

The Macro Impact of Short-Termism

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Abstract

R&D investment reduces current profits, so short-term pressure on managers to hit profit targets may distort R&D. Indeed, in the data, firms just meeting Wall Street forecasts have lower R&D growth, while managers just missing receive lower pay. However, short-termist distortions might wash out in the aggregate, so to quantify their macro impact I build and estimate a growth model in which managers of heterogeneous firms choose R&D while facing firm-level shocks and profit targets derived from rational forecasts. Short-termist pressure increases R&D volatility, lowering growth by 0.1% annually and output by 6% over 100 years.

Keywords: Short-Termism, Heterogeneous Firms, Endogenous Growth, Agency Conflicts, Earnings Manipulation

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Managers of the largest firms in the US economy face relentless scrutiny of their short-term profits. The managing director of McKinsey & Company recently summarized the situation, writing “the mania over quarterly earnings [profits] consumes extraordinary amounts of senior executive time and attention.” Commentators have long suspected that short-termist profit pressures might lead managers to sacrifice investment, innovation, or even financial stability.¹ However, short-termist pressures might not matter at all for the macroeconomy if they wash out due to aggregation or general equilibrium forces. In this paper, I argue using a quantitative macro model that short-termism does in fact matter, costing the entire economy lost growth each year.

Each fiscal period, public firms must disclose their profits or earnings. Small armies of analysts at stock brokerages forecast profits, and the financial press widely reports a consensus forecast for a given firm. During earnings season when profits are revealed, firm performance is routinely compared to these short-term targets. Around 90% of recently surveyed US managers report pressure to meet short-term profit targets (Graham et al., 2005), and the pattern of firm profits in the data supports this notion. Figure 1 plots the distribution of forecast errors, realized profits minus consensus analyst forecasts, for a large panel of US public firms over the past 30 years.² Two facts stand out. First, firm profits bunch just above forecasts or at zero in the error distribution.³ Second, relatively few firm-years display narrow misses. Figure 1 suggests some form of systematic pressure to meet profit targets.

In the face of short-term profit pressure, long-term investments like research and development (R&D) provide a choice target for manipulation, since they equal around 33% of profits for a typical firm.⁴ While the benefits of R&D may appear much later or fail to materialize altogether, the costs must be borne today through lower profits.⁵ Some firms must therefore choose between cuts to R&D or meeting their profit target. Almost half of surveyed US executives report that they would prefer to reject a positive net present value project over missing their analyst target (Graham et al., 2005).

Drawing on a dataset of millions of analyst forecasts, combined with long-term investment, executive compensation, and stock returns, I compare firms that just meet and just miss profit targets. Firms just meeting have about 2.6% lower R&D growth on average,

¹See Stein (1989), Haldane and Davies (2011), Duarte et al. (2015), Budish et al. (2015), Rahmandad et al. (2014), Gigler et al. (Forthcoming), or Kanodia and Sapra (2015). The quote is from Barton (2011).

²More details on data sources and variable definitions are in Section 1 and Appendix A.

³The McCrary (2008) sorting test strongly rejects continuity at zero.

⁴This statistic is the median ratio of R&D expenditures to profits, drawn from my combined Compustat-I/B/E/S database detailed in Section 1 and Appendix A.

⁵Since SFAS Rule No. 2 in 1974, the US Generally Accepted Accounting Principles (US GAAP) have dictated that R&D generally be expensed or subtracted from earnings.

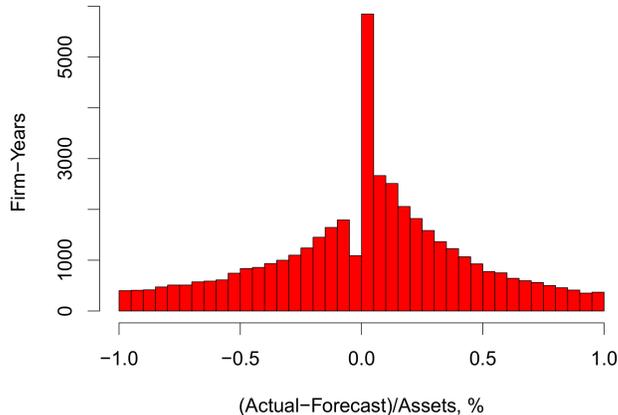


Figure 1: Firm profits bunch above targets

Note: Forecast errors are Street profits minus median analyst forecasts from a 2-quarter horizon, scaled by firm assets and expressed as a percentage. The histogram represents a panel of 43,688 firm years, covering 1982-2010 for 7,215 firms. 68% of the sample lies within the bounds plotted above, and 13% of firm years have forecast error in the middle bin. 10% of the sample exhibits exactly zero forecast error. Bin size is 0.05% of firm assets. Discontinuity or sorting is detected in the forecast error distribution at 0 at the 1% level according to the McCrary (2008) statistic.

consistent with opportunistic cuts. Moving to observable measures of incentives, CEOs just missing profit forecasts receive around 7% lower total compensation. Conditional upon even a narrow miss, their firms exhibit almost 1% lower stock returns. Managers and firms appear justified in fears of missing profit targets.

R&D is the key driver of growth in a wide class of macro growth models, so short-termist distortions may in principle reduce growth for the entire economy.⁶ To quantify the macro impact, I extend a standard growth model. Managers of heterogeneous firms choose R&D in the face of firm-level shocks. By investing in R&D, firms move up a quality ladder, and micro-level innovation drives macro growth. Each manager faces incentives to meet rational short-term profit forecasts. Managers can also choose to distort their reported profits using a flexible paper manipulation tool.

With this framework, I structurally estimate the micro shock process as well as the size of short-termist pressure on managers using GMM. I target the micro covariance matrix of forecast errors, R&D growth, and sales growth together with the long-term US growth rate. In the estimated model, managers perceive costs of missing a profit target equal to around 3.6% of yearly sales, a substantial consideration. Although the model was not estimated to

⁶See Romer (1990) or Aghion and Howitt (1992). Some recent papers model growth from idea flows (Perla and Tonetti, 2014). Since exploiting idea flows typically remains costly, the basic short-term tradeoff remains.

do so, my structure with short-term targets reproduces a range of basic data facts including forecast error bunching, the discontinuity in R&D growth, the dynamics of R&D, and cross-industry heterogeneity in bunching.

Short-term pressure is present each period and embodied in rational profit forecasts. The mean level of R&D changes very little in response to this constant pressure. However, targets increase the volatility or standard deviation of R&D by around 25% as managers often cut and then later splurge on R&D in response to short-term shocks. Decades of empirical research on R&D, patenting, and firm growth suggest that firms face diminishing returns to R&D, implying in my model that higher R&D volatility reduces overall innovation.⁷ Growth drops by almost 0.1% per year, leading to around 6% lower output over a century. In the baseline model, households suffer a loss in welfare of around 0.5% or \$50 billion of lost consumption each year.⁸ By comparison, recent quantitative estimates place the welfare costs of business cycles at around 0.1-1.8%, the static gains from trade in the area of 2.0-2.5%, and the welfare costs of inflation near 1%.⁹

My baseline results delineate the *costs* of short-term targets. However, managers may be badly behaved, in which case short-term pressures may provide discipline even while distorting R&D and growth. I extend the model to incorporate two forms of manager misbehavior: shirking and empire building. With badly behaved managers, short-term targets may increase firm value. However, the exact assumptions matter for the net social welfare impact. If managers are characterized by shirking problems, then targets typically push up consumption levels and overall welfare. By contrast, if managers exhibit empire building tendencies, then targets tend to push down R&D further away from socially optimal levels and reduce consumer welfare. While the *net* social welfare impact, the appropriate guide for policymaking, is ambiguous in general, the core prediction of the model remains: short-term targets distort R&D and reduce growth.

Overall my analysis suggests that the benefits of liquid capital markets, transparent reporting, and disciplined managers do not come for free. Instead, closely associated short-termist behavior creates a sizable drag on growth.

Section 1 analyzes short-term targets in the data. Section 2 presents my macro growth model. Section 3 checks the model against some basic facts from the micro data. Section 4 reports the costs of short-termism. Section 5 explores potential benefits from targets with manager misbehavior. Section 6 concludes. Online appendixes describe the data (Appendix A), theory (Appendix B), and numerical solution method (Appendix C).

⁷See Blundell et al. (2002), Klette and Kortum (2004), or Acemoglu et al. (2013).

⁸US consumption was around \$11.5 trillion in 2013 according to the BEA as of March 2014, so the 0.44% loss in the model equals a loss of around \$51 billion each year.

⁹For more details, see the explicit comparisons made in Section 4.

1 Short-Term Targets in the Data

I draw on two main data sources. First, I exploit millions of profit forecasts at the firm-analyst level from the Institutional Brokers Estimates System (I/B/E/S) database. Realized values of firm “Street” profits accompany analyst forecasts in I/B/E/S.¹⁰ I also use Compustat data from annual US public firm income statements. Linking the I/B/E/S and Compustat datasets results in a panel of around 25,000 firm-fiscal year observations with consensus analyst forecasts, Street realizations, and long-term investment. Around 4,000 firms from 1983-2010 are available in the combined unbalanced panel. My sample primarily consists of larger firms, accounting for around 11% of US employment, 67% of all US private R&D expenditures, and total sales of around 31% of US GDP.¹¹ I also incorporate Execucomp data on CEO and executive pay where possible, as well as Center for Research in Security Prices (CRSP) data on stock returns. Appendix A provides further detailed information on the datasets, variable definitions, sample construction, and descriptive statistics.

