

Mean differences around the forecast threshold. We report results from a simple OLS comparison of mean outcomes between firms that narrowly meet versus narrowly miss analysts' earnings forecasts. This exercise is important for two reasons. First, it provides a transparent and model-free check on the discontinuity evidence by comparing firms with nearly identical forecast errors. Second, it helps reinforce the interpretation of our baseline findings by showing that similar patterns hold when we remove functional form assumptions and instead rely on straightforward group means.

We construct a tight bandwidth of $\pm 0.15\%$ around the zero forecast error cutoff, consistent with the region where we observe excess mass (bunching) in the distribution of forecast errors. Within this narrow window, we compare the average changes in key firm-level outcomes–markup and CEO sentiment–between firms that just meet analysts' forecasts and those that just miss. The results, reported in Table 4, are consistent with our main findings:

Figure 7: Optimal Bandwidth in the RDD Estimation



Notes: The Figure plots the estimated discontinuity in markup growth as a function of the chosen bandwidth. Estimates are obtained from Equation (1) using a local linear RDD with a triangular kernel. The vertical dashed line marks the optimal bandwidth, approximately 0.0035, as determined by `rdrobust` following Calonico et al. (2020). The dependent variable is firm quarter markup growth, $\Delta \log \mu_{i,t}$, and the running variable is the forecast error, fe_{it}. Markups are estimated using Compustat data from 1990 to 2019 following the DEU methodology with cost of goods sold as the variable input. Forecast errors are computed as the difference between realized earning and the median IBES analyst earning forecast, scaled by total assets. Confidence intervals correspond to 90% coverage and are computed with standard errors clustered at the firm level. See Appendix A for additional details on variable construction.

firms that narrowly meet forecasts exhibit significantly higher markup growth and a decline in customer sentiment, relative to those that narrowly miss.

Alternative Measures. To ensure that our main findings are not driven by a specific measurement choice or by omitted variables, we conduct a set of robustness exercises that vary both the definition of our key variables. We begin by replacing our baseline markup measure with two alternative measures. The first alternative uses the methodology of De Loecker et al. (2020) but estimates output elasticities without overhead costs as factor of production. The second alternative replaces estimated input elasticities with a calibrated cost share. We then turn to CEO sentiment, where we again examine two alternatives to our baseline measure. The first measure focuses on the contemporaneous, 1-year change in CEO sentiment, allowing us to assess whether the timing of sentiment measurement affects the observed rela-

Table 4: OLS Estimates

	(1) Markup	(2) CEO Sentiment
Difference: Just Meet − Just Miss (p.p)	0.772	-9.246
	(0.389)	(3.500)
Methodology	OLS	OLS
Bandwith around 0 FE	0.1%	0.1%
Firm, Year FEs	Yes	Yes
Observations	2,662	307

Notes: The Table reports the difference in markup, profit margin and CEO customer sentimer growth for firms just meeting vs just missing profit targets. We estimate the difference in mean between the two groups using an OLS regression. We use a 0.1% bandwidth around the zero cutoff, selected to match the region where the distribution of forecast errors shows clear bunching of firms. All the the dependent variable are demened at firm-year level before estimation. Standard errors, clustered at the firm level, are reported in parentheses. See Appendix A for additional information on variables construction.

tionship with the forecast-error threshold. The second measure normalizes CEOs' sentiment by the total number of sentences in the earning call. Table 5 shows that, across all four alternative specifications, we find that the estimated discontinuity at the zero forecast-error cutoff remains of similar magnitude and sign to our baseline results.

Table 5: Alternative Measures of Markup and CEO Sentiment

	(1) Markup Alternative DEU	(2) Markup Calibrated Cost Share	(3) CEO Sentiment Alternative Measure	(4) CEO Sentiment Contemporaneous
Mean Change at 0 FE Cutoff (p.p.)	1.304	1.122	-9.366	-6.368
	(0.624)	(0.582)	(3.465)	(3.177)
Standardized (p.p.)	9.418	12.240	-26.489	-21.650
Firm, Year FEs	Yes	Yes	Yes	Yes
Mean (p.p.)	5.332	5.187	20.012	21.214
Median (p.p.)	2.283	2.086	14.705	16.252
Observations	14,956	14,955	1,705	2,843

Notes: The Table reports the estimated discontinuity in the outcome variable at the zero forecast-error cutoff for alternative definitions of markup and CEO sentiment. Columns (1) and (2) present results for two markup measures: Column (1) uses the output elasticities estimated without overhead costs as factor of production, while Column (2) employs a markup based on a calibrated cost share. Columns (3) and (4) present results for CEO sentiment: Column (3) uses a sentiment index normalized by the total number of sentences, and Column (4) uses the contemporaneous, 1-year growth rate. All specifications include firm and year fixed effects. The running variable is the forecast error, fe_{it}. Markups are computed from Compustat data between 1990 and 2019, and sentiment measures are extracted from earning call transcripts as described in Appendix A. Standard errors, clustered at the firm level, are shown in parentheses.

