Short-Termist Carbon Emissions*

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Abstract

Carbon abatement investments are inherently long-term in nature. Therefore, short-term profit pressure may distort these investments. Consistent with this idea, firms that just meet analysts' short-term profit targets have about 4.3 to 4.99 percentage points higher growth in carbon emissions than firms that just miss. I estimate a quantitative model with endogenous carbon emissions and short-term incentives for managers. Removing short-term incentives reduces firms' profits by 0.43% and carbon emissions by 2.19%. In aggregate, short-termist carbon emissions are as large as total U.S. aviation emissions in 2022. My estimates suggest that short-termism is welfare-reducing via the carbon emissions channel.

JEL Codes: G30, G32, G34

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1 Introduction

Corporate earnings reports are closely monitored by financial markets and evaluated against analysts' forecasts. A large literature in finance documents substantial negative stock price reactions when reported earnings (profits) fall short of expected targets. Consistently, survey evidence by Graham et al. (2005) shows that about 90% of U.S. managers feel pressured to meet short-term goals. Several public and private institutions highlight the potential negative effects of short-termism. For example, the United Nations Global Compact claims that "short-termism in investment markets is a major obstacle to companies embedding sustainability in their strategic planning and capital investment decisions".

In this paper, I quantify the impact of short-termism on carbon emissions. To this end, I develop and structurally estimate a quantitative model with endogenous carbon emissions and short-term incentives. In counterfactual simulations, I find that removing short-term incentives from managers' contracts lowers firms' profits by 0.43% and carbon emissions by 2.19%. At the aggregate level, short-termist carbon emissions amount to about 142 million tons, or as much as total U.S. aviation emissions in 2022. My estimates imply that each ton of carbon dioxide saved by eliminating short-term incentives costs about $\$84$ in terms of lower profits. As most conventional estimates of the social cost of carbon are significantly higher (see, Rennert et al., 2022), my analysis suggests that short-termism is welfare-reducing via the carbon emissions channel.

Investments in carbon-reducing technologies are sensitive to short-term pressures. The economic benefits of such investments are highly uncertain and may only realize in the long-term as climate change worsens, while the cost are incurred today. As a result, some managers on the verge of missing analysts' earnings targets may find themselves either cutting back on carbon abatement investments or missing targets. As more than half of all managers prefer to forgo positive NPV projects over missing profit goals (Graham et al., 2005), carbon abatement investments are a likely target for real-earnings management. The empirical analysis is complicated because direct data on carbon abatement investments are largely missing. However, the main outcome of carbon abatement investments, carbon emissions, is observable. Using a structural model, I can overcome the data limitation and infer the extent of carbon abatement investments from firm fundamentals and carbon emissions.

I document two stylized facts using data on carbon emissions from Trucost as well as realized earnings and analysts' earnings targets from IBES. First, I compute forecast errors as the difference between realized profits and the median analyst's forecast and show that firms cluster disproportionately just above the zero forecast error threshold, with relatively few firms having small misses. This finding is consistent with the view that managers engage in opportunistic behavior to meet short-term earnings targets. Similar patterns have been documented in the accounting and finance literature and associated with real-earnings management (e.g., Dechow et al., 1995, Roychowdhury, 2006, Marinovic et al., 2013, Hong and Kacperczyk, 2010, Errico et al., 2023, Terry, 2023).

Second, I document a sizable discontinuity in the growth rate of carbon emissions around the zero forecast error threshold.[1] In particular, I show that firms that just meet analysts' targets have carbon emission growth that is about 4.73 percentage points higher than firms that just miss, consistent with opportunistic cuts in carbon abatement investments to meet short-term earnings targets. This difference is economically significant, amounting to 12% relative to the standard deviation of carbon emission growth rates. The discontinuity also exists for the growth rate of carbon intensity, defined as carbon emissions scaled by assets or sales. Moreover, I show that the discontinuity persists for up to two additional years after the earnings surprise. Taken together, the results suggest that firms with slightly positive earnings surprises become less carbon efficient than firms that miss analysts' earnings targets by a small margin.

Several points are worth highlighting. The reduced-form results only represent the local discontinuity around the zero forecast error threshold and should not be interpreted as the average causal effect of short-termism on carbon emissions. One potential concern is that there may be endogenous selection across the threshold. For instance, firms with managers of higher skill may be more likely to slightly beat analysts' forecasts, while firms with managers of lower skill are more likely to miss targets by a small margin. Hence, the reduced-form evidence only serves as an endogenous detection mechanism for identifying short-

[1] Lyubich et al. (2018) document substantial heterogeneity in carbon intensities across plants, even within narrowly defined industries. Thus, managers can plausibly influence their firms' carbon emissions through abatement investments.

term pressures and the associated opportunistic changes in carbon emissions. Moreover, the reduced-form stylized facts only represent local, relative variation that may not survive aggregation. Finally, local discontinuities do not provide counterfactuals for an economy without short-term incentives. To address these concerns, I develop and estimate a quantitative model in the spirit of Terry (2023) with endogenous carbon emissions and short-term incentives for managers. The model allows me to directly quantify the aggregate impact of short-termism on carbon emissions, while explicitly accounting for equilibrium forces.

To establish the intuition for the quantitative model, I start with a simple two-period toy model. In the first period, firms earn exogenous revenues and choose their carbon emissions. Reducing carbon emissions is costly today, but creates value for firms in the long-run due to, e.g., regulatory action against brown firms or shifts in consumer demand toward green products. In addition, managers are subject to private cost from carbon emissions, which may arise for several reasons. Some managers may care about climate change and therefore incur non-pecuniary cost from high carbon emissions. Other managers may not care about climate change, but they may well care about their firm's carbon emissions for career reasons. For example, managers communicate their firm's emissions policy to the public, such as in earnings calls or press interviews, where they may be held accountable for high carbon emissions. Being portrayed as an environmentally irresponsible manager is a risk to successful career advancement, so managers derive private disutility from carbon emissions.[2]

Overall, these private cost represent an agency conflict that pushes managers to reduce carbon emissions more than is optimal from the perspective of the firm. In response, the board of directors optimally chooses to penalize managers for missing short-term profit tar-

[2]Private cost for CEOs may be motivated by anecdotal evidence that CEOs are increasingly scrutinized by the public for their environmental policies. Examples include Starbucks' new CEO Brian Niccol, who was criticized for his 1,000-mile commute by private jet, or oil CEOs, who were grilled by Congress over their climate policies. Moreover, there is a debate in the academic literature whether ESG investment is a manifestation of good governance or a sign of agency conflicts. The empirical evidence on this question is mixed (e.g., Ferrell et al., 2016, Gillan et al., 2010, Cheng et al., 2023). I take an intermediate position and assume that managers incur private costs from carbon emissions, but at the same time the value-maximizing board imposes optimal short-term incentives to mitigate the agency conflict. Technically speaking, the private cost from carbon emissions rationalize the existence of short-term incentives and allow me to characterize the optimal contract endogenously. Importantly, *my main results do not rely* on assuming that managers derive private cost from carbon emissions, but I could alternatively assume exogenous short-term incentives, consistent with survey evidence (e.g., Graham et al., 2005).

gets. In equilibrium, the board-induced short-termism solves the agency conflict and increases carbon emissions to the value-maximizing level. This outcome is consistent with Hart and Zingales (2017), who predict that public companies, with their dispersed shareholder base and resulting low levels of personal responsibility, tend to adopt less pro-social policies.

I incorporate the key mechanism of the toy model into a quantitative model of heterogeneous firms with endogenous carbon emissions and short-term incentives for managers. Firms generate sales that follow an exogenous lognormal process. In addition, firms are subject to non-fundamental profit noise. Risk-neutral managers with private cost of carbon emissions have private information about profit noise and choose firms' carbon emissions. As in the toy model, carbon emissions are costly to reduce today, but lower carbon emissions reduce the probability of negative cash flow shocks in the future. Analysts observe firms' fundamentals, correctly process managers' incentives, and issue rational profit forecasts. The board chooses short-term incentives for managers that maximize firm value. Short-term incentives increase carbon emissions, but are also distortive due to opportunistic actions when managers are close to the zero forecast error threshold. Unlike in the toy model, short-term incentives do not restore the equilibrium without agency conflicts because managers have private information about profit noise.