My measure of the forecast error for a given firm-year is the realized value of Street profits minus the median of analyst forecasts made from the middle of the same fiscal year, a two-quarter horizon, scaled by firm assets. This measure, plotted in Figure 1, guarantees comparability with existing empirical work and reflects the need to normalize by some measure of scale.¹² The profit bunching just above forecasts suggests that firms near their target may engage in some behavior(s) to avoid small misses. If so, firms just meeting short-term targets may differ on observables from firms just missing. Motivated by this logic, I compare firms that just meet and just miss, applying a standard regression discontinuity estimator to various outcomes of interest by estimating a local linear regression

$$X_{jt} = \alpha + \beta fe_{jt} + \gamma fe_{jt} \mathbb{I}(fe_{jt} \geq 0) + \delta \mathbb{I}(fe_{jt} \geq 0) + \varepsilon_{jt}.$$

Here, X_{jt} is some outcome of interest for firm j in year t and fe_{jt} is the associated forecast error. The estimate of interest, $\hat{\delta}$, represents the local difference in the conditional mean of X between firms just meeting relative to firms just missing short-term analyst forecasts.

¹⁰“Street” earnings, over which firms possess more discretion, are more widely followed than the GAAP profit measures reported in Compustat (Bradshaw and Sloan, 2002).

¹¹For these comparisons, US employment is total nonfarm payrolls in 2000 (St. Louis FRED variable PAYEMS), while Compustat employment is the variable `emp`. US R&D expenditures are from the National Science Foundation Survey of Industrial Research and Development in 2000, with R&D from Compustat variable `xrd`. US nominal GDP in 2000 comes from St. Louis FRED variable GDPA, with Compustat gross sales in variable `sale`.

¹²The exact definition is not crucial. Bunching remains with a mean consensus measure, from different horizons, or with alternative normalizers such as tangible capital.

Table 1: Estimates of firm regression discontinuities in forecast errors

	(1)	(2)	(3)	(4)	(5)	(6)
Method	Local Linear	Local Linear	Local Linear	Local Linear	Local Linear	Local Linear
Dependent Variable	Investment Rate	Intangibles Growth	R&D Growth	CEO Pay	Executive Pay	Abnormal Returns
Running Variable	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error	Forecast Error
Cutpoint	0	0	0	0	0	0
Discontinuity	0.35 (0.40)	-2.66** (0.95)	-2.57* (1.44)	6.78** (2.68)	4.88*** (1.75)	0.64*** (0.21)
Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Market-Adjusted
Years	1983-2010	1983-2010	1983-2010	1992-2010	1992-2010	1983-2010
Firms	3969	3969	3969	2349	2382	7794
Observations	23084	23084	23084	17661	114296	48297
Relative to Mean	1.4%	-27.0%	-32.9%	6.78% ^a	4.88% ^a	0.64% ^a

Note: *,**,*** denote 10, 5, 1% significance. The regression discontinuity estimation relies on local linear regressions and a triangular kernel, with bandwidth chosen via the optimal Imbens and Kalyanaraman (2011) approach. Standard errors are clustered at the firm level. The estimates represent the mean predicted differences for firms just meeting forecasts relative to firms missing forecasts. Forecast errors are Street earnings minus median analyst forecasts from a 2-quarter horizon, scaled by firm assets as a percentage. Investment Rate is the percentage tangible annual investment rate. Intangibles growth is annual percent selling, general, and administrative expenditures growth. R&D growth is annual percent research and development expenditures growth. CEO Pay, Executive Pay are the log of total pay for the CEO and several most highly compensated executives at a firm, respectively. Abnormal Returns are the cumulative abnormal returns for a firm in a ten-day window to the announcement date, market adjusting using the returns of the S&P 500. For returns analyst forecasts are drawn from a 1-quarter horizon.

^a Executive pay and stock returns are already in normalized form, and these values duplicate discontinuity estimates.

The first three columns of Table 1 report differences for three forms of investment: the tangible investment rate, overall intangible expenditures growth, and R&D growth.¹³ Intangible expenditures are a proxy for long-term investment including R&D but also advertising and broad nonproduction expenses.¹⁴ In each column of Table 1, I first demean outcomes by firm then year, controlling for both permanent heterogeneity across firms as well as business-cycle effects.¹⁵ I detect no discontinuity in tangible investment rates, entirely natural given that tangible investment is drawn from profits gradually through depreciation charges rather than as an immediate cost. By contrast, intangibles growth and R&D growth, representing investments directly drawn from profits today, are both approximately 2.5% lower for firms just meeting targets. The discontinuities are meaningful, each a local drop of around 30% relative to mean.¹⁶

I later verify in my model that the R&D growth discontinuity is consistent with opportunistic cuts to meet short-term targets, structurally validating a long-standing literature which treats related results as *prima facie* evidence of manipulation.¹⁷ Note for interpretation that Table 1 does not report treatment effects. Endogenous sorting of firms to the right of the zero forecast error threshold is an apparent equilibrium outcome lying at the core of my argument for the economic impact of short-term targets. The regression discontinuity estimator serves simply as a useful detection mechanism.

I now directly examine short-term incentives on firms and managers. Columns 4 and 5 of Table 1 reveal that total CEO pay is around 7% lower for those managers just missing targets, while the several most highly paid managers receive on average around 5% lower pay.¹⁸ Column 6 documents that firms just missing targets see approximately 0.64% lower cumulative abnormal returns in a ten-day window to the earnings release date.¹⁹ Discontinuous

¹³In the absence of a natural normalizer, I use growth rates for R&D and intangibles, a convention I maintain consistently in my structural exercise when required.

¹⁴Intangibles expenditures are selling, general, and administrative (SG&A) expenditures. SG&A, a basic accounting item, includes not only R&D but also nonproduction expenses such as management pay, training costs, and advertising costs. A large empirical literature concludes that intangible expenditures help explain long-term profitability, macro productivity, and stock returns. See for example Eisfeldt and Papanikolaou (2013), Gourio and Rudanko (2014), McGrattan and Prescott (2014), or Corrado et al. (2013).

¹⁵Therefore Table 1 results are based upon a two-stage procedure. Table 1 follows the literature by relying upon straightforward clustering at the firm level for standard errors. For robustness, Table A.3 in Appendix A reports results with no qualitative changes based on a block bootstrap procedure taking into account within-firm correlation as well as uncertainty associated with the first-stage demeaning of outcome variables.

¹⁶See Table A.2 in Appendix A for placebo checks. Appendix Figure A.1 plots checks to bandwidth choice alternatives to the optimal Imbens and Kalyanaraman (2011) value.

¹⁷See, for example, similar threshold exercises conducted using a range of outcomes and profit thresholds in Roychowdhury (2006) or Burgstahler and Eames (2006).

¹⁸In the Execucomp dataset, total pay includes salary, bonuses, and realized options.

¹⁹Horizon matters for the interaction between targets and outcomes. Changes in R&D expenditures take time to implement. The results in this paper use forecasts made for the full fiscal year from a two-quarter horizon. The single exception is the discontinuity in abnormal returns, which relies on a forecast horizon of

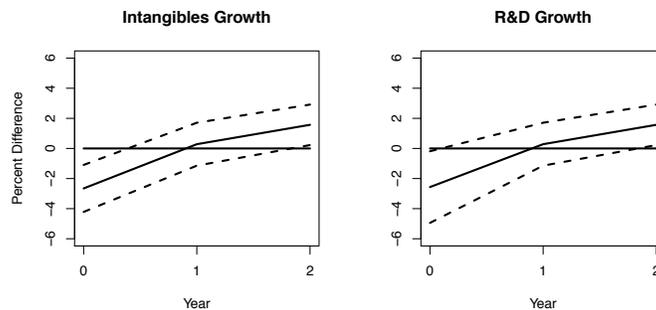


Figure 2: R&D growth dynamics in the data

Note: The solid line is the discontinuity in long-term investment growth for firms just meeting relative to just missing analyst forecasts. Year k on the horizontal axis reports estimates based on the growth of long-term investment in the year $t + k$ with forecasts from year t . Intangibles growth and R&D growth are the annual percentage growth rate in selling, general, and administrative expenditures and research and development expenditures, respectively. The estimates are locally and nonparametrically computed using a local linear regression discontinuity estimator with bandwidth chosen according to the Imbens and Kalyanaraman (2011) approach. The running variables is forecast error or Street earnings minus median analyst forecasts from a 2-quarter horizon, scaled by firm assets as a percentage. Standard errors are clustered at the firm level, with 90% pointwise confidence intervals plotted in dashed lines. Sample drawn from the baseline Compustat-I/B/E/S discontinuity estimation sample with 23,083 firm-years spanning 1983-2010 with 3,969 firms.

manager incentives and stock returns both link to a large empirical literature on executive compensation and a capital market premium to meeting or beating analyst forecasts.²⁰

I now compare long-term investment behavior in future years $t + k$ for firms just meeting relative to just missing in year t . Figure 2 plots results for intangibles growth in the left panel and R&D growth on the right. In the period in which firms just meet a profit target, their long-term investment growth is lower, replicating Table 1. However, by two years onwards, long-term investment growth exhibits a reversal and overshoot. These dynamics place strong discipline on the channel through which targets may impact R&D efficiency, suggesting that volatility channels are more plausible than persistent level effects.

I also explore heterogeneity across industries in my sample. For a given 4-digit SIC industry cell, I compute forecast error bunching as the ratio of the mass of firms just meeting to just missing short-term targets. Figure 3 plots this bunching measure on each horizontal axis. In each panel, I plot one of four industry characteristics: R&D intensity (the median R&D-to-assets ratio), R&D sensitivity (the estimated coefficient of R&D growth on sales growth in an industry panel regression), analyst coverage (the median number of analysts

one quarter. Following Bhojraj et al. (2009), these timing choices strike a balance between allowing for R&D and investment choices to be implemented, on the one hand, and incorporating a fuller range of information available to capital market participants when examining return patterns on the other hand.