B Quantitative Model

B.1 Derivation of Customer Accumulation and Demand

Each household, indexed by i, belongs to a continuum of measure 1 and maximizes a static utility function:

$$U_i = \max_{\{c_{j_m}, j_m\}} U\left(C_i\right) \tag{36}$$

subject to:

$$\begin{cases} \displaystyle\int_0^1 p_{j_m} c_{j_m}\, dm = W + \Pi, \\ C_i = \left\{ \displaystyle\int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \varepsilon_{j_m} \right) c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}}, \\ j^*_{j_m,t} = j_{j_m,t-1} \qquad \text{if } i \text{ is locked-in with probability } (1-\theta) \end{cases} \tag{37}$$

where p_{j_m} is the price of firm j_m, c_{j_m} is the quantity consumed from firm j in type m, η is the elasticity of substitution across product types, σ is the elasticity of substitution across firms within each type, and ε_{j_m} is an idiosyncratic preference shock (Gumbel distributed).

The household decision-making process occurs in two steps:

1. Firm Selection: With probability $1 - \theta$, the household remains locked into its previous firm and cannot re-optimize. With probability θ, the household is free to select a new firm j^*_m that maximizes its utility.

2. Consumption Allocation: Given the firm selection j^*_m, the household optimally allocates its expenditure across product types to maximize utility, subject to the budget constraint.

Step 1 allows us to derive the law of motion for the customer base of a firm j_m in the economy, while Step 2 determines the demand for good j_m at firm j_m. This structure implies that firms face demand from both locked-in and re-optimizing consumers, affecting their pricing and market share dynamics.

Step 1. Firm selection and customer base. Each household selects one firm j in each product type m to maximize their consumption, subject to their budget constraint. Given total household expenditure E_m on product type m, the quantity of good j_m consumed is:

$$c_{j_m} = \frac{E_m}{p_{j_m}}. \tag{38}$$

The corresponding taste-adjusted consumption level from choosing firm j_m is:

$$\tilde{c}_{j_m} = \exp\left(\frac{1}{\sigma - 1}\varepsilon_{j_m}\right) c_{j_m}, \tag{39}$$

where $\varepsilon_{j_m} \sim$ Gumbel is an idiosyncratic taste shock, c_{j_m} is the quantity consumed, and $\sigma - 1$ governs the weight of taste shocks in consumption.

Given the budget constraint, the household chooses firm j_m to maximize taste-adjusted consumption:

$$j_m^* = \arg\max_j \left\{ \exp\left(\frac{1}{\sigma - 1}\varepsilon_{j_m}\right) \frac{E_m}{p_{j_m}} \right\}. \tag{40}$$

Taking the logarithm of the taste-adjusted consumption:

$$\log \tilde{c}_{j_m} = \frac{1}{\sigma - 1}\varepsilon_{j_m} - \log p_{j_m} + \log E_m. \tag{41}$$

Since E_m is constant across firms within product type m, the household's choice depends only on the price and the taste shock:

$$j_m^* = \arg\max_j \left\{ \frac{1}{\sigma - 1}\varepsilon_{j_m} - \log p_{j_m} \right\}. \tag{42}$$

Because ε_{j_m} follows a Gumbel distribution, the probability that a re-optimizing household selects firm j in product type m follows a multinomial logit structure. For a finite number of firms, the probability of choosing firm j_m is:

$$\text{Prob}\left(j_m = j\right) = \frac{p_{j_m}^{1-\sigma}}{\sum_{j' \in J_m} p_{j'_m}^{1-\sigma}}. \tag{43}$$

where the denominator is the price index for product type m, which we can write as:

$$P_m = \left[\frac{1}{J_m} \sum_{j' \in J_m} p_{j'_m}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}. \tag{44}$$

Then, the choice probability can be rewritten as:

$$\text{Prob}\left(j_m = j\right) = \frac{1}{J_m} \left(\frac{p_{j_m}}{P_m} \right)^{1-\sigma}. \tag{45}$$

This solution easily extent to the case of atomistic firms. When firms are atomistic within each product type, household choices follow a probability density. Let J_m denote the total measure of firms in product type m. The mass of households choosing a firm with price p is:

$$f(p) = \frac{1}{J_m} \left(\frac{p}{P_m} \right)^{1-\sigma}, \tag{46}$$

where the price index, derived from the law of large numbers, is:

$$P_m = \left[\int p^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}}. \tag{47}$$

Finally, the law of motion for the customer base depends on the previous period and newly acquired customers. Denote $b_{j_m}^t$ as the mass of customers served by firm j_m in product type m at time t. Due to consumption inertia, this includes both locked-in customers from the previous period, denoted $b_{j_m}^{t-1}$, who continue purchasing from firm j_m, and new customers who re-optimize and select firm j_m. The mass of new customers selecting firm j_m in t is:

$$\theta f(p) = \theta \frac{1}{J_m} \left(\frac{p_{j_m}}{P_m} \right)^{1-\sigma}. \tag{48}$$

Thus, given the fraction of unattached customers θ, the law of motion for the customer base can we written as:

$$b_{j_m}^t = (1-\theta) b_{j_m}^{t-1} + \theta \frac{1}{J_m} \left(\frac{p_{j_m}}{P_m} \right)^{1-\sigma}, \tag{49}$$

where the first term represents locked-in customers who remain with firm j_m, and the second term accounts for new customers who re-optimize and choose firm j_m.