I structurally estimate eight parameters of the model using the Simulated Method of Moments (SMM). I target 13 moments computed from the Compustat/IBES/Trucost merged data set. Truecost compiles and reports carbon emissions of publicly traded companies. The parameters related to firm fundamentals are identified from the correlation matrix of sales growth, profitability, carbon intensity, and forecast errors. In addition, the extent of bunching above the zero forecast error threshold helps to identify managers' private cost of carbon emissions, which is reflected in the degree of short-termism in the model. Finally, I target the average carbon emissions intensity to calibrate the ratio of cost and benefits of reducing carbon emissions. Overall, the model matches all signs of the targeted correlations and the simulated moments are generally close to their empirical counterparts.

I use the estimated model to run counterfactual simulations and quantify the impact of short-termism on carbon emissions and firm value. I find that eliminating short-termism from managers' contracts lowers firms' profits by 0.43% and carbon emissions by 2.19%. At the aggregate level, short-termist carbon emissions amount to about 142 million tons of CO_2 when benchmarked against the level of aggregate emissions in the U.S. economy in 2022. Overall, my results suggest a trade-off between climate change mitigation and financial value. As such, I contribute to the value-versus-values discussion (see, Starks, 2023).

At the macro level, carbon emissions generate a negative externality due to, for example, global warming. Thus, private incentives for shareholders and social incentives are not aligned. Therefore, in most models with an endogenous climate element, short-termism will increase firm value at the micro level but decrease social welfare at the macro level due to the non-internalized social cost of carbon. The average firm in my sample earns $\$1015$ million in annual profits while emitting 2.39 million tons of CO_2. Thus, each ton of carbon dioxide saved by eliminating short-termist incentives costs about $\$84$ in 2017 USD. Rennert et al. (2022) estimate that the social cost of carbon ranges from $\$42$ to $\$397$, with the preferred estimate being $\$178$ in 2017 USD. Since the social cost of carbon tends to be higher than the implicit cost of removing short-term incentives, short-termism is likely to be welfare-reducing at the aggregate level.

I conduct a number of additional robustness analyses. First, I estimate the structural model on different subsamples and find that the results are driven by the before-2015 Paris Agreement period and are more pronounced for firms with high baseline carbon intensity. Second, I calculate the quantitative impact of counterfactually varying the baseline parameter estimates. The quantitative impact of short-termism is stable. Third, I extend the baseline model to include private firms, as one concern may be that my baseline analysis overstates the impact of short-termism due to the presence of private firms where short-term incentives are weaker. I find that my results are still quantitatively meaningful when I allow for a conservatively large mass of private firms in the model.

Related Literature. I contribute to two strands of literature. First, I add to the literature on the economic effects of short-termism. Graham et al. (2005) interview more than 400 executives and find substantial short-termism among U.S. managers: about 90% of U.S. managers feel pressure to meet short-term targets and 78% would sacrifice long-term value to smooth earnings. To reach short-term targets, managers use a variety of tools including accruals-based manipulation (e.g., Dechow et al., 1995, Kothari et al., 2005, Cohen et al., 2008), cuts in discretionary expenditures like advertising or R&D (e.g., Bhojraj et al., 2009, Corredoira et al., 2021, Terry, 2023), markup increases (e.g., Errico et al., 2023), or adjustments in the quantity produced (e.g., Roychowdhury, 2006, Zhang and Gimeno, 2010). Using different empirical settings, several authors find substantial evidence that short-term incentives increase the likelihood of share repurchases as well as mergers and acquisitions, inhibit investment, and decrease long-term productivity (e.g., Almeida et al., 2016, 2024, Edmans et al., 2017, 2022, Ladika and Sautner, 2020). I add to this literature by showing that short-term incentives for corporations fuel climate change.

Second, I contribute to the growing literature on climate finance. One part of this literature focuses on the asset pricing and financial market implications of corporate environmental policies. Pedersen et al. (2021) derive an ESG-adjusted CAPM and characterize when ESG increases or decreases the required rate of return. Similarly, Pastor et al. (2021) show that green assets have low expected returns because they hedge climate risk and some investors like to hold them. The empirical evidence on the pricing of climate risk is mixed. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) document that firms with higher carbon emissions earn higher returns. However, the positive carbon premium disappears when focusing on disclosed instead of vendor-estimated emissions, when analyzing carbon intensity rather than unscaled emissions, or when correcting for the publication lag of emissions data (Aswani et al., 2024, Zhang, 2024). Ilhan et al. (2021) document that climate policy uncertainty is priced in the option market. Hsu et al. (2023) show that higher polluting firms, on average, command a higher return because they are exposed to environmental litigation risk. Engle et al. (2020) construct an index of climate news and propose a dynamic strategy to hedge climate change news. Moreover, several studies examine the ESG investment behavior of financial institutions and the welfare consequences of sustainable investing (e.g., Dyck et al., 2019, Berg et al., 2022, Gibson Brandon et al., 2022, Hong et al., 2023, Ilhan et al., 2023, Pastor et al., 2023, Hoepner et al., 2024).

The other part of the climate finance literature focuses on questions primarily related to corporate finance. Gillan et al. (2021) provide an excellent review of the literature on

ESG research in corporate finance. In an early contribution, Heinkel et al. (2001) show that ethical investing can raise polluting firms' cost of capital. Pastor et al. (2024) quantify the carbon burden of the U.S. corporate sector and find that the total carbon burden is 131% of total corporate equity value. Financial constraints are shown to play an important role for carbon emissions and toxic releases (e.g., Bartram et al., 2022, Xu and Kim, 2022). Akey and Appel (2021) document the role of firm boundaries in corporate pollution policy, while Dai et al. (2021) find that firms outsource their emissions to foreign suppliers rather than invest in abatement technology. Various authors examine the cash flow channel of ESG (e.g, Derrien et al., 2021, Houston et al., 2022, Duan et al., 2023, Meier et al., 2023). In particular, Meier et al. (2023) use barcode-level data and show that ESG investments positively affect consumer demand, while Houston et al. (2022) find that ESG incidents lead to lower sales. Several authors analyze the role of ESG performance metrics in executive compensation and find that while ESG targets have become more prevalent in recent years, they are largely discretionary and do not affect executive pay in a quantitatively meaningful way (e.g., Cohen et al., 2023, Badawi and Bartlett, 2024, Efing et al., 2024).

One of the key tensions in the literature on ESG and corporate finance is whether ESG investment is a manifestation of good governance or a sign of conflicted managers acting in their own interests (e.g., Bénabou and Tirole, 2010). The good governance view interprets ESG actions as the equilibrium outcome of optimal contracting, while the agency conflict view interprets ESG actions as the result of an agency conflict where managers derive non-pecuniary private benefits from ESG investments. The empirical evidence is mixed. Various authors find results consistent with the optimal contracting view (e.g., Gillan et al., 2010, Ferrell et al., 2016), while others support the agency conflict view and find that managers derive private benefits from ESG investments (e.g., Cheng et al., 2023). In my baseline model, I assume that managers derive private disutility from carbon emissions, so they would like to invest more in carbon abatement than is optimal from a shareholder perspective. In response, the board endogenously imposes short-term cost discipline on managers to mitigate the agency conflict. Thus, I effectively take an intermediate position between the good governance view and agency conflict view. In summary, I add to the literature on climate finance by showing that short-term incentives increase firm value but have negative consequences for the environment.