²⁰See MacKinlay (1997), Bartov et al. (2002), Kasznik and McNichols (2002), Matsunaga and Park (2001), and Edmans et al. (2013).

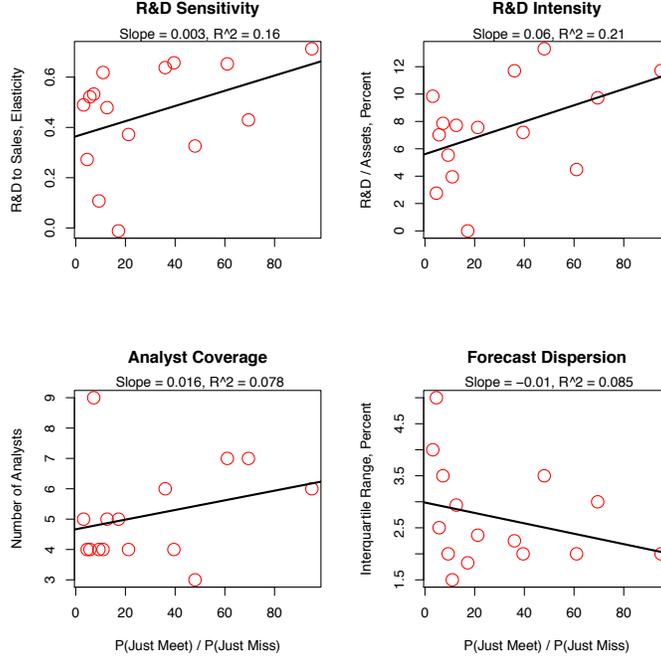


Figure 3: Bunching varies across industries

Note: Horizontal axis is the ratio of firm-years just meeting to just missing forecasts in a 4-digit SIC industry cell, based on a 0.05% bandwidth relative to firm assets. Top left panel is the empirical elasticity $\hat{\beta}$ from estimates of $(\text{R\&D Growth})_{jt} = \beta (\text{Sales Growth})_{jt} + f_j + g_t + \varepsilon_{jt}$. Top right panel is the median R&D to assets ratio. Bottom left panel is the median number of analysts per firm. Bottom right panel is the median interquartile range of analyst forecasts, relative to firm assets. Sample based on the baseline Compustat-I/B/E/S estimation sample with 23,083 firm-years spanning 1983-2010. Fitted lines, slopes, and R^2 's included for reference.

forecasting profits for each firm), and forecast dispersion (the median interquartile range of forecasts across analysts within a firm). The bottom two panels in Figure 3 reveal that bunching is higher in industries with more analysts or with lower forecast disagreement. These patterns corroborate evidence from Stein and Wang (2014), which rationalizes them in the context of a time-varying uncertainty model. Turning to R&D, the top right panel documents that industries with higher R&D intensity, and hence larger R&D budgets ripe for manipulation, tend to bunch more. Finally, in the top left panel, industries with higher R&D sensitivity to sales growth exhibit more bunching. My notion of R&D sensitivity links to a long empirical tradition of computing the observed sensitivity of firm-level investment to cash flows.²¹ I return later to examine the equilibrium cross-sectional links between bunching and both R&D intensity and R&D sensitivity in my model.

²¹See, for example, Fazzari et al. (1988), Gilchrist and Himmelberg (1995), Kaplan and Zingales (1997). A second strand of papers (Brown et al., 2009; Himmelberg and Petersen, 1994) studies R&D investment rather than tangible investment.

The micro evidence in this section is consistent with systematic pressure on managers to meet short-term profit targets and opportunistic manipulation of R&D. However suggestive or suspicious, such empirical patterns are mostly silent on questions of aggregate impact, which I now consider in a quantitative model.

2 A Model of Short-Termist Incentives & Growth

In this section I present a quantitative model of macro growth and short-term profit targets, followed by a discussion of the equilibrium concept, numerical solution method, and structural estimation of the model.

Time is discrete, and a representative household subject to no aggregate uncertainty maximizes utility from a flow of aggregate consumption C_t denominated in units of a numeraire final good. Utility takes a standard constant relative risk aversion form with subjective discount rate ρ and intertemporal elasticity of substitution $\frac{1}{\sigma}$. The household purchases shares S_{jt} at price P_{jt} , receives dividends D_{jt} from a fixed continuum of intermediate goods firms $j \in [0, 1]$, inelastically supplies labor L to a final goods sector at wage rate w_t , and makes a savings choice B_{t+1} in a one-period bond with interest rate R_{t+1} . The household problem is

$$\max_{C_t, B_{t+1}, \{S_{jt}\}} \sum_{t=0}^{\infty} \rho^t \frac{C_t^{1-\sigma}}{1-\sigma}$$

$$C_t + B_{t+1} + \int_0^1 P_{jt} S_{jt} dj = R_t B_t + w_t L + \int_0^1 (P_{jt} + D_{jt}) S_{jt-1} dj.$$

There are both intermediate and final goods sectors. The final good is produced in a competitive constant returns to scale environment demanding intermediate goods X_{jt} from each intermediate firm j and demanding labor in the amount L_t^D to produce output Y_t in each period. The labor share is β , and the final goods technology, broadly following Acemoglu and Cao (2015), is given by

$$Y_t = \frac{L_t^{D\beta}}{(1-\beta)} \int_0^1 [Q_{jt}(a_{jt} + \varepsilon_{jt})]^\beta X_{jt}^{1-\beta} dj.$$

Each intermediate goods firm j at time t has a quality level Q_{jt} . As discussed in more detail below, each firm faces an exogenous profitability shock $a_{jt} + \varepsilon_{jt}$ made up of a persistent component a_{jt} and a transitory component ε_{jt} . Together, these determine the marginal product of intermediate input X_{jt} in final goods production. The final goods profit maximization

problem is

$$\max_{\{X_{jt}\}, L_t^D} Y_t - \int_0^1 p_{jt} X_{jt} dj - w_t L_t^D.$$

The final goods problem yields a standard isoelastic downward-sloping demand curve for variety j

$$X_{jt} = p_{jt}^{-1/\beta} L Q_{jt} (a_{jt} + \varepsilon_{jt}).$$

The continuum of intermediate goods firms $j \in [0, 1]$ is fixed.²² Each firm faces idiosyncratic uncertainty in the form of stationary exogenous profitability shocks a_{jt} and ε_{jt} satisfying

$$a_{jt} = (1 - \rho_a) + \rho_a a_{jt-1} + \zeta_{jt}, \quad \zeta_{jt} \sim N(0, \sigma_a^2)$$

$$\varepsilon_{jt} \sim N(0, \sigma_\varepsilon^2).$$

The transitory shock process ε_{jt} buffets firms in each period, while the AR(1) process a_{jt} persists.²³

Firm j is linked to a manager who in each period chooses a monopoly price p_{jt} and R&D investment z_{jt} , together with some other firm policies discussed below. Variable profits $\Pi_v(Q_{jt}, a_{jt}, \varepsilon_{jt}, p_{jt})$ equal total revenue minus total production costs. Intermediate goods firms can convert final goods output to their own variety j of intermediate output at constant marginal cost ψ , yielding

$$\Pi_v(Q_{jt}, a_{jt}, \varepsilon_{jt}, p_{jt}) = p_{jt} X_{jt} - \psi X_{jt}.$$

The isoelastic form of the final goods sector's demand for input j implies an optimal constant markup pricing rule for p_{jt} over marginal cost ψ ,²⁴ and eventually variable profits take the following homogenous form in Q_{jt} :

$$\Pi_v(Q_{jt}, a_{jt}, \varepsilon_{jt}, p_{jt}) = \beta Q_{jt} (a_{jt} + \varepsilon_{jt}) L.$$

Firm j 's scaled R&D choice z_{jt} implies a total expenditure of $z_{jt} Q_{jt}$ and leads to an innovation arrival with probability $\Phi(z_{jt}) = A z_{jt}^\alpha$. The parameter $\alpha \in (0, 1)$ governs the elasticity of innovation arrival with respect to R&D.²⁵ An innovation yields a proportional

²²I abstract from entry and exit, an assumption made more palatable by estimation of the model using data from large public firms with lower exit hazards.

²³See Franco and Philippon (2007), Roys (2011), or Gourio (2008) for similar decompositions of firm volatility.

²⁴For notational ease I assume $\psi = 1 - \beta$ leading to a monopoly price of $p_{jt} = \frac{1-\beta}{1-\beta} = 1$.

²⁵Innovation arrival depends on the flow z_{jt} of R&D, as is standard in the growth literature, rather than an accumulated stock of "R&D capital." Estimated depreciation rates for R&D are so high (Li, 2012) that

move up a quality ladder by $\lambda > 1$, so that the level of long-term quality Q_{jt+1} for firm j in period $t + 1$ is

$$Q_{jt+1} = \begin{cases} \lambda Q_{jt}, & \text{with probability } \Phi(z_{jt}) \\ \max(Q_{jt}, \omega Q_{t+1}), & \text{with probability } 1 - \Phi(z_{jt}) \end{cases}.$$

Eventually, if firm j lags and does not innovate for long enough, the firm receives a diffusion of some small fraction ω of the average quality level Q_{t+1} .²⁶

To allow for substitute channels of profit manipulation other than R&D managers make paper manipulation choices m_{jt} which shift reported profits. m_{jt} accounts for the considerable flexibility of managers in practice over accounting factors such as accruals or the timing of recognition of revenues into profits, among other tricks known generally as “accruals manipulation.” I define overall profits Π_{jt}^{Street} in the model as variable profits net of R&D expenditures and paper manipulation:

$$\Pi_{jt}^{Street} = \Pi_v(Q_{jt}, a_{jt}, \varepsilon_{jt}, p_{jt}) - z_{jt}Q_{jt} + m_{jt}Q_{jt}.$$

Profit forecasts evolve over time based on the rational projections of an outside sector of identical analysts. Profits Π_{jt}^{Street} are homogeneous in long-term quality Q_{jt} , and analysts forecast normalized values $\pi_{jt} \equiv \Pi_{jt}^{Street}/Q_{jt}$. Analysts fully understand the structure of the economy, including the exogenous shock processes and potential paper manipulation. Forecasters possess an information set at time t consisting of lagged normalized profits π_{jt-1} , consistent with survey evidence in Brown et al. (2015) on the production of analyst profit forecasts.²⁷ Forecasts in the model satisfy $\pi_{jt}^f(\pi_{jt-1}) = \mathbb{E}(\pi_{jt}|\pi_{jt-1})$.²⁸ The manager of firm j observes their profit target π_{jt}^f before choosing firm policies.