Step 2. Optimal consumption allocation and demand. Given the choice of product variety j for each product type m, households allocate consumption across product types to minimize total expenditure:

$$\min_{\{c_{j_m}\}} \int_0^1 p_{j_m} c_{j_m} dm \tag{50}$$

subject to the Dixit-Stiglitz aggregator:

$$C_t = \left\{ \int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \varepsilon^i_{j_m} \right) c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}}. \tag{51}$$

Define the Lagrangian function:

$$\mathcal{L} = \int_0^1 p_{j_m} c_{j_m} dm + \lambda \left[C_t - \left\{ \int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \varepsilon^i_{j_m} \right) c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}} \right], \tag{52}$$

where λ is the Lagrange multiplier. The first-order condition with respect to c_{j_m} is:

$$p_{j_m} - \lambda \cdot C_t^{\frac{1}{\eta}} \exp\left(\frac{\eta - 1}{(\sigma - 1)\eta} \varepsilon^i_{j_m} \right) c_{j_m}^{-1/\eta} = 0. \tag{53}$$

Rearranging for c_{j_m}:

$$c_{j_m} = \exp\left(\frac{\eta - 1}{\sigma - 1} \varepsilon^i_{j_m} \right) \left(\frac{p_{j_m}}{\lambda} \right)^{-\eta} C_t. \tag{54}$$

In the cost minimization problem, the Lagrange multiplier represents the price index across product types, which is:

$$\lambda = \left\{ \int_0^1 \left[p_{j_m} \exp\left(\frac{1}{1 - \sigma} \varepsilon_{j_m} \right) \right]^{1-\eta} dm \right\}^{\frac{1}{1-\eta}} = P. \tag{55}$$

Thus, the optimal consumption allocation for the good j_m is:

$$c_{j_m} = \exp\left(\frac{\eta - 1}{\sigma - 1} \varepsilon^i_{j_m} \right) \left(\frac{p_{j_m}}{P} \right)^{-\eta} C_t. \tag{56}$$

Firms with lower prices relative to P attract higher demand. The preference shock ε_{j_m} shifts demand toward firms that are randomly favored by individual consumers, and the elasticity parameter η determines how sensitive demand is to price changes.

From Consumption Allocation to Expected Firm Demand. From the firms' perspective, the expected total demand faced by firm j_m aggregates the consumption levels across all households choosing that specific variety:

$$y_j = \int_{i:j_m=j} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right)\left(\frac{p_j}{P}\right)^{-\eta} C_t \, di. \tag{57}$$

This expression can be separated into the contributions from locked-in consumers and from those who actively re-optimize:

$$y_j = \left[\int_{i:j_m=j,\,\text{lock-in}} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) di + \int_{i:j_m=j,\,\text{re-optimize}} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) di\right]\left(\frac{p_j}{P}\right)^{-\eta} C_t. \tag{58}$$

The first term in parentheses in Equation (58) represents the expected contribution of taste shocks from locked-in consumers:

$$\int_{i:j_m=j,\,\text{lock-in}} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) di. \tag{59}$$

Since locked-in consumers were selected in previous periods based on past prices, the firm's current price does not reveal any information about the taste shocks drawn by these consumers. Therefore, the firm computes expectations over the unconditional distribution of taste shocks. Under the assumption that these shocks are i.i.d. and Gumbel-distributed, the expectation for a given consumer i is:

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right)\right] = \Gamma\left(1+\frac{\eta-1}{\sigma-1}\right). \tag{60}$$

Because taste shocks are i.i.d. across consumers, multiplying by the mass of locked-in consumers yields the final expression:

$$\int_{i:j_m=j,\,\text{lock-in}} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) di = (1-\theta)b^{t-1}_{j_m}\Gamma\left(1+\frac{\eta-1}{\sigma-1}\right). \tag{61}$$

The second term in parentheses in Equation (58) represents the expected contribution of taste shocks from re-optimizing consumers:

$$\int_{i:j_m=j,\,\text{re-optimize}} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) di. \tag{62}$$

Unlike locked-in consumers, re-optimizing households actively choose a firm to maximize their taste-adjusted utility. Since lower prices increase the likelihood of being chosen, this selection process biases the expected taste shock upward. Using properties of the Gumbel distribution, the conditional expectation of the exponentiated taste shock is:

$$\mathbb{E}\left[\exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) \mid \text{re-optimize}\right] = \Gamma\left(1+\frac{\eta-1}{\sigma-1}\right)\left(\frac{p_j}{P_m}\right)^{\eta-1}. \tag{63}$$

Multiplying by the mass of re-optimizing consumers gives:

$$\int_{i:j_m=j,\,\text{re-optimize}} \exp\left(\frac{\eta-1}{\sigma-1}\varepsilon^i_{j_m}\right) di = \left[b^t_{j_m} - (1-\theta)b^{t-1}_{j_m}\right]\Gamma\left(1+\frac{\eta-1}{\sigma-1}\right)\left(\frac{p_j}{P_m}\right)^{\eta-1}. \tag{64}$$