Two papers are methodologically close to my study, the first is Terry (2023) and the second is Errico et al. (2023). Terry (2023) examines the effect of short-termism on R&D investment. He develops and estimates a general equilibrium, endogenous growth model. In his model, short-term incentives mitigate an agency conflict and increase firm value. However, short-termism reduces R&D and thus aggregate welfare because of the positive externalities associated with R&D. In a similar spirit, Errico et al. (2023) incorporate short-term incentives into a macro model of customer capital. They show that short-termism leads to higher markups and firm value at the micro level. However, consumers' welfare and total market capitalization is reduced at the macro level. I extend this line of research by analyzing the impact of short-termism on carbon emissions.

Roadmap. The remainder of this article is structured as follows. In Section 2, I present two stylized facts using data on forecast errors and carbon emissions. Section 3 develops a toy model that features endogenous short-termism and carbon emissions. Section 4 introduces my quantitative model, followed by the quantitative results in Section 5. Section 6 concludes.

2 Short-Termism and Carbon Emissions in the Data

In this section, I provide evidence on the relation between short-termism and carbon emissions. I start by introducing my data and the variable definitions. Then, I show that firms bunch disproportionately just above the zero forecast error threshold, with relatively few firms displaying small misses. Finally, I document that firms that just meet analysts' targets have carbon emission growth that is 4.3 to 4.99 percentage points higher than firms that just miss.

2.1 Data and Variable Definitions

Data Sources. I use three different data sources to conduct my empirical analysis. First, I obtain firm fundamentals from Compustat. Second, I collect professional analysts' earnings forecasts from the Institutional Broker's Estimate System (IBES) database. I aggregate individual analysts' forecasts at the firm-year level by taking the median of all earnings forecasts across all analysts. Third, I obtain firm-level carbon emissions data from Trucost. Trucost compiles its data from several publicly available sources, including firms' financial reports and environmental data sources such as the Carbon Disclosure Project. If companies do not report their emissions, Trucost imputes the missing data points using an extended input-output model. Aswani et al. (2024) show that imputed carbon emissions are an almost deterministic function of firm fundamentals such as assets and sales. Since my structural estimation requires observing variation in carbon emissions that is not deterministically linked to firm fundamentals, I exclude all data points that are imputed by Trucost.

I merge Compustat, IBES, and Trucost using standard firm identifiers. Following the literature, I remove all regulated (SIC 4900-4999) and financial (SIC 6000-6999) firms. In my empirical analysis, I focus on Scope 1 and Scope 2 carbon emissions. Scope 1 includes direct emissions from sources owned or controlled by the firm, while Scope 2 includes emissions from the consumption of purchased energy associated with a firm's direct operations.[3] My final sample captures earnings surprises, financial data, and carbon emissions for 3,147 observations from 493 firms between 2006 and 2019.[4] Detailed summary statistics are presented in Tables A.1 and A.2 of the Online Appendix.

Forecast Errors. I follow Terry (2023) and use IBES profit forecasts and realized annual earnings to construct the forecast error for firm i in year t as

$$fe_{it} = \frac{street_{it} - consensus_{it}}{assets_{it}}, \tag{1}$$

where $street_{it}$ is the dollar value of realized IBES street earnings and $consensus_{it}$ is the median of all analysts' four-quarter-ahead profit forecasts. I use four-quarter ahead profit forecasts to ensure that managers have enough time to meaningfully affect carbon emissions in

[3]Scope 3 includes indirect upstream and downstream emissions produced by assets not owned or controlled by the firm. I exclude Scope 3 emissions because they are not directly controlled by the firm itself.

[4]The Trucost sample has reasonable coverage between 2005 and 2021. I exclude the years 2020 and 2021 because of the disruptions caused by the Covid pandemic. For example, the lockdowns in 2020 caused production and carbon emissions to collapse, followed by a rapid recovery in 2021. Since I examine growth rates of carbon emissions, my analysis would be contaminated by these effects. Also, my final sample starts in 2006 because I lose one year of observations when calculating growth rates.

the same fiscal year. Moreover, I normalize by book assets, $assets_{it}$, to account for differences in firm size. In the Online Appendix, I show that scaling by lagged sales instead of assets, using a relative forecast error measure, and using the mean forecast across all analysts as the consensus forecast does not qualitatively affect my results.

Carbon Emissions. I first calculate the sum of Scope 1 and Scope 2 emissions to obtain a comprehensive measure of carbon emissions under the direct control of the firm.[5] There is a discussion in the literature as to whether total carbon emissions or carbon intensity is the correct metric to consider (e.g., Aswani et al., 2024). I do not take a position in this discussion and also construct two additional measures of carbon intensity, the first scaling total emissions by assets and the second scaling total emissions by sales. Finally, I compute the growth rate of scaled and unscaled emissions for firm i in year t as $\widehat{CO}_{2_{it}} = \log CO_{2_{it}} - \log CO_{2_{i,t-1}}$.

2.2 Forecast Errors and Carbon Emissions

I provide two stylized facts. The first concerns the empirical distribution of forecast errors and replicates existing evidence (e.g., Dechow et al., 1995, Roychowdhury, 2006, Marinovic et al., 2013, Hong and Kacperczyk, 2010, Errico et al., 2023, Terry, 2023). The second concerns the discontinuity of carbon emission growth at the zero forecast error and is novel.

I start by examining the distribution of forecast errors, which is displayed in Figure 1. I find that firms bunch disproportionately just above the zero forecast error threshold, with relatively few firms showing small misses.[6] The figure suggests the existence of systematic pressure to reach short-term profit targets, consistent with survey evidence (Graham et al., 2005). Managers may take opportunistic actions, such as cutting discretionary expenditures like advertising or R&D (e.g., Bhojraj et al., 2009, Corredoira et al., 2021, Terry, 2023), increasing markups (e.g., Errico et al., 2023), or adjusting the quantity produced (e.g., Roychowdhury, 2006, Zhang and Gimeno, 2010) to respond to short-term pressures. Investments in

[5] In a robustness test, I show that my results are not affected when Scope 1 and Scope 2 emissions are considered separately (see Table B.4).

[6] In the Online Appendix, I show that the pattern described in Figure 1 is robust to other forecast error measures (see Figure B.1).

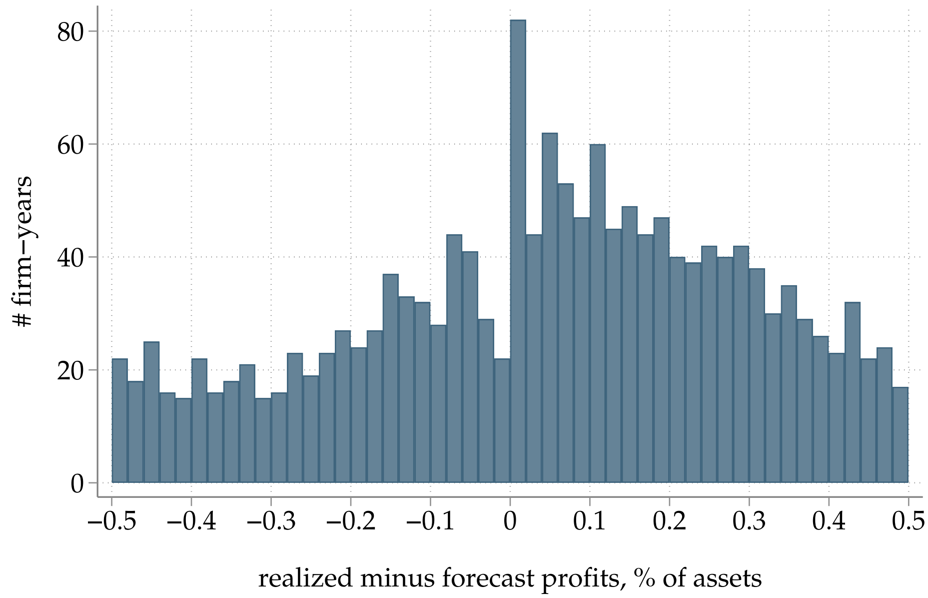

Figure 1—BUNCHING AT THE ZERO FORECAST ERROR

Notes: The figure plots the histogram of forecast errors based on the Compustat/IBES/Trucost merged sample, which includes 3,147 observations from 493 firms between 2006 and 2019. Realized profits are fiscal year dollar street earnings. Forecast profits are median analyst earnings forecasts at a four-quarter horizon. The difference between realized and forecast profits is scaled by book assets. Realized street profits and forecast profits are from IBES, while assets are from Compustat.

carbon abatement are a likely target for earnings manipulation as the uncertain benefits may only materialize in the long-term, while the cost decrease earnings today.