The manager of firm j maximizes the expected discounted flow of their personal utility,

a realistically calibrated model with R&D capital would likely yield similar quantitative results.

²⁶The diffusion structure follows Acemoglu and Cao (2015) and ensures existence of a stationary distribution of normalized firm-level quality levels Q_{jt} on a balanced growth path.

²⁷In practice, analysts may use more information than lagged profits alone. Appendix Table C.7 shows that only marginal improvements in forecasting performance result from broader information sets including lagged forecast errors or R&D expenditures. Crucially, the assumption that outsiders do not separately observe transitory and persistent shocks a_{jt} and ε_{jt} prevents unraveling.

²⁸Hong and Kacperczyk (2010) and Marinovic et al. (2012) review evidence on the career concerns and compensation of analysts, suggesting that analysts face incentives for accuracy. Given a mean squared error loss function for measuring accuracy, it is trivial to microfound the rational forecast errors I assume in this model.

solving²⁹

$$\max_{\{z_{jt}, m_{jt}, p_{jt}\}_t} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \left(\frac{1}{R} \right)^t D_{jt}^M \right\}.$$

Given manager choices for R&D, paper manipulation, and pricing, manager flow utility is

$$D_{jt}^M = \theta_d D_{jt} - \xi \mathbb{I}(\Pi_{jt}^{Street} < \Pi_{jt}^f) Q_{jt}.$$

The first term in D_{jt}^M is the manager's share of dividends D_{jt} , with an exogenous ownership fraction θ_d in their firm. The second term encapsulates the impact of short-term profit targets on incentives. A manager missing their profit target suffers an exogenous fixed loss governed by the parameter $\xi \geq 0$. Firm dividends D_{jt} in period t equal variable profits minus R&D expenditures and some costs of paper manipulation:

$$D_{jt} = \Pi_v(Q_{jt}, a_{jt}, \varepsilon_{jt}, p_{jt}) - z_{jt} Q_{jt} - \gamma_m m_{jt}^2 Q_{jt}.$$

The final term in dividends D_{jt} is a quadratic cost of paper manipulation, standing in for some manager attention costs, higher auditor expenses, or even increased probability of detection by outsiders implied by higher levels of profit manipulation.³⁰

When target miss costs satisfy $\xi = 0$ the manager problem nests pure firm value maximization. Note that the discontinuous, fixed nature of the miss cost is a natural choice given forecast error bunching. In general, I allow for manager miss costs to be purely private costs, firm resource costs, or manager pay cuts $\xi = \xi^{manager} + \theta_d \xi^{firm} + (1 - \theta_d) \xi^{pay}$. The first component, $\xi^{manager}$, is purely private and could include manager reputational concerns which loom large in surveys (Dichev et al., 2013). The second term, ξ^{firm} , affects managers through the ownership share θ_d and reflects any resource, disruption, or other costs borne by firms directly upon missing a target. Surveyed managers report that avoiding target misses helps maintain low-cost external finance, avoids triggering debt covenants, and even avoids costly shareholder litigation (Graham et al., 2005). The third and final component, ξ^{pay} , represents the potential for a firm to explicitly condition manager pay on targets. If pay includes not only a dividend share but also an amount $\xi^{pay} Q_{jt}$ clawed back conditional upon a miss, the net loss to a manager is $(1 - \theta_d) \xi^{pay}$. The evidence in Section 1 suggests that total pay is discontinuously lower for managers just missing targets. My estimation strategy identifies the combined cost ξ rather than the three individual components $\xi^{manager}$, ξ^{firm} ,

²⁹On the balanced growth path which I will consider in this paper, interest rates are constant at an equilibrium value R allowing me to drop the subscript for interest rates R_t .

³⁰See Dichev et al. (2013), Zakolyukina (2013), or Sun (2014) for further discussion of profit manipulation and its costs. Also, note that m_{jt} could be trivially re-interpreted as forecast manipulation rather than profit manipulation.

and ξ^{pay} . When making quantitative statements about the costs of targets, I generally assume that the entirety of the term ξ represents personal costs $\xi^{manager}$. This conservative approach implies that any change in aggregates stems from distorted policies rather than mechanical resource costs.

The model admits a balanced growth path equilibrium in which all aggregates, including average quality $Q_t = \int_0^1 Q_{jt} dj$, grow at constant rate g . Appendix B defines the equilibrium, which involves four major components: 1) optimal household consumption and savings decisions C_t , S_{jt} , and B_{t+1} given the budget constraint, 2) competitive final goods firm optimization over intermediate goods X_{jt} and labor demand L_t^D , 3) manager optimization over monopoly pricing p_{jt} , R&D investment z_{jt} , and paper manipulation m_{jt} , and 4) rational analyst forecasts π_{jt}^f for each firm. An economy-wide resource constraint, labor market clearing, asset market clearing, and aggregate consistency conditions complete the definition.

I normalize the manager dynamic problem by the average quality level Q_t to obtain a stationary recursive formulation in Appendix B as a function of four state variables: q (normalized endogenous long-term quality), a (exogenous persistent profitability), ε (exogenous transitory profitability), and π^f (endogenous analyst forecasts). I notationally omit dependence on j or t for readability, indicating future and lagged values by $'$ and $_{-1}$, respectively. I solve the manager problem using standard numerical dynamic programming techniques. I also rely upon a polynomial approximation to the analyst expectation $\pi^f = \mathbb{E}(\pi|\pi_{-1})$.³¹ For a given parameterization of the model and solution to the manager's problem, I compute a stationary distribution $\mu(q, a, \varepsilon, \pi^f)$ of firm states. Model aggregates are a function of the stationary distribution μ . My solution method, explained in detail in Appendix C, involves a hybrid dampened fixed-point and bisection algorithm iterating over the growth rate g , interest rate R , and forecast function $\pi^f(\pi_{-1})$ such that the following three conditions hold:

1. The constant interest rate R and growth rate g satisfy the household Euler equation $R = \frac{1}{\rho}(1 + g)^\sigma$.
2. The growth rate g results from aggregation of R&D policies z and the innovation arrival function $\Phi(z)$ over the stationary distribution μ .³²
3. Analyst profit forecasts are rational given the equilibrium distribution μ , i.e. $\pi^f = \mathbb{E}_\mu(\pi|\pi_{-1})$.

³¹Table C.7 in Appendix C records forecast accuracy statistics with alternative forecast systems using higher order approximations in π_{-1} above the baseline linear rule. In all cases, the higher-order approximations yield little quantitative gain in forecast accuracy.

³²See Appendix B equation (1) for the exact statement of this condition.

Table 2: Outside calibration of common parameters

Parameter	Explanation	Source, Value
σ	CRRA	Hall (2009), 2.0
ρ	Discount rate	Annual interest rate $\approx 6\%$, 0.98
β	Labor share	NIPA, 0.67
L	Human capital scale	Normalization, 1.0
α	R&D curvature	Blundell et al. (2002), 0.5
λ	Quality step	25% increment, 1.25
ω	Quality diffusion boundary	Normalization, 0.08
θ_d	Manager equity share	Nikolov and Whited (2014), 5.1%

Note: The table displays the notation (first column) as well as an explanation (second column) of each model parameter fixed by outside calibration. The third column lists the source and value of each common parameter.

Numerical analysis of the baseline model requires fixing the values of many parameters. For the most part I follow a structural estimation strategy based on GMM using firm-level moments from my joint sample of Compustat and I/B/E/S data. However, before estimating the model I externally calibrate some parameters reported in Table 2.

The model period is one year. An intertemporal elasticity of substitution of 0.5 or $\sigma = 2$, a subjective discount rate of $\rho = 1/1.02 \approx 0.98$, and a targeted growth rate of near 2% yield annual interest rates of around 6%. A labor share of $\beta = 2/3$ matches standard values in the quantitative macro literature, and a value of $\lambda = 1.25$ implies long-term quality increases of 25% upon innovation arrival.³³ The diffusion boundary ω determines the lower endpoint of the state space in relative quality q . I choose its value so that in my numerical solution the ratio between the highest and lowest quality levels for firms is normalized to the round figure of 150, requiring $\omega = \frac{1}{\sqrt{150}} \approx 0.08$.³⁴ I normalize labor supply to $L = 1$, and choose a manager equity share equal to $\theta_d = 5.1\%$ based on the data in Nikolov and Whited (2014). Based on micro-level estimates of the relationship between R&D expenditures and patenting in Blundell et al. (2002), I fix the elasticity of innovation arrival to R&D expenditures at $\alpha = 0.5$. I report an extensive set of robustness checks to alternative values of externally calibrated parameters, as well as the remaining parameters estimated below. The results are in Appendix Table C.6, with little variation in the crucial long-term growth implications.

My GMM approach requires informative moments for identification of the remaining six

³³I fix quality step size at the round value of 25%. Structural estimates of the quality step size from Peters (2013) or Acemoglu et al. (2013) would suggest values on the order of 7-14% instead. As shown in Appendix Table C.6, my choice of a higher, round value for λ is unimportant for growth and welfare statements.