Substituting both the locked-in and re-optimizing integrals into the total firm demand expression, and using the identity for total expenditure $C_t = \frac{W+\Pi}{P}$, we obtain:

$$y_j = \left[(1-\theta)b^{t-1}_{j_m} + \left(b^t_{j_m} - (1-\theta)b^{t-1}_{j_m}\right)\left(\frac{p_j}{P_m}\right)^{\eta-1}\right]\Gamma\left(1+\frac{\eta-1}{\sigma-1}\right)\left(\frac{p_j}{P}\right)^{-\eta}\frac{W+\Pi}{P} \tag{65}$$

Finally, using the law of motion for the customer base and substituting total expenditure, $C_t = \frac{W+\Pi}{\tilde{P}}$, and the aggregate price index, this simplifies to:

$$y_j = \left[(1-\theta)b^{t-1}_{j_m}p^{-\eta}_{j_m} + \theta p^{-\sigma}_{j_m}P^{\sigma-\eta}_m\right]\frac{W+\Pi}{(1-\theta)P^{1-\eta}_B + \theta P^{1-\eta}_m}. \tag{66}$$

B.2 Solution Algorithm

We compute the stationary equilibrium of the model using a value function iteration procedure. The distribution of firms across the idiosyncratic state space is calculated using a non-stochastic simulation approach, following Young (2010). The general equilibrium algorithm involves three nested fixed-point loops and is used both for model estimation and to quantify the effects of short-termism, as detailed in the paper.

Grid. We use a three-dimensional grid to represent the firm's state variables: its customer base, productivity, and observed accounting noise. The continuous exogenous processes for productivity (a) and observed accounting shocks (ε) are discretized into Markov chains using the method outlined in Tauchen (1986), with 51 grid points for a and 7 for ε. The customer base, denoted b, is defined over 81 non-equally spaced points within a finite interval, with denser coverage in the lower range of the distribution to better capture the behavior of smaller firms. The grid spans from a minimum of 0.2 to a maximum of 3. Accrual manipulation (m) is modeled as a static decision variable and is defined over a grid of 31 equally spaced points ranging from 0 to 10% of actual profits. To ensure that the ergodic distribution of firms does not assign zero mass to firms at the boundaries, we implement appropriate checks. Once all grids are established, we solve the model using value function iteration.

Algorithm. We compute the stationary general equilibrium of the full-model through the following iterative procedure:

1. Set initial guesses for the aggregate price indexes P_m, P_b, and profits Π and solve:

   1.1 Guess a value for the short-term incentive cost, θ_π, and iterate over the following two fixed points:

      a) Guess analysts' forecast policies for accruals m_0^f and prices p_0^f, conditional on the customer base, and solve the manager's problem:

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

         ii) For each point on the grid, find the policy function (b', m) that solves the Bellman equation;

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

         iv) Iterate until convergence: $\max ||V_1^M - V_0^M|| < \epsilon$.

b) Update analysts' forecast policies, m_1^f and p_1^f, based on managers' optimal decisions:

   i) Calculate the implied firm policies m_0 and p_0 over all states;

   ii) Compute the updated forecasts m_1^f and p_1^f using unconditional probabilities from the transition matrix.

c) Iterate on the analysts' forecasts (m^f, p^f) until the maximum forecast difference is below a chosen tolerance.

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

1.3 Compute the implied mean firm value objective of boards given θ_π.

1.4 If the board objective is optimized, realized short-term incentives θ_π^* are computed. If not, update the guess for θ_π and repeat.