To measure opportunistic cuts in carbon abatement investments, I apply a standard regression discontinuity estimator and estimate the following local linear regression

$$\widehat{CO}_{2_{it}} = \alpha + \beta fe_{it} + \gamma fe_{it}\mathbb{1}(fe_{it} \geq 0) + \delta\mathbb{1}(fe_{it} \geq 0) + \tau_t + \eta_i + \varepsilon_{it}, \tag{2}$$

where $\widehat{CO}_{2_{it}}$ is the growth rate of carbon emissions or intensity and fe_{it} is the forecast error for firm i in year t. I include firm and year fixed effects when estimating equation (2) to control for time-invariant heterogeneity across firms and business cycle effects. The parameter of interest, δ, captures the average difference in carbon emissions growth between firms that just hit and firms that just missed their profit targets.

Table 1 reports the results. Column (1) shows that firms that just meet analysts' profit targets have carbon emission growth that is about 4.73 percentage points higher than firms

Table 1—Carbon emissions at the zero forecast error threshold

	(1)	(2)	(3)
Emissions Growth	CO_2	CO_2/Assets	CO_2/Sales
Mean Change at	4.73	4.99	4.30
0 Threshold (p.p.)	(2.51)	(2.52)	(2.30)
Standardized (%)	11.74	11.93	10.70
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Obs.	3,147	3,147	3,147

Notes: The table reports the estimated mean differences in firms' emissions policies around the zero forecast error threshold. Standardized values express the point estimates in terms of the standard deviation of the outcome variable. Column (1) compares the growth rate of carbon emissions, column (2) carbon emissions scaled by assets, and column (3) carbon emissions scaled by sales for firms that just beat and firms that just missed the consensus earnings forecast. Estimates are obtained using local linear regression with a triangular kernel and optimal Calonico, Cattaneo, and Farrell (2020) bandwidth. Standard errors are clustered by firm and robust t-statistics are shown in parentheses.

that just miss, consistent with opportunistic cuts in carbon mitigation investments to meet short-term earnings targets. This difference is economically significant, amounting to 12% relative to the standard deviation of carbon emission growth rates. The discontinuity is equally pronounced when I examine the growth rate of carbon intensity in columns (2) and (3), i.e., carbon emissions scaled by assets or sales, consistent with the interpretation that firms to the right of the discontinuity do not solely grow faster than firms to the left, but actually become less carbon-efficient.

One caveat is that I do not observe actual carbon abatement investments, only firms' carbon emissions, which are the result of the abatement process. If the discontinuities documented in Table 1 were due to opportunistic cuts in abatement investment, I would expect only some persistence, with growth differentials becoming gradually insignificant over time. Figure 2 plots the average difference in carbon emissions growth for the years t to $t + 3$ between firms that just meet analysts' profit targets and firms that just miss them in year t. When firms beat earnings targets by a small margin in year t, Panel A shows that their unscaled carbon emissions growth is significantly higher for the years t and $t + 1$, and then becomes gradually insignificant again. Moreover, Panels B and C indicate that the discontinuity is slightly more pronounced for the carbon intensity, consistent with a short-term drop in carbon efficiency induced by cuts in carbon abatement investments.

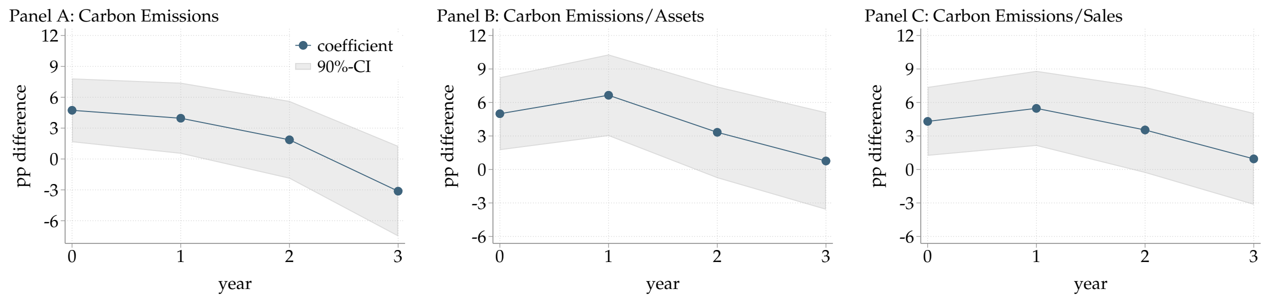

Figure 2—DYNAMIC EFFECT ON CARBON EMISSIONS

Notes: The figure plots the average difference in carbon emissions growth for the years t to $t+3$ between firms that just meet analysts' profit targets and firms that just miss them in year t. Panel A compares the contemporaneous and future growth rates of carbon emissions, Panel B carbon emissions scaled by assets, and Panel C carbon emissions scaled by sales for firms that just beat and firms that just missed the consensus earnings forecast in year t. Estimates are obtained using local linear regression with a triangular kernel and optimal Calonico, Cattaneo, and Farrell (2020) bandwidth. Standard errors are clustered by firm and 90% confidence bands are displayed.

An alternative explanation could be that firms on the verge of missing analysts' increase output to shift fixed costs to future periods (e.g., Roychowdhury, 2006, Zhang and Gimeno, 2010). Such actions would increase carbon emissions in t, similar to reductions in carbon abatement investments. However, since firms are unlikely to produce in excess of demand for an extended period of time, one would expect the growth in output and thus carbon emissions to be significantly lower or even negative in future years, which is inconsistent with the evidence presented in this section. In summary, the results are consistent with discretionary short-termist cuts in carbon abatement investments.

2.3 Robustness of Reduced-Form Results

I perform several tests to show that the reduced-form results are robust. In Figure B.1, I document that the bunching pattern is robust to the use of alternative forecast error measures. In particular, I show that scaling by lagged sales instead of assets, using a relative forecast error measure computed via $2\frac{fe_{it}}{|street_{it}|+|consensus_{it}|}$, and using the mean forecast across all analysts as the consensus forecast does not qualitatively affect my results.

In my baseline estimation, I exclude observations for which Trucost imputed carbon emissions because their estimates are shown to depend heavily on firm fundamentals such as sales and assets (Aswani et al., 2024). In Table B.3, I present the discontinuity results based on the full sample. Specifically, the estimated discontinuities become smaller in magnitude but remain statistically significant for unscaled carbon emissions and carbon emissions scaled by assets. For carbon emissions scaled by sales, the results become insignificant. This overall pattern is to be expected, as the variation in imputed emissions may well be controlled for by the normalization and firm fixed effects. Moreover, I show that the results become stronger when Scope 1 emissions are considered individually and continue to hold for Scope 2 emissions (Table B.4). The main specification in Table 1 uses the optimal bandwidth bw^* according to Calonico et al. (2020). In Figure B.2, I vary the bandwidth in the range $[0.5bw^*, 1.5bw^*]$ and find that the results are robust.

Several points are important to highlight. The results in this section do not represent the causal effect of short-termism on carbon emissions. As in Terry (2023), the discontinuities are not the causal effect of achieving a profit target, but serve only as an endogenous detection mechanism. Moreover, these reduced-form stylized facts represent only local, relative variation that may not survive aggregation. Finally, local discontinuities do not provide counterfactuals for an economy without short-term incentives. In the remainder of this paper, I develop and estimate a quantitative model to address these concerns.