³⁴Naturally, this requires that the upper endpoint for relative quality in my numerical solution is equal to $\sqrt{150}$ to deliver the desired maximum quality ratio.

Table 3: Data and model moments

Moment, %	Data	Baseline	No Targets
Aggregate Growth Rate, g	1.98	2.25	2.31
σ (R&D Growth)	30.1	27.7	16.1
σ (Sales Growth)	25.9	22.0	22.0
σ (Fcst. Error)	36.4	24.2	21.8
Corr(R&D Growth, Sales Growth)	0.36	0.41	0.47
Corr(R&D Growth, Fcst. Error)	-0.001	-0.03	0.05
Corr(Sales Growth, Fcst. Error)	0.09	0.29	0.65

Note: The data moments from the covariance matrix of sales growth, R&D growth, and forecast errors above are computed from the estimation sample composing a panel of US firms in Compustat and I/B/E/S, with 4,839 firms and 32,597 firm-years from 1982-2010. σ implies standard deviation, “Corr” implies correlation. The aggregate growth rate is the mean US per capita real GDP annual growth rate. The Baseline moments are computed from the stationary distribution of the estimated baseline model, while the No Targets figures are computed from the counterfactual model stationary distribution with no manager miss cost, i.e. $\xi = 0$, holding all other parameters fixed at Baseline levels.

parameters, including the persistence and volatility of profitability shocks (ρ_a , σ_a , and σ_ε), the magnitude of miss costs ξ , the R&D productivity level A , and paper manipulation costs γ_m . Table 3 lists my seven targeted moments together with their data and model values.³⁵ At the macro level I target the GDP growth rate, and at the micro level I target the covariance matrix of sales growth, R&D growth, and forecast errors.

First, I describe my GMM estimation algorithm for $\theta = (\rho_a, \sigma_a, \sigma_\varepsilon, A, \gamma_m, \xi)'$, with details in Appendix A. After choosing a weighting matrix W , I estimate $\hat{\theta}$ through numerical minimization

$$\hat{\theta} = \arg \min_{\theta} [m(\theta) - m(X)]' W [m(\theta) - m(X)],$$

where $m(X)$ and $m(\theta)$ are the vector of moments from the data X and model with parameters θ , respectively. The moment weighting matrix W I use results in a sum of squared percentage deviations objective.

The mapping between moments and estimated parameters in the model is joint and not one-to-one. However, certain moments are particularly influential for the identification of a given parameter. I investigate this mapping by computing Gentzkow and Shapiro (2014) sensitivity statistics as reported in Appendix Figure C.5. These sensitivity measures represent the estimated coefficients of a theoretical regression of parameters on model moments over their joint asymptotic distribution. The R&D productivity parameter A depends heavily on the aggregate growth rate, because higher innovation arrival rates imply higher growth.

³⁵The underlying GMM estimation is performed using the untransformed covariance matrix. See Appendix A for the raw moments and exact variable definitions.

Table 4: GMM parameter estimates

Parameter	Explanation	Estimate (SE)
ρ_a	Prof. persistence	0.903 (0.0325)
σ_a	Prof. volatility	0.070 (0.0029)
σ_ε	Transitory shock vol.	0.099 (0.0071)
A	R&D level	0.256 (0.1168)
ξ	Miss cost	0.001 (0.0006)
γ_m	Manipulation cost	0.290 (0.3679)

Note: The parameter estimates above are computed from an unbalanced panel of income statement and forecast data, with 4,839 firms and 32,597 firm-years from 1982-2010 in the US, together with data on the US per capita real GDP growth rate. The estimation procedure is standard overidentified GMM, with a moment covariance matrix reflecting time series correlation of the aggregate growth rate using a stationary bootstrap and arbitrary time series correlation within firm-level clusters for all micro moments. Optimization was performed using particle swarm optimization, a stochastic global minimization routine. The weighting matrix is chosen so that the GMM objective equals the sum of squared percentage deviations.

Forward-looking R&D feeds into realized forecast errors, implying that persistent shock volatility σ_a loads particularly upon R&D growth as well as forecast error volatility. By contrast, the estimated transitory shock volatility σ_ε depends relatively more upon overall sales growth volatility. Estimation of the persistence ρ_a links to the behavior of forward-looking R&D, placing weight on each of the volatility moments in the data but also crucially on the covariance between sales and R&D growth. Since easier paper manipulation in the model dampens passthrough of sales growth to profits, the cost parameter γ_m is determined in large part by the observed covariance between sales growth and forecast errors. Finally, I show below that the primary manifestation of pressure from miss costs ξ is higher R&D volatility, as firms sometimes react to shocks by cutting R&D to boost profits above targets. Naturally, therefore, the estimated level of ξ depends crucially upon both R&D growth volatility as well as the covariance between forecast errors and R&D growth.

Table 4 reports the estimated parameters and standard errors. The persistent component of profitability is highly autocorrelated, with ρ_a approximately equal to 0.9, and the combination of persistent and transitory volatility, $\sqrt{\sigma_a^2 + \sigma_\varepsilon^2}$, is moderate at around 12% annually. The persistence and volatility compare closely to the parameters in both Gou-rio and Rudanko (2014) as well as Hennessy and Whited (2007), which are also based on dynamic firm-level problems and Compustat data.

The paper manipulation and R&D productivity parameters γ_m and A are in model units. However, I can naturally examine the plausibility of the estimated costs ξ in terms of observables. In the estimated model, managers are indifferent between missing a profit target and a loss of around 3.6% of firm sales on average, with the miss cost statistically distinguishable

from zero at the 5% level. For comparison, Taylor (2010) structurally estimates a perceived cost to firms of CEO turnover of around 5.9% of assets, equal to 8.9% of firm revenues given the mean assets to revenues ratio in my data. Since CEO firing events are rare at a 2% frequency relative to profit target misses which occur at a 44% rate in my data, my lower miss cost estimate compares sensibly. Also, researchers have for decades sought to quantify the costs of price adjustment at firms, another crucial fixed cost. Zbaracki et al. (2004) provides direct estimates of price adjustment costs at a particular large firm. Total costs are about 1.2% of firm revenues. Given that price changes predictably occur each year within their studied firm, my slightly higher estimate of miss costs again compares sensibly.

Given the overidentified and highly nonlinear structure of the model, I can not in general expect an exact match to data moments. However, Table 3 demonstrates that the Baseline estimated model leads to a broadly successful fit.³⁶ In particular, the Baseline delivers a growth rate around the 2% level in the data, together with substantial volatility in sales growth. The Baseline model delivers somewhat less volatile forecast errors than the data, but higher volatility than a model without short-term pressure (moments of this No Targets case with $\xi = 0$ are also reported in Table 3). Furthermore, in both the Baseline and the data, forecast errors negatively covary with R&D growth. Targets cause some cuts to R&D growth which are driven by a desire to meet forecasts and are therefore correlated with higher forecast errors. By contrast, the No Targets model in which R&D responds only to investment opportunities produces a positive correlation of forecast errors with R&D growth. The presence of targets in the Baseline causes R&D to depend on transitory shocks, increasing the volatility of R&D growth substantially, while the No Targets model underpredicts R&D growth volatility by a large margin. Finally, paper manipulation in the Baseline leads to lower correlation between sales growth and forecast errors, closer to the data, while a No Targets model overpredicts this correlation substantially.

3 Assessing the Model

Along multiple dimensions - the cross-section of forecast errors, apparent opportunistic cuts to R&D growth, the dynamics of R&D, and the cross-section of industry heterogeneity - I show in this section that the estimated model delivers some basic facts from the micro data. The single substantive departure from pure value maximization in the model is the parsimonious introduction of the fixed cost ξ , and each of these patterns goes untargeted in my estimation.

³⁶Note, however, that the amount of data used for GMM estimation of the model implies that the J-test of overidentifying restrictions for the model is quite stringent, producing a rejection of the model.

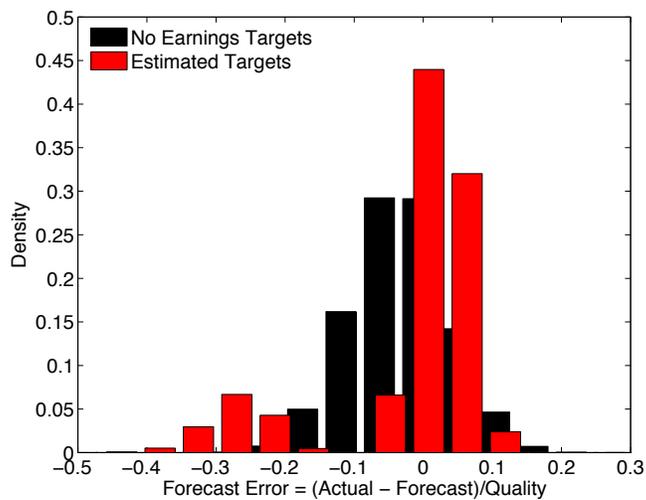


Figure 4: Forecast errors and bunching in the model

Note: The figure above represents the distribution of forecast errors $\pi - \pi^f$ computed from the stationary distribution of the balanced growth path associated with the estimated miss cost $\hat{\xi}$ (in red) and the counterfactual $\xi = 0$ (in black). The model is a calibrated version of the estimated Baseline including ex-ante measurement error of targets on the part of firms.

Empirically, forecast errors display bunching. For comparison, Figure 4 plots forecast errors in the Targets model with estimated short-term incentives (in red bars) and in the No Targets counterfactual with no short-term incentives or $\xi = 0$ (in black bars). The presence of short-term targets leads to substantial bunching of forecast errors. Fixed costs imply that managers prefer to avoid small misses when possible. At odds with the data, the model without short-term targets delivers a smooth forecast error distribution.