2. Compute the new implied aggregate price indices P_m^1, P_b^1, and profits Π^1.

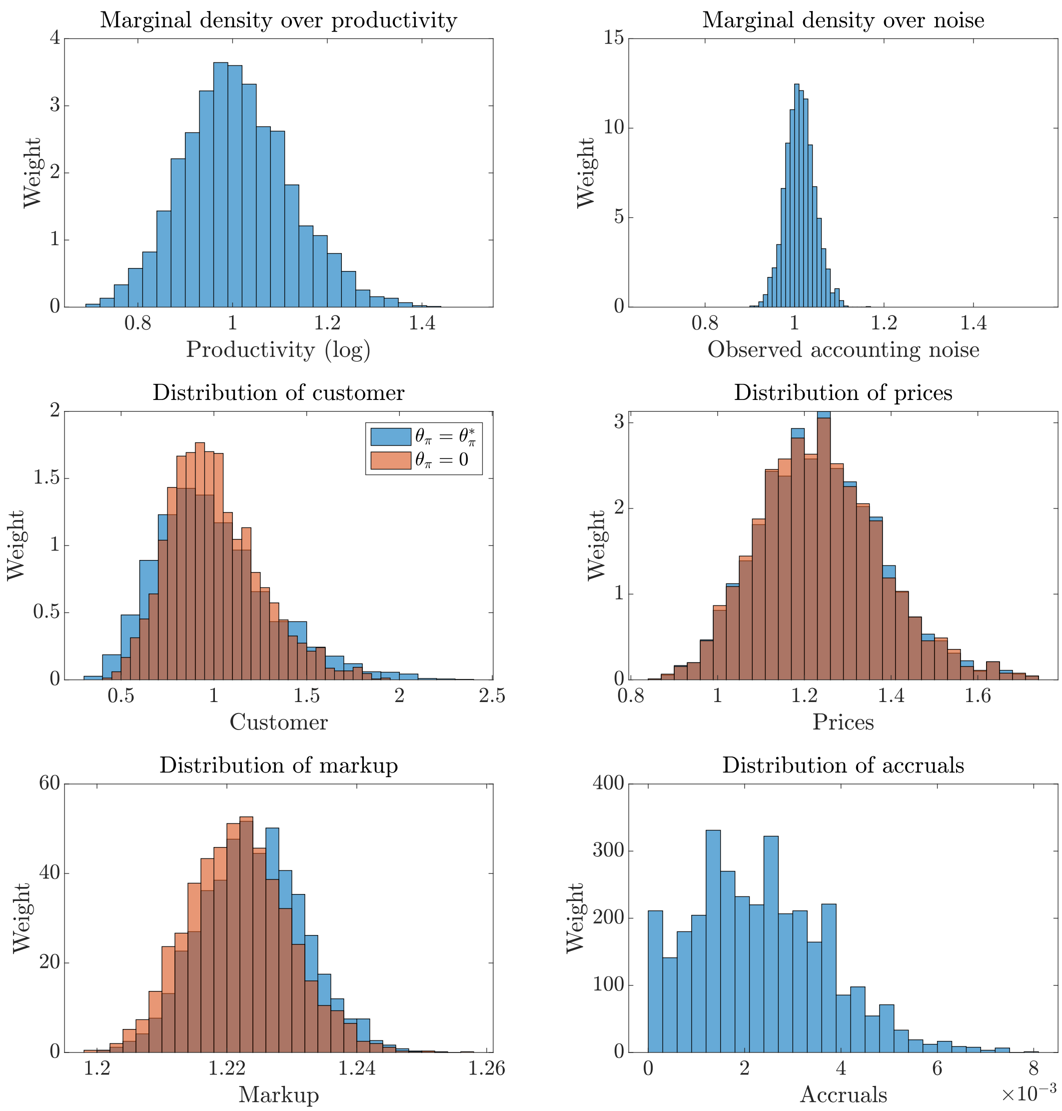
3. Check whether the maximum difference from the previous iteration is below the convergence threshold. If not, update the aggregate objects and return to step 1.1.

In each iteration, the optimal value of θ_π is computed using Brent's algorithm. To improve computational efficiency, we initialize the general equilibrium variables using the solution obtained in the absence of short-term incentives. With this step, the model takes approximately 5 minutes to solve for a given set of parameters. The code is written in Fortran and compiled using `gfortran` on a 2024 MacBook Pro M3. For the counterfactual experiments, we solve the model without optimizing over the short-term parameter θ_π.

Simulation. We simulate firm behavior based on the model's optimal policy functions to compute the target moments. Specifically, we generate a panel of 3,000 firms over 150 years, discarding the initial 50 years as a burn-in period. The covariance matrix of the simulated moments, Σ, is estimated using the Delta method, following Hansen and Lee (2019). The optimal weighting matrix is then given by the inverse of the covariance matrix: $W = \Sigma^{-1}$.

B.3 Distribution of Prices and Manager Policies

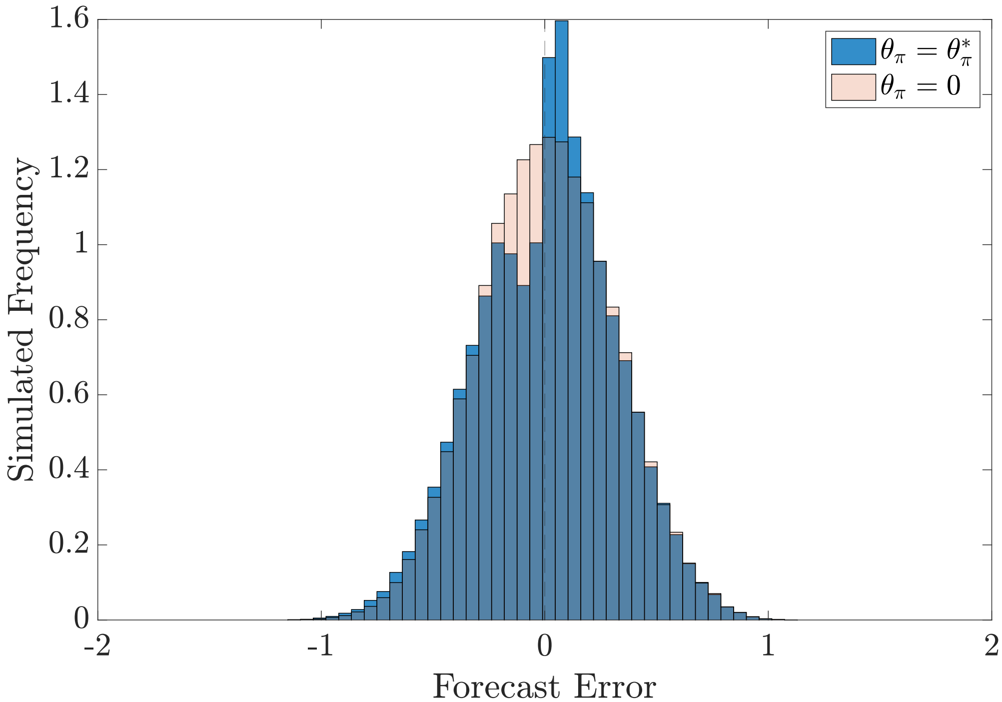
Figure 8: Distribution of prices and manager policies



Notes: In red bars, the histogram of the policy functions for markup and costumers without 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 productivity (left) and observed accounting noise (right). The second and third row plot the distribution of customers, markups, prices 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 3,000 simulated firms over 50 periods before plotting.