3 A Toy Model of Short-Termism and Carbon Emissions

Environment. I develop a stylized two-period toy model with optimal short-term incentives for managers and endogenous carbon emissions to illustrate the key mechanism through which short-termism affects carbon emissions. The model consists of a single firm, risk-neutral managers, a board of directors, and outside analysts.

The firm lives for two periods, t and $t+1$, and generates exogenous revenues Q per period.[7] The firm faces a trade-off when deciding its carbon emissions policy: reducing carbon emissions e_t in t is costly, but high carbon emissions in t may trigger a negative cash

[7] I assume that the firm's revenues, i.e., the outcome of supply and demand shocks, are exogenous. In particular, I abstract away the possibility that managers may choose to increase output in response to short-term pressures for two reasons. First, the evidence presented in Figure 2 is inconsistent with significant short-run adjustments in the quantity produced. Second, from a conceptual point of view, adjusting output may be more difficult than delaying investment.

flow shock in $t+1$. The cost of carbon abatement is given by

$$c(Q, e_t) = \psi \left(\frac{Q}{e_t}\right)^2 = \frac{\psi}{\eta_t^2}, \tag{3}$$

where higher values for ψ imply that the firm is less cost-efficient in reducing carbon emissions and η_t is the firm's carbon intensity.[8] High carbon emissions in t may cause costly regulation or decreasing demand from consumers, so cash-flows in $t+1$ are reduced in expectation by αe_t. Thus, managers face an intertemporal trade-off between costly emission reductions today and negative cash flow shocks in the future. Firm value $V(e_t)$ is therefore given by

$$V(e_t) = Q - \psi \left(\frac{Q}{e_t}\right)^2 + \frac{1}{R}\left(Q - \alpha e_t\right), \tag{4}$$

where $R > 1$ is the real interest rate, which is taken given by the firm. Moreover, per-period profits in t are cash flows plus accounting noise

$$\Pi_t = Q - \psi \left(\frac{Q}{e_t}\right)^2 + \nu_t, \quad \nu_t \sim N(0, \sigma_\nu^2).$$

The noise term ν_t, with cdf F_ν and pdf f_ν, is unobserved by managers when determining carbon emissions.

There exists a representative outside analyst who observes Q and issues profit forecasts according to

$$\Pi_t^f = Q - \psi \left(\frac{Q}{e_t^f}\right)^2. \tag{5}$$

The board of directors determines the compensation package for managers, which consists of an equity component θ_d and a short-term clawback θ_π that the manager must pay if she fails to meet analysts' profit forecasts.[9] In addition, managers incur private cost $\phi_e < 0$

[8] There are no carbon abatement investments in period $t+1$ as this is the final period in the toy model.

[9] One might ask why boards do not contract directly on carbon emissions. An intuitive answer might be that carbon emissions are difficult to measure and therefore difficult to enforce. In contrast, analysts' profit forecasts are a widely available tool to impose cost discipline on managers, either by explicitly modeling compensation as discussed in this section, or by refusing to insulate managers from external pressures. Moreover, I abstract away from modeling ESG performance pay as recent studies show that ESG performance goals do not affect executive pay in a quantitatively meaningful way (e.g., Badawi and Bartlett, 2024, Efing et al., 2024).

from carbon emissions.[10] These private cost may arise for several reasons. First, some managers may care about climate change and therefore incur non-pecuniary cost from high carbon emissions. Second, even if managers do not care about climate change, they may care about their firm's carbon emissions because of career concerns. Consistent with anecdotal evidence, managers communicate their firm's emissions policy to the public, such as in earnings calls or press interviews, where they may be held accountable for high carbon emissions. Being portrayed as an environmentally irresponsible manager is a risk to successful career advancement, so managers derive private disutility from carbon emissions. The manager's objective is

$$V_m(e_t|\theta_\pi, \Pi_t^f) = Q - \psi \left(\frac{Q}{e_t}\right)^2 + \frac{1}{R}(Q - \alpha e_t) - \theta_\pi \mathbb{P}(\Pi_t < \Pi_t^f) + \phi_e e_t, \tag{6}$$

where I normalized the equity share $\theta_d = 1$ without loss of generality. Importantly, the probability of missing profit targets $\mathbb{P}\left(\Pi_t < \Pi_t^f\right) = F_\nu\left(\psi Q^2\left[(1/e_t)^2 - (1/e_t^f)^2\right]\right)$ is decreasing in carbon emissions e_t.

Equilibrium. An equilibrium with rational expectations, optimal short-term incentives, and unbiased analyst forecasts is defined as: i) managers determine carbon emissions e_t to maximize their utility conditional on analysts' profit forecasts and board-determined short-term incentives θ_π; ii) analysts issue rational forecasts conditional on their information set; iii) the board of directors optimally chooses short-term incentives θ_π^* to maximize firm value given managers' choices.

Optimal Policies. Figure 3 plots firm value and manager payoffs as a function of carbon emissions in an illustrative paramterization. The level of carbon emissions that maximizes firm value (4) is given by

$$e_t^* = \left(\frac{2R\psi Q^2}{\alpha}\right)^{1/3}. \tag{7}$$

[10] As noted above, I assume that managers derive private costs from carbon emissions to rationalize the existence of short-term incentives and to endogenously characterize the optimal compensation contract. However, my main results do not rely on the assumption that managers incur private costs from carbon emissions, but I could alternatively assume that short-term incentives exist for exogenous reasons unrelated to carbon emissions, consistent with survey evidence (e.g., Graham et al., 2005).

Manager payoffs without short-term incentives are depicted by the thick grey line in Figure 3. Since managers incur private cost from carbon emissions, the optimal level of carbon emissions from the manager's perspective and in the absence of short-term incentives is

$$e_t^{\text{noST}} = \left(\frac{2R\psi Q^2}{\alpha - R\phi_e} \right)^{1/3}, \tag{8}$$

with $e_t^{\text{noST}} < e_t^*$ as $\phi_e < 0$.[11] Thus, without short-term incentives, the manager chooses a level of carbon emissions that is lower than the value-maximizing level from the perspective of shareholders. To restore the level of carbon emissions, e_t^*, that maximizes firm value, the board of directors optimally introduces short-term incentives according to[12]

$$\theta_\pi^* = -\frac{R\phi_e}{\alpha f_\nu(0)}. \tag{9}$$

The resulting manager payoff is plotted by the blue thick line and shows that the optimal level of carbon emissions from the perspective of shareholders is restored in equilibrium.

Intuitively, short-term incentives preserve firm value maximization because they impose cost discipline on conflicted managers. Since managers incur private cost from carbon emissions, in the absence of short-term incentives they would want to choose lower levels of carbon emissions relative to shareholders. However, with short-term incentives, reducing carbon emissions increases the likelihood of missing short-term profit targets, which pushes managers back to the firm's value-maximizing level e_t^*. Although the toy model conveys the mechanism by which short-term incentives can increase carbon emissions, it lacks features that make it realistic enough to confront the data. I now develop a quantitative model with endogenous carbon emissions and short-term incentives for managers that can replicate key moments in the data.

[11] Expression (8) is obtained by maximizing Equation (6) with respect to carbon emissions e_t and setting $\theta_\pi = 0$.

[12] Expression (9) is pinned down by maximizing Equation (4) with respect to θ_π, taking managers' choices and analysts' rational profit forecasts as given.