Before proceeding further, note that Figure 4 and the rest of the results in Section 3 incorporate some noise in short-term targets within the model laid out above. Why is this addition useful? Quantitative models with fixed costs and heterogeneity routinely yield stark sorting across thresholds (Berger and Vavra, 2015; Garicano et al., 2013; Khan and Thomas, 2008), and my model is no exception. A range of forecast errors just below zero never occurs if measurement error is ignored. The literature routinely incorporates some quantitative addition, such as measurement error or maintenance investment depending on the context, in order to allow for looser sorting. Appendix B lays out my extended model of manager decisions with a decomposition of transitory profitability shocks into two separate components: ε_{jt} (known to managers when policies are decided) and another component ν_{jt} (unknown to managers when policies are decided). In practice the noise ν_{jt} serves as target measurement error, since the exact threshold for meeting the target is ex-ante uncertain.

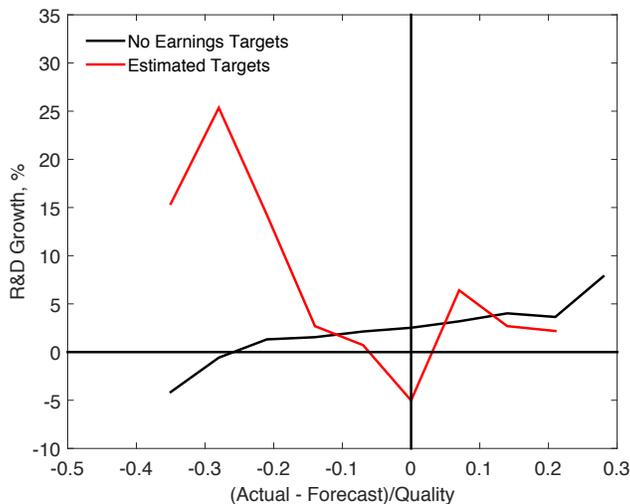


Figure 5: R&D growth and forecast errors in the model

Note: The figure plots average R&D growth in the estimated benchmark model with miss cost $\hat{\xi}$ (in red) and no miss costs (in black) conditional upon the forecast error $\pi - \pi^f$. R&D growth series were computed from a simulation of 500 firms over 1,000 years each, discarding the first 500 years of data to cleanse initial conditions. The model is a calibrated version of the estimated Baseline including ex-ante measurement error of targets on the part of firms.

Outside of Section 3, in which direct comparison of firm outcomes to forecast errors is not the object of interest, I discuss results generated by the Baseline model without noise. This choice is not crucial but instead is conservative for my conclusions about the growth impact of targets.³⁷ Importantly, this logic also implies that my choice to target the second moments of forecast errors, rather than the exact shape of the forecast error distribution, is conservative as well. The additional noise required to explicitly match Figures 4 and 1 would increase the impact of short-term targets on growth.

What lies behind bunching? Figure 5 plots model forecast errors on the horizontal axis and the associated conditional mean of R&D growth from a panel of simulated firm data on the vertical axis (the model with targets in red, the model without targets in black). Firms just meeting targets have lower R&D growth, since opportunistic cuts allow such firms to meet their target. By contrast, in the model without short-term targets, those firms exhibit higher R&D growth, because on average they have experienced higher growth of persistent

³⁷In particular, in the presence of noise more managers face a possible miss, causing a larger overall growth reduction. Compare Table 6 to Appendix Table C.6 for exact differences. The analogue to Figure 4 without measurement error is Appendix Figure C.4. Finally, note that for Figures 4-6, I calibrate the decomposition of known and unknown transitory shock volatilities to attribute approximately half of the total estimated transitory volatility to each source, since I draw profit forecasts in the data from the middle of the fiscal year.

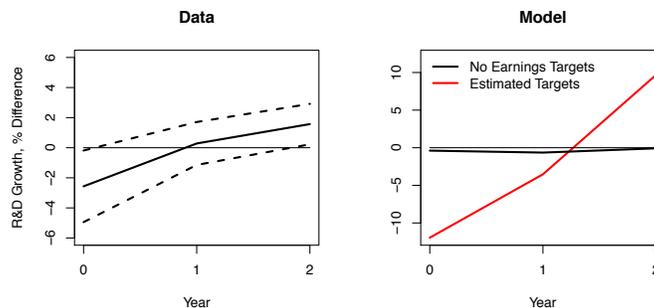


Figure 6: R&D growth dynamics in the data and the model

Note: Both panels plot in solid lines the estimated discontinuity in annual percentage R&D growth for firms just meeting relative to just missing analyst forecasts. Year k on the horizontal axis reports estimates based on year $t + k$ R&D growth and year t forecasts. All estimates are computed using a local linear regression discontinuity estimator, with a running variable equal to earnings forecast errors normalized by firm assets (data, bandwidth from Imbens and Kalyanaraman (2011)) and firm quality q (model, bandwidth = 0.2). The data panel reports 90% pointwise confidence intervals (dotted lines). The model panel reports estimates from the baseline model (in red, with $\hat{\xi}$) and from the model with no earnings targets (in black, with $\xi = 0$). Data estimates rely on the baseline Compustat-I/B/E/S discontinuity estimation sample with 23,083 firm-years spanning 1983-2010 with 3,969 firms. Model estimates rely on simulation of 500 firms over 1,000 years each, discarding the first 500 years of data to cleanse initial conditions.

profitability and possess better investment opportunities.³⁸ Figure 5 reveals that those firms far below their targets actually have *higher* R&D growth in the presence of short-termist incentives. A dynamic force is at work. Managers far below their target understand that they face the fixed miss cost regardless of their R&D choice. By increasing R&D growth today, they lower current profits and hence expectations of next period’s profits, ensuring an easier-to-meet future target. Colloquially, commentators refer to dynamic shifting of profits into a single large miss as a “big bath,” a pattern of long-standing concern to Securities and Exchange Commission regulators.³⁹ A model without short-termist incentives fails to generate this dynamic profit shifting.

Firms in the data just meeting targets in year t have on average lower R&D growth. However, Figure 2 from Section 1 reveals that in subsequent years such firms have *higher* R&D growth. To investigate, I first replicate the dynamics from Figure 2 in the left panel of Figure 6. In the right panel I plot the results of an analogous empirical exercise conducted with simulated model data. In the model I apply the same regression discontinuity estimator to measure the average difference in R&D growth between firms just meeting and missing targets. Moving along the horizontal axis, I trace out the difference in subsequent years.

³⁸The model also generates upward paper manipulation for firms just meeting targets. Such patterns are consistent with evidence from Burgstahler and Eames (2006) and are absent in a model without targets.

³⁹See the remarks by the SEC chairman in Levitt (1998).

Table 5: Bunching as miss costs ξ and R&D productivity A vary

ξ	Bunching	R&D Sensitivity	A	Bunching	R&D Intensity
80% of $\hat{\xi}$	3.67	0.27	80% of \hat{A}	7.86	3.44
$\hat{\xi}$	8.45	0.33	\hat{A}	8.45	7.36
120% of $\hat{\xi}$	13.14	0.43	120% of \hat{A}	10.13	8.81

Note: The first three columns report moments from varying the miss costs ξ around their estimated value $\hat{\xi}$, and the second three columns report moments from varying the R&D productivity parameter A around its estimated value \hat{A} . Bunching is the ratio of the mass of firm-years just meeting to just missing analyst forecasts, using a bandwidth of 0.2 in units of firm quality q . R&D sensitivity is the asymptotic limit of the coefficient $\hat{\beta}$ from the regression $(\text{R\&D Growth})_{jt} = \beta (\text{Sales Growth})_{jt} + \varepsilon_{jt}$. R&D intensity is the mean ratio of R&D expenditures to firm assets. For these cross-industry experiments, the aggregate growth rate and interest rates are held at their baseline values, but the analyst forecast system re-adjusts to a new fixed point. Results rely on simulation of 500 firms over 1,000 years each, discarding the first 500 years of data to cleanse initial conditions.

The model with short-term targets (the red line) exhibits lower R&D growth for firms just meeting targets. However, two years in the future, R&D growth is higher for firms that just met targets today. Opportunistic cuts and subsequent rebounds follow the pattern seen in Table 1 and Figure 2 in the data. These rich dynamics are absent in the model without short-term targets (the black line). What economic force is at work? In the model with short-term incentives, firms just meeting targets due to opportunistic cuts have lower R&D, relative to investment opportunities, than firms missing targets. Because they met expectations today with slightly higher profits, they also face more stringent forecasts for future periods. The result is a rebound in subsequent relative R&D growth, as some of the current manipulators take big baths or exploit favorable transitory shocks to increase future R&D growth.