B.4 Forecast Error Distribution in the Model

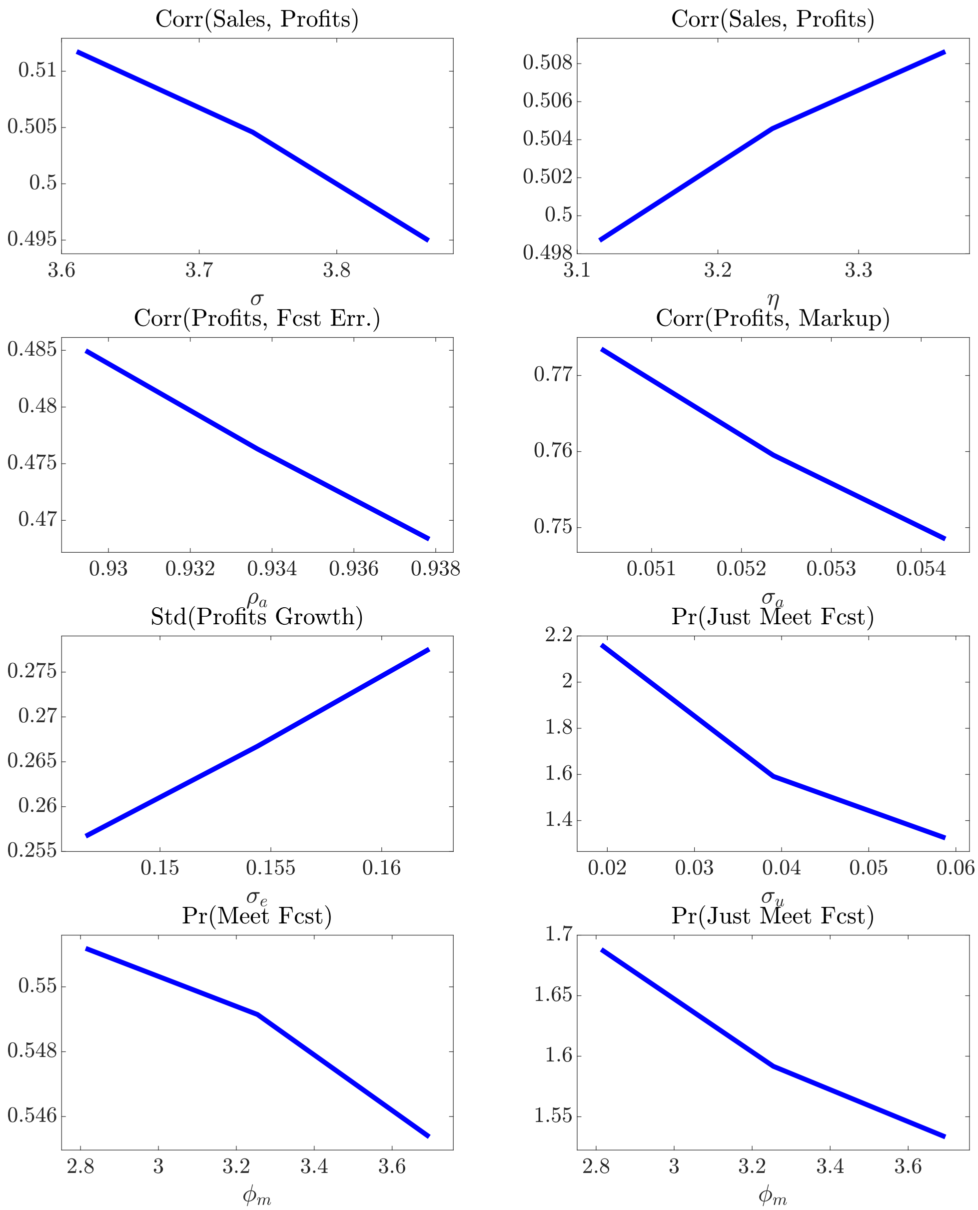
Figure 9: Forecast error distributions



Notes: The Figure compares the distribution of forecast errors generated in the model with (blue, θ_π^*) and without (red, $\theta_\pi = 0$) short-term incentives. The distribution of forecast errors in the model is computed on a panel of simulated data of 3,000 firms for 50 years. 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.

B.5 Identification of the Other Parameters

Figure 10: Relationship between selected moments and other parameters



Notes: This Fgure displays the unweighted sensitivity of each empirical moment to individual structural parameters in the model. Each cell shows the effect of perturbing one parameter by $\pm$ 1 standard deviation on a given simulated moment, holding all other parameters fixed. The contributions are computed using finite differences and normalized by the parameter change, so that values represent the change in the moment per one standard deviation unit change in the parameter.