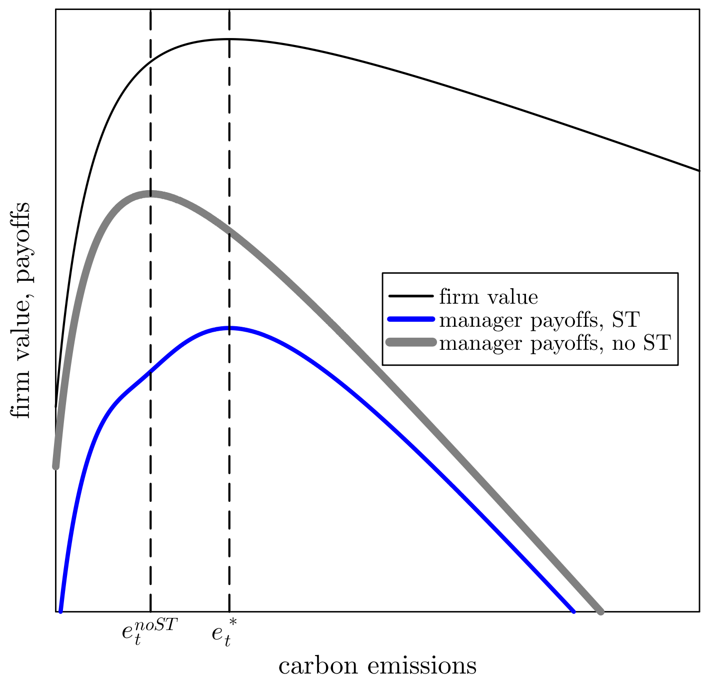

Figure 3—CARBON EMISSIONS IN THE TOY MODEL
Notes: The figure plots firm value (thin grey line) and manager payoffs (thick grey and blue lines) as a function of carbon emissions e_t in an illustrative parameterization.

4 Quantitative Model

In the spirit of Terry (2023), I analyze the quantitative effect of short-termism on carbon emissions in a dynamic, infinite-horizon, discrete-time model with heterogeneous firms, optimal short-term incentives for managers, and endogenous carbon emissions. Although the quantitative model is more involved, the main intuition from the toy model carries over.

4.1 Model Environment

Firms. The economy is populated by a unit mass of firms, indexed by i. Each firm is managed by a risk-neutral manager whose compensation contract is determined by the board of directors. Firms generate sales that follow an exogenous lognormal process

$$\log q_{i,t+1} = \rho \log q_{i,t} + z_{i,t+1}, \quad z_{i,t+1} \sim N(0, \sigma_z^2). \tag{10}$$

I assume that variable inputs absorb a fixed share, so operating revenues are $(1-l)q_{i,t}$, where l is the labor share.

Managers choose the level of carbon emissions $e_{i,t}$. The cost of carbon abatement is given by

$$c(q_{i,t}, e_{i,t}) = \psi \left(\frac{q_{i,t}}{e_{i,t}}\right)^2 = \frac{\psi}{\eta_{i,t}^2}, \tag{11}$$

where higher values of ψ imply that firms are less cost-efficient in reducing carbon emissions. Note that $c(q_{i,t}, e_{i,t})$ goes to zero as carbon intensity, $\eta_{i,t}$, approaches infinity, while cost explode as carbon intensity approaches zero. Therefore, reducing carbon intensity becomes more costly as carbon intensity decreases, a property similar to diminishing returns in standard production functions.

High carbon emissions in t may cause costly regulation or decreasing demand from consumers, so cash-flows in $t+1$ are reduced in expectation by $\alpha e_{i,t}$. Thus, managers face an intertemporal trade-off between costly emission reductions today and negative cash flow shocks in the future. This structure is realistic for two reasons. First, carbon emissions are reported with a time lag. Second, Meier et al. (2023) shows that sales respond to one-year lagged ESG information. Firm profits are operating revenues adjusted for cash flow shocks from past carbon emissions, carbon abatement cost, and accounting noise:

$$\Pi_{i,t} = (1-l)q_{i,t} - \alpha e_{i,t-1} - \psi \left(\frac{q_{i,t}}{e_{i,t}}\right)^2 + q_{i,t}\varepsilon_{i,t} + q_{i,t}\nu_{i,t}, \tag{12}$$

where $\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$ is noise observable to the manager when decisions are made, while $\nu_{i,t} \sim N(0, \sigma_\nu^2)$ is noise unobservable to the manager when decisions are made.

Managers. In each period, a risk-neutral manager maximizes her utility by choosing the level of carbon emissions. As in the toy model, the manager incurs private cost $\phi_e < 0$ per unit of carbon emissions, which incentivizes the manager to reduce carbon emissions below the level that is optimal from shareholders' perspective. However, as explained above, private costs are only necessary to rationalize the existence of short-termism and to characterize optimal compensation in the model. Importantly, my main results do not rely on this specific assumption, but I could simply assume that short-term incentives exist for exogenous reasons, which would be consistent with survey evidence (e.g., Graham et al., 2005).

The manager's contract consists of an equity component θ_d, and a short-term clawback θ_π that the manager must pay if she fails to meet analysts' earnings targets. As in the toy model, I abstract away from modeling ESG performance pay as ESG performance goals do not affect executive pay in a quantitatively meaningful way (e.g., Badawi and Bartlett, 2024, Efing et al., 2024). Thus, the manager solves the dynamic problem

$$\begin{aligned} V_M(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t}) = \max_{e_{i,t}} \Bigg\{ & \theta_d \left[(1-l)q_{i,t} - \alpha e_{i,t-1} - \psi \left(\frac{q_{i,t}}{e_{i,t}} \right)^2 \right] \\ & - q_{i,t}\theta_\pi \mathbb{P}_\nu \left(\Pi_{i,t} < \Pi^f_{i,t} \right) \\ & + \phi_e e_{i,t} + \frac{1}{R_t} \mathbb{E}_t \left[V_M(e_{i,t}, q_{i,t+1}, \varepsilon_{i,t+1}) \right] \Bigg\}, \end{aligned} \tag{13}$$

where I set the equity share $\theta_d = 1$ without loss of generality when solving and estimating the model.

Analysts. A mass of risk-neutral, rational analysts receives private benefits from accurately predicting firms' profits. Analysts issue their optimal forecasts conditional on the available information at time t. In particular, analysts observe revenues $q_{i,t}$ and past emissions $e_{i,t-1}$ of the firm. Moreover, analysts observe the cost structure of the firm. However, they do not observe either component of the profit noise, $\varepsilon_{i,t}$ or $\nu_{i,t}$. I assume that analysts' private benefits decline in mean squared prediction error, so rational forecasts are characterized by

$$\Pi^f_{i,t}(e_{i,t-1}, q_{i,t}) = \arg\min_{\Pi^f_i} \mathbb{E}_t \left\{ \left(\Pi_{i,t} - \Pi^f_i \right)^2 \mid e_{i,t-1}, q_{i,t} \right\} = \mathbb{E}_t[\Pi_{i,t} \mid e_{i,t-1}, q_{i,t}]. \tag{14}$$

Board of Directors. Because of the private cost of carbon emissions, managers are conflicted and want to choose lower carbon emissions than is optimal from the firm's perspective. The board knowingly implements short-term incentives $\theta_\pi > 0$ to impose cost discipline on managers and align their interests with those of shareholders. Given managers' optimal emissions policy $e^*_{i,t}$, the value of the firm reads as

$$V_F(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t}) = \left\{(1-l)q_{i,t} - \alpha e_{i,t-1} - \psi\left(\frac{q_{i,t}}{e^*_{i,t}}\right)^2 + \frac{1}{R_t}\mathbb{E}_t\left[V_m(e^*_{i,t}, q_{i,t+1}, \varepsilon_{i,t+1})\right]\right\}. \quad (15)$$

Let $F(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t})$ be the unconditional stationary distribution from a given choice of short-term incentives θ_π. The board of directors of each firm determines the optimal level of short-term incentives θ^*_π to maximize the firm's unconditional mean value by solving for

$$\theta^*_\pi = \arg\max_{\theta_\pi} \int V_F(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t} \mid \theta_\pi) dF(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t} \mid \theta_\pi). \quad (16)$$

Three points are worth discussing. Without the agency conflict, the manager problem coincides with the firm problem and the optimal short-term incentives are $\theta^*_\pi = 0$. With private cost from carbon emissions for managers, optimal short-term incentives increase firm value and carbon emissions. Unlike in the toy model, short-term incentives do not restore the equilibrium without agency conflicts because managers have private information about profit noise.