Recall that bunching varies across industries in the data. To construct a notion of industries for model comparison, I first fix the growth rate g and the interest rate R at Baseline levels. Then I vary certain parameters away from their estimated values and update only analyst forecasts. I compute bunching from simulated data as the ratio of the mass of firms just meeting short-term targets divided by the mass of firms just missing. In the data, bunching and the empirical sensitivity of R&D growth to sales growth co-move positively across industries (top left panel of Figure 3). The first three columns of Table 5 report bunching and R&D sensitivity as miss costs ξ range from 80% to 120% of their estimated level. As short-termist incentives grow, bunching more than triples. At the same time, R&D growth becomes more responsive to forecast errors and short-term profitability shocks, increasing the observed sensitivity of R&D growth to sales growth. In the data, bunching is higher in more R&D-intensive industries (top right panel of Figure 3). The final three columns in Table 5 reveal that as R&D productivity A increases, both bunching and R&D

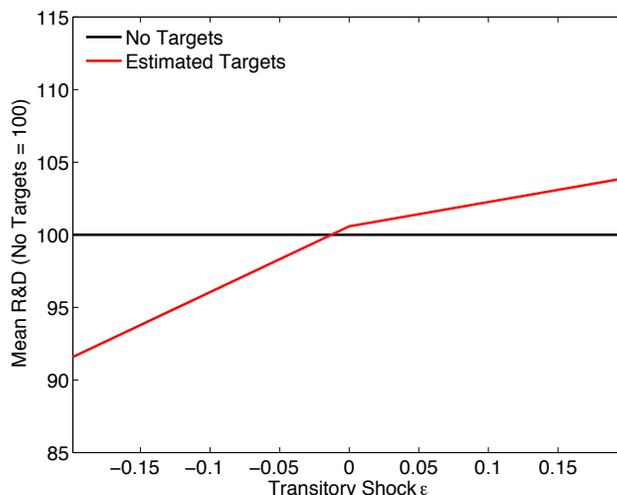


Figure 7: R&D and short-term shocks in the model

Note: The figure plots the mean R&D policy z in the counterfactual No Targets (in black, with $\xi = 0$) and Baseline estimated model (in red, with $\hat{\xi}$) conditional upon the value of the transitory profitability shock ε . For readability, the constant mean level of R&D z in the No Targets model is normalized to 100.

intensity do as well. The model matches this pattern because higher R&D relative to profit levels leads to more scope for manipulation and hence bunching.

4 The Costs of Short-Termism

In this section I describe the economic costs of short-termist incentives. Throughout, I center my analysis on a comparison of the Baseline estimated economy with short-term targets to the No Targets counterfactual.

Short-term targets make R&D responsive to transitory shocks. Figure 7 displays the mean R&D choice z for the Baseline and No Targets economies conditional upon the value of the transitory shock ε . Forward-looking R&D in the No Targets economy optimally ignores transitory shocks. By contrast, the Baseline R&D policy z is upward-sloping in the short-term shock, generating R&D misallocation. Although a negative transitory shock doesn't contain information about the payoff to R&D, managers cut their long-term investment on average to avoid missing their target. Conversely, high transitory shocks allow for a higher level of R&D while meeting targets.

Overall, because of sensitivity to transitory shocks as well as the big baths phenomenon, short-termist incentives increase the standard deviation of the R&D policy z by around 23%. Targets only induce a muted change in levels, with around a 0.3% drop in z on

Table 6: Short-termist incentives reduce growth

	%		%
$g^{Targets}$	2.25	Δ Welfare	0.44
$g^{NoTargets}$	2.31	Δ Firm Value	1.03
100-yr ΔY	5.82		

Note: The entries above compare various aggregate quantities across the estimated baseline economy with Targets (and $\hat{\xi} > 0$) and the counterfactual No Targets economy with $\xi = 0$. The moments are computed from the stationary distributions μ of the respective economies, and comparisons are directly across balanced growth paths. Δ Welfare represents the percentage consumption equivalent variation of $\xi = 0$ relative to the Baseline economy. The change in firm value is the mean partial equilibrium percent change in firm value when $\xi = \hat{\xi} \rightarrow \xi = 0$ for an individual firm, averaged over the stationary distribution for $\hat{\xi}$. The 100-year change in Y is the percentage difference in output after 100 years from a No Targets growth rate rather than a Baseline growth rate, using identical initial conditions.

average. The link $\Phi(z)$ in the model between R&D expenditures and innovation features diminishing returns or concavity with an elasticity $\alpha < 1$. Higher volatility of R&D therefore causes fewer innovation arrivals, even in the absence of aggregate changes in R&D levels.⁴⁰ This force cuts macro growth.⁴¹ My baseline curvature calibration mediating the volatility channel, $\alpha = 0.5$, follows a remarkably consistent set of estimates from micro empirical work targeting the elasticity of innovation outcomes such as patents to R&D expenditures. Papers including Blundell et al. (2002) and Acemoglu et al. (2013) each exploit within- or across-firm variation to arrive at estimates near 0.5. Extreme calibrations removing all curvature $\alpha \rightarrow 1$ would mechanically undo any volatility effects. However, the baseline growth drops I discuss below are robust to moderate changes in α , as reported in Appendix Table C.6. To understand this robustness, note that slightly increased curvature with $\alpha < 0.5$ directly heightens the volatility effect. However, somewhat less curvature with $\alpha > 0.5$ leads to higher R&D expenditure on average, and more scope for manipulation, even as it reduces the direct volatility effect.

Table 6 reports the macro growth rate in the Baseline model, $g^{Targets} = 2.25\%$, which is around 6 basis points lower than growth in the No Targets economy, $g^{NoTargets} = 2.31\%$. Lower growth leads to compounding effects far into the future.⁴² At the horizon of a century

⁴⁰This statement is a straightforward implication of Jensen’s inequality.

⁴¹A negative link between volatility and growth is familiar. Barlevy (2004) describes a model in which volatility of tangible investment increases business cycle costs through lower growth.

⁴²My model has permanent growth effects, while (Jones, 1995) argues for use of semi-endogenous growth models with only temporary growth changes. In other work, in the context of trade liberalization (Bloom et al., 2015), I compare the quantitative implications of models such as mine to semi-endogenous versions. For realistic calibrations, the differences in growth are discounted heavily and quantitatively limited because they occur far in future. For tractability I do not consider a semi-endogenous version of this model, but I suspect similar logic would apply.

the absence of short-term targets would deliver around 6% higher output.

I also conduct a simple accounting exercise for aggregate welfare. The second column of Table 6 displays the consumption-equivalent welfare gain to consumers from the removal of short-term targets. The welfare gain, around 0.44%, is the percentage increase in each period's consumption which would make the Baseline household indifferent to the No Targets consumption stream, comparing directly across balanced growth paths.⁴³ Costs from short-termist incentives on the order of half a percent should be compared to other macro factors. Recent estimates of the welfare costs of business cycles range from 0.1-1.8% (Krusell et al., 2009), and recent estimates of the static gains from trade range from 2.0-2.5% (Costinot and Rodríguez-Clare, 2015; Melitz and Redding, 2013). At the macro level, the quantitative costs due to short-termist targets are sizable.

Table 6 also reports the change in average firm value resulting in partial equilibrium from the removal of targets, equal to around 1%.⁴⁴ For perspective, I turn to evidence from corporate finance quantifying the loss in value from CEO turnover frictions at around 3% (Taylor, 2010) or from manager agency frictions affecting cash holding at around 6% (Nikolov and Whited, 2014). At the micro level, the quantitative costs of short-term targets also appear sizable.

Note that my counterfactual exercise assumes that US public firms, representing around two-thirds of all private R&D expenditures, are a reasonable proxy for all US firms. On one hand, private firms are not typically subject to profit reporting requirements or to analyst forecasts. However, on the other hand, private-firm executives surveyed in Graham et al. (2005) report almost identical levels of pressure to meet profit targets as their public-firm counterparts. For private firms, profit targets are presumably internal, stemming from monitoring or goals set by boards or private investors. On net, it is not clear ex-ante whether private firms are more or less insulated from short-termist pressures.⁴⁵ However, if private firms are indeed less subject to short-termist pressures, their decision to publicly list may be distorted, potentially leading to heightened financial frictions in the economy with targets. The comparison seems rich, but a fuller treatment remains beyond the scope of this paper.

The distortions to R&D and the resulting losses in firm value, growth rates, and consumption laid out above represent the costs of short-term targets. However, targets may provide benefits such as discipline for badly behaved managers. Benefits from targets matter

⁴³Recall that to be conservative I assume that all of the term ξ in the manager payoff is apportioned to personal costs for the manager. If the effect of the miss costs is entirely due to firm resource costs or disruptions overall household gains are 0.48% instead.

⁴⁴For conservatism I assume miss costs are private to the manager. If miss costs are borne as resource costs to the firm, the change in firm value is 1.3%.

⁴⁵However, see recent empirical work on this topic by Bernstein (2015), Asker et al. (2014), and Aghion et al. (2013).

for at least two reasons. First, gains from removal of short-term pressure in my counterfactual might fail to materialize in practice if policymakers eliminate targets and extinguish their benefits. Second, benefits may microfound or rationalize the existence of targets. At the cost of making assumptions about the nature of manager misbehavior, I explore these issues in the next section. My central prediction of lower growth due to short-termist targets remains.

5 Badly Behaved Managers

Pressure to meet profit targets might arise from the efforts of the board or distributed shareholders of a firm to exert discipline on badly behaved managers. In this section, I consider two forms of agency conflicts which serve to microfound and to provide countervailing benefits from short-termist targets. First, I consider shirking or effort provision problems which could also be interpreted as unobserved resource diversion towards manager personal use. Second, I allow for empire-building tendencies and overinvestment by managers. Both frictions draw conceptually on long literatures.⁴⁶ In general, the welfare implications of manager misbehavior in growth models are ambiguous, a point emphasized by Iacopetta et al. (2015).