B.6 Sensivity Analysis of the Aggregate Results

Table 6: Sensitivity analysis of the impact of short-termism

Parameter experiment	Price %	Income %	Welfare %
Low persistence of idiosyncratic productivity, ρ_a	0.1083	0.1484	0.7433
High persistence of idiosyncratic productivity, ρ_a	0.1708	0.0235	-2.4035
Low std of idiosyncratic productivity, σ_a	0.0949	0.1069	0.2266
High std of idiosyncratic productivity, σ_a	0.1670	0.0119	-2.5276
Low std of observed accounting noise shock, σ_e	0.1334	0.1278	-0.0982
High std of observed accounting noise shock, σ_e	0.1170	0.1421	0.4405
Low std of unobserved accounting noise shockσ_u	0.0780	0.1382	1.0545
High std of unobserved accounting noise shockσ_u	0.1181	0.1949	1.3471
Low quadratic manipulation cost, ϕ_m	0.1104	0.1365	0.4575
High quadratic manipulation cost, ϕ_m	0.0766	0.1416	1.1394
Low private benefit manager, ϕ_e	0.0908	0.0933	0.0447
High private benefit manager, ϕ_e	0.1729	0.2260	0.9313

Notes: The Table reports the sensitivity of aggregate outcomes – price level, income, and real consumption– to ± 1 standard deviation perturbations in the structural parameters around the baseline estimates. Each row corresponds to the change in a single parameter, holding all other parameters fixed. Results are expressed as percentage deviations from the baseline equilibrium model without short-term incentives.

C Model Extension with Static Marketing

The derivation of the model with static marketing follows the same steps as in the benchmark case. Here, we briefly highlight only the main differences.

Each household, indexed by i, belongs to a continuum of measure 1 and maximizes a static utility function. The consumption bundle now also reflects marketing effort through the expression:

$$C_i = \left\{ \int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \varepsilon_{j_m} \right) h_{j_m} c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}} \tag{67}$$

where h_{j_m} captures marketing effort, and ε_{j_m} is an idiosyncratic preference shock (Gumbel distributed), as in the benchmark model.

Customer accumulation with static marketing. With static marketing, the household's taste-adjusted consumption is modified by a firm-specific term h_{j_m}, entering multiplicatively:

$$\tilde{c}_{j_m} = \exp\left(\frac{1}{\sigma - 1} \varepsilon_{j_m} \right) h_{j_m} \frac{E_m}{p_{j_m}}. \tag{68}$$

As in the baseline case, firm choice follows a multinomial logit structure. Letting $\tilde{p}_{j_m} = p_{j_m}/h_{j_m}$ denote the marketing-adjusted price, the probability density of re-optimizing households selecting firm j_m becomes:

$$f(\tilde{p}) = \frac{1}{J_m} \left(\frac{\tilde{p}}{\tilde{P}_m} \right)^{1-\sigma}, \quad \tilde{P}_m = \left[\int \tilde{p}^{1-\sigma} dj \right]^{\frac{1}{1-\sigma}}. \tag{69}$$

The law of motion for the customer base then becomes:

$$b_{j_m}^t = (1-\theta) b_{j_m}^{t-1} + \theta \frac{1}{J_m} \left(\frac{\tilde{p}_{j_m}}{\tilde{P}_m} \right)^{1-\sigma}, \tag{70}$$

where the first term captures locked-in customers who remain with the firm, and the second term reflects newly acquired customers based on marketing-adjusted price competitiveness.

Demand with static marketing. Given the choice of variety j in each product type m, households allocate consumption to minimize total expenditure subject to a Dixit-Stiglitz aggregator that includes a marketing effort term h_{j_m}:

$$C_t = \left\{ \int_0^1 \left[\exp\left(\frac{1}{\sigma - 1} \varepsilon^i_{j_m} \right) h_{j_m} c_{j_m} \right]^{\frac{\eta-1}{\eta}} dm \right\}^{\frac{\eta}{\eta-1}}. \tag{71}$$

Solving the expenditure minimization problem yields the optimal consumption spending to good j_m:

$$c_{j_m} = \exp\left(\frac{\eta - 1}{\sigma - 1} \varepsilon^i_{j_m} \right) \left(\frac{p_{j_m}}{\tilde{P}} \right)^{-\eta} h_{j_m}^{\eta-1} C_t, \tag{72}$$

where $\tilde{P}$ is the marketing-adjusted price index:

$$\tilde{P} = \left\{ \int_0^1 \exp\left(\frac{\eta - 1}{\sigma - 1} \varepsilon_{j_m} \right) \left(\frac{p_{j_m}}{h_{j_m}} \right)^{1-\eta} dm \right\}^{\frac{1}{1-\eta}}. \tag{73}$$

As before, expected total demand for firm j_m is obtained by integrating across both locked-in and re-optimizing customers:

$$y_j = \left[(1-\theta) b_{j_m}^{t-1} + \left(b_{j_m}^t - (1-\theta) b_{j_m}^{t-1} \right) \left(\frac{\tilde{p}_j}{\tilde{P}_m} \right)^{\eta-1} \right] \Gamma\left(1 + \frac{\eta - 1}{\sigma - 1} \right) \left(\frac{p_j}{\tilde{P}} \right)^{-\eta} h_{j_m}^{\eta-1} C_t \tag{74}$$