4.2 Equilibrium

An equilibrium with rational expectations and optimal short-term incentives consists of a policy function $e^*(e_{-1}, q, \varepsilon)$, manager and firm value functions, $V_M(e_{-1}, q, \varepsilon)$ and $V_F(e_{-1}, q, \varepsilon)$, a schedule of optimal profit forecast $\Pi^f(e_{-1}, q)$, optimal short-term incentives θ^*_π, and a stationary distribution of firms $F(e_{-1}, q, \varepsilon)$ such that:

(i) The manager chooses $e^*(e_{-1}, q, \varepsilon)$ to solve Equation (13) given analysts' short-term profit forecasts $\Pi^f(e_{-1}, q)$ and board-determined short-term incentives θ_π;

(ii) Analysts' profit forecasts solve Equation (14) conditional on the optimal emissions policy $e^*(e_{-1}, q, \varepsilon)$ set by managers;

(iii) The board of directors determines θ^*_π to solve Equation (16) conditional on managers' optimal emissions policy $e^*(e_{-1}, q, \varepsilon)$ and analysts' forecasts $\Pi^f(e_{-1}, q)$;

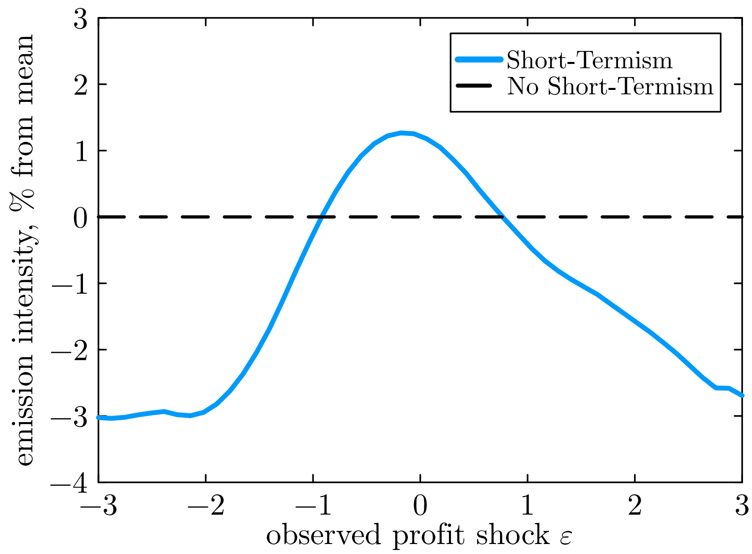

Figure 4—CARBON EMISSIONS POLICY

Notes: The figure plots the model-implied emissions intensity as a function of the observed profit shock ε. The blue line illustrates the emissions policy with optimal short-term incentives (θ_π^*). The dashed line depicts the emissions policy with no short-term incentives ($\theta_\pi = 0$). The emissions intensity is expressed in percentage deviations from the mean. The observed profit shock is expressed in standard deviations. The policy is based on the estimated parameters reported in Table 2.

(iv) The stationary distribution of firms $F(e_{t-1}, q, \varepsilon)$ is consistent with the stochastic processes for q and ε and managers' emissions policy $e^*(e_{-1}, q, \varepsilon)$.

In Appendix C.1, I describe the numerical algorithm used to find the stationary equilibrium.

4.3 Manager Policies

In Figure 4, I plot the model-implied emissions intensity as a function of the observed profit noise ε. The blue line shows the emissions policy under my baseline parameter estimates with optimal short-term incentives ($\theta_\pi = \theta_\pi^*$), while the dashed line shows the counterfactual emissions policy with no short-term incentives ($\theta_\pi = 0$). The emissions intensity is expressed in percentage deviations from the mean. The observed profit shock is expressed in standard deviations. Without short-termism, managers rationally ignore the profit noise ε. With short-term incentives, however, managers react to profit noise. For small absolute values of profit noise, managers correctly infer that they are close to the target, and opportunistically cut spending on carbon abatement to reduce the probability of missing analysts' profit targets.

In contrast, for large absolute values of profit noise, managers understand that they will either miss or beat short-term profit targets, so their optimal emissions policy in such states is dominated by their private disutility from carbon emissions, leading to below-average emissions intensity.

In summary, short-termism affects carbon emissions in two ways. First, carbon emissions show increased sensitivity to profit noise due to opportunistic cuts in carbon abatement investments when managers are close to targets. Second, short-termism poses a persistent threat of missing targets for managers. In particular, the perceived marginal cost of carbon abatement can be obtained from differentiating managers' time-t payoffs with respect to carbon emissions

$$\frac{2\psi q_{i,t}^2}{e_{i,t}^3} + \phi_e - q_{i,t}\theta_\pi \frac{\partial}{\partial e_{i,t}} \mathbb{P}_\nu \left(\Pi_{i,t} < \Pi_{i,t}^f \right).$$

The total marginal cost of carbon abatement consists of the physical cost of carbon abatement, $\frac{2\psi q_{i,t}^2}{e_{i,t}^3}$, net of managers' private disutility from carbon emissions, $\phi_e < 0$, and the expected marginal loss in compensation due to a higher probability of missing analysts' profit targets. Since the probability of missing analysts' profit targets decreases in carbon emissions, i.e., $\frac{\partial}{\partial e_{i,t}} \mathbb{P}_\nu \left(\Pi_{i,t} < \Pi_{i,t}^f \right) < 0$, short-termism increases the marginal cost of carbon abatement and thus carbon emissions in equilibrium. I estimate the magnitude of this effect in my quantitative analysis.

5 Quantitative Results

In this section, I structurally estimate the model and quantify the impact of short-termism on carbon emissions. Section 5.1 discusses the structural estimation of the parameters, while Section 5.2 documents the quantitative impact of short-termism on carbon emissions. Finally, I present a range of additional robustness analyses in Section 5.3.

5.1 Structural Estimation

I externally calibrate the real interest rate and the labor share. Following Terry (2023), I set the real interest rate R to 1.06 per year. The labor share is set to 0.6 (Karabarbounis, 2024).

Table 2—BASELINE MODEL RESULTS

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.9305	0.0000
Std of sales shock	σ_z	0.0866	0.0003
Std of observed profit shock	σ_ε	0.0094	0.0005
Std of unobserved profit shock	σ_ν	0.0081	0.0009
Private cost of managers	ϕ_e	-0.2097	0.0015
Cost of carbon abatement	ψ	0.0091	0.0003
Future cost of carbon	α	1.3730	0.0010
Std of measurement error in carbon emissions	σ_e	0.0779	0.0139
Panel B: Targeted moments	**Data**	**Model**	**t-stat**
Mean carbon intensity	0.1746	0.2366	-3.00
Std of forecast error	0.3329	0.3863	-4.91
Std of sales growth	0.1104	0.0990	1.83
Std of profitability	0.0322	0.0423	-4.66
Std of carbon intensity	0.0737	0.0812	-0.40
Correlation of sales growth, profitability	0.1222	0.6849	-13.83
Correlation of sales growth, carbon intensity	-0.1480	-0.0471	-4.61
Correlation of profitability, carbon intensity	-0.1039	-0.1272	0.60
Correlation of profitability, forecast error	0.1877	0.2699	-3.46
Correlation of carbon intensity, forecast error	-0.0106	-0.0073	-0.09
Correlation of sales growth, forecast error	0.1333	0.0678	13.07
Prob of meeting forecast	0.5703	0.5578	4.94
Prob. of just meeting to prob. of just missing	1.4864	1.3635	27.21
Panel C: Quantitative Impacts			
Optimal short-term incentives, θ_π^*			0.24%
Mean carbon abatement cost increase from short-termism			6.90%
Δ Firm profits without short-termism			-0.43%
Δ Carbon emissions without short-termism			-2.19%

Notes: The table reports the baseline results from the structural estimation. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. The actual data moments are computed from a panel that comprises earnings surprises, financial data, and carbon emissions for 3,147 observations from 493 firms between 2006 and 2019. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ_π^*, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Simulated Methods of Moments. I estimate the remaining parameters of the model in Table 2. Measuring carbon emissions is much more difficult than measuring other firm fundamentals such as assets or sales. Therefore, I assume that there is measurement error in carbon emissions. So, I add i.i.d. Gaussian noise with variance σ_e^2 to carbon emissions in the simulation and determine σ_e in the structural estimation. In total, I estimate eight parameters using SMM. My identification strategy considers 13 moments computed from the merged Compustat/IBES/Trucost dataset. I target the full correlation matrix of sales growth, profitability, carbon intensity, and forecast errors.[13] These moments are particularly informative about the parameters that drive firm fundamentals.