In the extended model, managers in each period choose either to shirk ($s_{jt} = 1$) or to exert effort ($s_{jt} = 0$). If managers shirk, they receive a private benefit governed by the parameter $\lambda_s \geq 0$. Shirking implies a proportional drop in firm quality, output, and profits by some fraction $\gamma_s \in (0, 1)$. Managers also receive an empire-building private benefit governed by the parameter $\lambda_e \geq 0$ which scales with firm quality and hence size. The rest of the model is similar to before, but managers now solve

$$\max_{\{z_{jt}, m_{jt}, p_{jt}, s_{jt}\}_t} \mathbb{E} \left\{ \sum_{t=0}^{\infty} \left(\frac{1}{R} \right)^t D_{jt}^M \right\}.$$

$$D_{jt}^M = \theta_d D_{jt} - (1 - \theta_d) \xi^{pay} \mathbb{I}(\Pi_{jt}^{Street} < \Pi_{jt}^f) Q_{jt} + \lambda_s s_{jt} Q_{jt} + \lambda_e Q_{jt}.$$

Manager flow returns D_{jt}^M include a contract with a fixed dividend share $\theta_d \in (0, 1)$ and clawback by the firm of $\xi^{pay} \mathbb{I}(\Pi_{jt}^{Street} < \Pi_{jt}^f) Q_{jt}$ conditional upon missing a profit target.⁴⁷ I take the form of such a contract as exogenously given. The final components of manager payoffs are the private benefit $\lambda_s s_{jt} Q_{jt}$ when shirking and the private empire-building benefit $\lambda_e Q_{jt}$. The costs of shirking enter dividends, written here gross of manager clawback

⁴⁶See, for shirking, Grossman and Hart (1983) or Beyer et al. (2014). See, for empire building, Jensen (1986) or Nikolov and Whited (2014).

⁴⁷In this section I attribute the entirety of the estimated ξ term to ξ^{pay} .

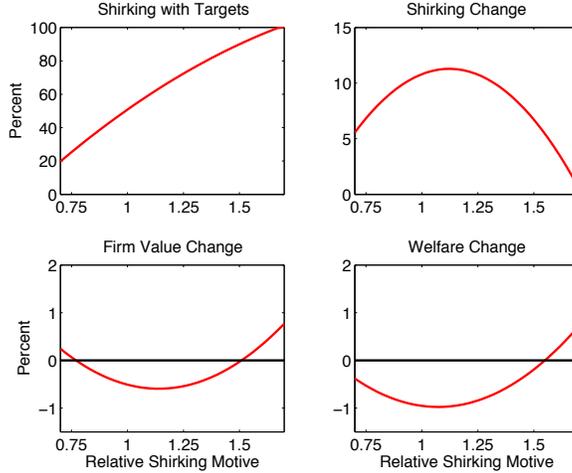


Figure 8: Targets can prevent shirking

Note: Horizontal axis is $r(\lambda_s) = \lambda_s / \mathbb{E}(\theta_d \Pi_v \gamma_s / q)$, where $\gamma_s = 0.075$. The top left panel plots the average shirking level $100\mathbb{E}_\mu s$ with targets, the top right panel plots the percent difference in shirking from target removal, the bottom left panel plots the average PE percent change in firm value from target removal, and the bottom right panel plots the GE total consumption equivalent percent change in social welfare from target removal. Numerical comparative statics are smoothed using a polynomial approximation.

compensation:

$$D_{jt} = \Pi_v(Q_{jt}, a_{jt}, \varepsilon_{jt}, p_{jt})(1 - \gamma_s s_{jt}) - z_{jt} Q_{jt} - \gamma_m^2 m_{jt} Q_{jt}.$$

How does manager misbehavior relate to targets? In the absence of profit pressure managers weigh a private gain from low effort equal to $\lambda_s Q_{jt}$ versus a firm-wide loss diluted through their equity share of $\theta_d \Pi_v \gamma_s$. However, by conditioning pay on the target, firm owners augment the costs of shirking by the net amount $(1 - \theta_d) \xi^{pay} \mathbb{I}(\Pi_{jt}^{Street} < \Pi_{jt}^f) Q_{jt}$. For those firm-years in which shirking leads to a miss, the prospect of lost pay may induce effort. Similar logic applies for empire-building. The ex-ante expected profitability of R&D investment may be manager private information, so overinvestment might be difficult to detect. However, because higher R&D lowers current profits, short-term targets curtail overinvestment on average.

I conduct two quantitative experiments. First, I set all pre-existing model parameters to their estimated values. Then, I vary the private motive for shirking λ_s without empire-building incentives in Figure 8. Finally, I vary the empire-building incentive λ_e without shirking incentives in Figure 9.

For the shirking experiment, Figure 8 plots four quantities: the shirking rate in an economy with targets (top left), the average increase in shirking if targets are removed (top

right), the average partial equilibrium change in firm value from target removal (bottom left), and the general equilibrium consumption equivalent change in welfare for consumers from target removal (bottom right). Throughout this exercise, I fix the proportional loss to variable profits at the firm from shirking at the round figure of $\gamma_s = 7.5\%$.⁴⁸ The horizontal axis plots the ratio between the average private benefit and the loss from shirking for a given value of λ_s , both normalized by firm quality q . As the shirking motive grows from left to right, managers unsurprisingly shirk more (top left). However, there is a hump-shaped pattern to the increase in shirking seen if profit discipline is removed (top right). For very low levels of shirking motive managers usually exert effort already, so targets accomplish little. By contrast, for intermediate levels of shirking benefit, managers are close to indifferent between shirking or effort, and targets cause a relatively large portion of managers to provide effort. Finally, if managers receive large shirking benefits, miss costs do not dissuade shirking much. The hump-shaped pattern to the prevention of shirking feeds into counterfactual changes in firm value and social welfare. For intermediate levels of private shirking benefits, average firm value would be lower if a firm removed targets even though targets distort R&D (bottom left). The production loss from shirking if targets are removed also leads to a loss for the aggregate household, so targets enhance welfare when they prevent a lot of costly shirking (bottom right).

For the empire-building exercise reported in Figure 9, the horizontal axis in each panel is equal to the ratio between the manager's private return to size and their average return to variable profits, both normalized by firm quality q . As empire-building motives grow from left to right, the R&D-to-sales ratio unsurprisingly increases (top left). However, the scope for targets to provide discipline, or the change in the R&D-to-sales ratio when targets are removed, increases as well (top right). For relatively low empire motives, firms gain in partial equilibrium from target removal (bottom left). However, for higher empire motives firms would lose value on average from target removal because of the resulting overinvestment. By contrast, in this experiment the aggregate household always experiences higher welfare when targets are removed (bottom right). Firms realize producer surplus, but managers ignore consumer surplus as emphasized by Jones and Williams (2000). The result is underinvestment in R&D relative to its social value, and targets exacerbate this underinvestment.⁴⁹

If managers behave badly, Figures 8 and 9 suggest that firm owners may benefit from exploiting outside analyst targets. In principle, discontinuous incentives might be improved upon even further. Although a full optimal contracting analysis is beyond the scope of

⁴⁸Further details are in Appendix B. As a robustness check, Appendix Figure C.6 plots the analogous results for a smaller value of $\gamma_s = 2.5\%$.

⁴⁹Diffusion of average quality to lagging firms leads to a separate inefficiency.

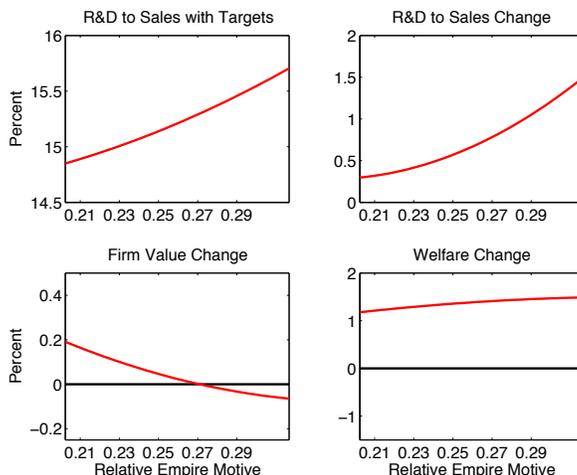


Figure 9: Targets can restrain empires

Note: Horizontal axis is $r(\lambda_e) = \lambda_e / \mathbb{E}(\theta_d \Pi_v / q)$. The top left panel plots the average R&D to sales ratio with targets, the top right panel plots the percent difference in the R&D to sales ratio from target removal, the bottom left panel plots the average PE percent change in firm value from target removal, and the bottom right panel plots the GE total consumption equivalent percent change in social welfare from target removal. Numerical comparative statics are smoothed using a polynomial approximation.

the paper, Appendix C reports the additional firm value from optimally chosen incentives within a class of smooth polynomial contracts. The resulting improvement is small, with substantially less than 1% in incremental firm value typically resulting from implementation of smooth incentives relative to targets. In an environment with information frictions or space constraints in financial reporting, discontinuous targets may be a particularly logical disciplining device.

Figures 8 and 9 reveal ambiguity in the net welfare impact of short-termist incentives. If shirking is prevalent, consumers may benefit from the discipline of short-term targets. However, if empire-building matters most, then consumers may lose. By contrast with the welfare implications, the growth implications are entirely clear-cut. In particular, short-termist incentives universally lead to reductions in growth ranging from 0.04% to 0.09% in this section's experiments. As policymakers seek to promote the benefits from liquid capital markets, transparent reporting procedures, and increased manager discipline, my results suggest caution. Closely linked short-termist behavior causes a large drag on long-term growth.

6 Conclusion

In the data, profits bunch directly above short-term targets. Firms just meeting targets have lower R&D growth, and managers just missing receive lower pay. These patterns suggest both short-termist incentives for managers as well as manipulation of R&D. An estimated model of macro growth due to micro-level R&D reveals that short-termist targets matter quantitatively. More volatile R&D at firms leads to a drop in firm value of around 1% at the micro level and lower growth by around 0.1% per year at the macro level. The persistent drag on growth represents a quantitatively sizable macro cost.

Two avenues for further investigation seem promising. First, short-termism may also work through channels other than profit targets. There is suggestive evidence that managers close to departure from a firm engage in lower levels of R&D investment (Dechow and Sloan, 1991) or that firms may apply disproportionately high hurdle rates to projects (Poterba and Summers, 1995). Either channel would lower effective discount rates. Second, as noted above, my analysis exclusively considers public firms. Anticipation of short-termist distortions by private firms may distort public listing, imposing financial frictions and distorting firm life cycles.

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