Using the law of motion for the customer base and substituting total expenditure $C_t = \frac{W+\Pi}{\tilde{P}}$ and the aggregate price index expression, this simplifies to:

$$h_j y_j = \left[(1-\theta) b_{j_m}^{t-1} \tilde{p}_{j_m}^{-\eta} + \theta \tilde{p}_{j_m}^{-\sigma} \tilde{P}_m^{\sigma-\eta} \right] \frac{W + \Pi}{(1-\theta)\tilde{P}_B^{1-\eta} + \theta \tilde{P}_m^{1-\eta}}. \tag{75}$$

C.1 Results of the Extended Model with Marketing

Table 7: Estimated parameters, moments and impact of short-termism

A. Estimated parameters	Symbol	Estimate	Std. Error
Elasticity of substitution within products	σ	3.7869	0.1282
Elasticity of substitution across variaties	η	2.9842	0.1252
Persistence of idiosyncratic productivity	ρ_a	0.9378	0.0079
Std of idiosyncratic productivity	σ_a	0.0653	0.0034
Std of observed profit shock	σ_e	0.1720	0.0050
Std of unobserved profit shock	σ_u	0.0605	0.0083
Quadratic manipulation cost	ϕ_m	2.4993	0.6428
Private benefit manager	ϕ_e	0.0182	0.0064
Cost of marketing	ξ	0.2027	0.0108
B. Targeted moments	Data	Std. Error	Model
Std. deviation of sales growth	0.1689	0.0036	0.1668
Correlation of sales growth, profits growth	0.6530	0.0118	0.4939
Correlation of sales growth, forecast error	0.2162	0.0149	0.2690
Std. deviation of profits growth	0.3441	0.0059	0.2905
Correlation of profits growth, markup growth	0.6685	0.0111	0.8078
Correlation of profits growth, forecast error	0.3556	0.0157	0.5047
Std. deviation of markup growth	0.0670	0.0023	0.0571
Correlation of markup growth, forecast error	0.2561	0.0154	0.3959
Std. deviation of forecast error	0.3862	0.0076	0.3052
Probability of meeting forecasts	0.5439	0.0035	0.5333
Probability of just meeting forecasts	1.5109	0.0558	1.2675
Average profit margin	1.2029	0.0051	1.2334
Average marketing intensity	0.2402	0.0041	0.2389
C. Impact of short-termism			Estimates %
Average markup			0.1737
Firm profits			1.2045
Accrual manipulation			0.2072
Firm value			0.9359
Aggregate price level			0.0883
Aggregate income			0.1743
Real consumption			0.0859
Lifetime utility			0.1457

Notes: Panel A's SMM parameter estimates use efficient moment weighting. Panel B's data moments use a 2003-2019 Compustat-IBES panel of 2,522 firms for 9,319 firm-years. Model moments use a 25-year simulated panel of 3,000 firms. Panel C the impact of short termism on micro and macro variables in percentage change from a counterfactual model without short-term pressure. Moment units are proportional (0.01 = 1%). Standard errors are firm clustered.

C.2 Results of the CES Model

Table 8: Estimated parameters, moments and impact of short-termism

A. Estimated parameters	Symbol	Estimate	Std. Error
Elasticity of substitution within products	σ	5.4778	0.1538
Persistence of idiosyncratic productivity	ρ_a	0.6779	0.0291
Std of idiosyncratic productivity	σ_a	0.0352	0.0015
Std of observed profit shock	σ_e	0.2113	0.0087
Std of unobserved profit shock	σ_u	0.0692	0.0240
Quadratic manipulation cost	ϕ_m	6.9462	6.4952
Private benefit manager	ϕ_e	0.0083	0.0067
B. Targeted moments	Data	Std. Error	Model
Std. deviation of sales growth	0.1689	0.0036	0.1803
Correlation of sales growth, profits growth	0.6530	0.0118	0.6911
Correlation of sales growth, forecast error	0.2162	0.0149	0.4143
Std. deviation of profits growth	0.3441	0.0059	0.3764
Correlation of profits growth, markup growth	0.6685	0.0111	0.8824
Correlation of profits growth, forecast error	0.3556	0.0157	0.5953
Std. deviation of markup growth	0.0670	0.0023	0.0575
Correlation of markup growth, forecast error	0.2561	0.0154	0.5248
Std. deviation of forecast error	0.3862	0.0076	0.3191
Probability of meeting forecasts	0.5439	0.0035	0.5369
Probability of just meeting forecasts	1.5109	0.0558	1.6153
Average profit margin	1.2029	0.0051	1.2145
C. Impact of short-termism			Estimates %
Average markup			0.1044
Firm profits			2.3102
Accrual manipulation			1.5704
Firm value			0.6938
Aggregate price level			0.1004
Aggregate income			0.1217
Real consumption			0.0213
Lifetime utility			4.7089

Notes: Panel A's SMM parameter estimates use efficient moment weighting. Panel B's data moments use a 2003-2019 Compustat-IBES panel of 2,522 firms for 9,319 firm-years. Model moments use a 25-year simulated panel of 3,000 firms. Panel C the impact of short termism on micro and macro variables in percentage change from a counterfactual model without short-term pressure. Moment units are proportional ($0.01 = 1\%$). Standard errors are firm clustered. Results are obtained imposing $\theta = 1$, and $\sigma = \eta$.