Moreover, I focus on two local moments around the zero forecast error, one being the probability of meeting analysts' forecasts, defined as the percentage of positive forecast errors, and the other being the extent of bunching above the zero forecast error threshold. More specifically, the latter moment is defined as the ratio of the number of firms whose earnings exceed analysts' forecasts by a maximum of ten percent to the number of firms whose earnings fall short of analysts' expectations by a maximum of ten percent. As in Terry (2023), these two local moments help to identify managers' private cost of carbon emissions, which is reflected in the degree of short-termism in the model. Finally, I target the average carbon intensity to pin down the ratio of cost and benefits of reducing carbon emissions.

I choose the parameter vector θ so that the simulated moments from the model are close to the actual data moments. More formally, the optimal parameter vector, $\hat{\theta}_{SMM}$, is defined by

$$\hat{\theta}_{SMM} = \arg\min_{\theta} \Big(m(X \mid \theta) - m(X)\Big) W \Big(m(X \mid \theta) - m(X)\Big)', \tag{17}$$

where $m(X)$ is the moment vector computed from the actual data and $m(X \mid \theta)$ is the moment vector computed from the simulated data. I use the optimal weight matrix W and cluster standard errors by firm (Hansen and Lee, 2019). For a given parameter vector θ, I generate a panel of $1,000$ firms for 25 years with a burn-in period of 25 years. I then compute the simulated moments and compare them to the actual data moments. I use the Simulated Annealing algorithm to find the minimum in Equation (17).

[13] Sales growth is defined as $2\frac{q_{i,t}-q_{i,t-1}}{|q_{i,t}|+|q_{i,t-1}|}$, which uses a robust growth rate formula that is conveniently bounded between -2 and 2 (Davis and Haltiwanger, 1992). Profitability and carbon intensity are profits and carbon emissions scaled by sales. Moreover, I follow Terry (2023) and use the percentage forecast error in my structural estimation, which is computed according to $2\frac{\Pi_{i,t}-\Pi^f_{i,t}}{|\Pi_{i,t}|+|\Pi^f_{i,t}|}$.

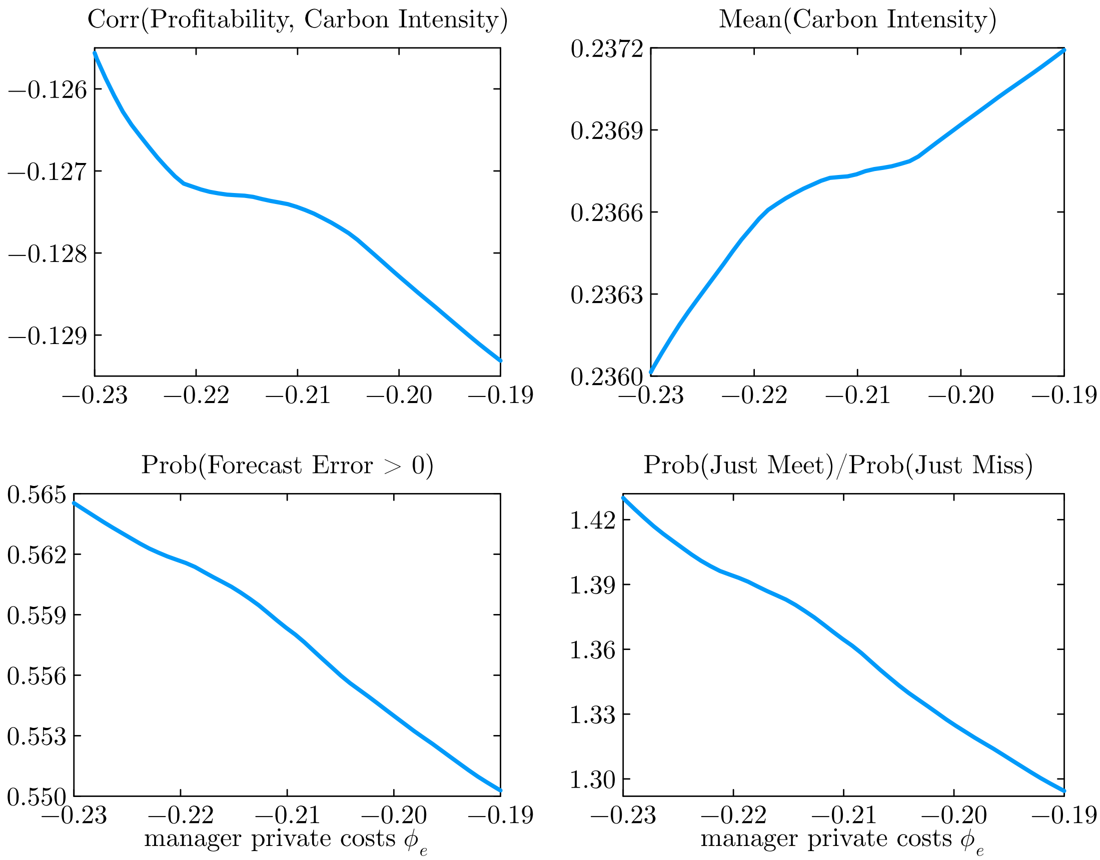

Figure 5—IDENTIFICATION OF PRIVATE MANAGER COST PARAMETER ϕ_e

Notes: The figure plots selected, smoothed moments as a function of managers' private cost of carbon emissions ϕ_e for values below and above the estimated $\phi_e = -0.21$.

Identification. Next, I discuss the identification of the parameters. Figure 5 plots selected moments that are particularly helpful in identifying managers' private cost of carbon emissions ϕ_e. With lower ϕ_e and thus more short-termism, managers engage more in opportunistic cuts in carbon abatement investments. Hence, the correlation between profitability and carbon intensity increases moderately (top left). If managers care more about carbon emissions, the mean carbon intensity decreases (top right). Although short-term incentives neutralize the agency conflict to some extent, they do not fully eliminate managers' private incentives because managers have private information about profit noise. Moreover, a lower ϕ_e induces managers to meet profit forecasts more often (bottom left). Likewise, the bunching around the zero forecast error increases with the degree of short-termism (bottom right). Thus, the agency conflict parameter ϕ_e is identified from global moments related to firm fundamentals and local moments related to forecast error patterns.

The identification of the other parameters is standard. Figure C.3 in the Online Appendix shows selected targeted moments that are particularly useful for identifying the remaining parameters of the model. The correlation between sales growth and profitability decreases with the persistence of sales ρ (top left). Increased volatility in the sales shock σ_z intuitively generates a higher standard deviation of sales growth (top middle). The top right panel shows that an increase in profits noise observable to the manager σ_ε leads to a higher standard deviation of forecast errors because the amount of private information available to managers increases. In contrast, an increase in unobservable profit noise σ_ν reduces the extent of bunching at zero forecast error because managers can no longer accurately target analysts' forecasts (middle left). A higher cost of carbon abatement ψ increases the mean carbon intensity in the model (middle middle), while higher future cost of carbon α lead to a lower mean carbon intensity (middle right). Finally, the bottom middle panel shows that the standard deviation of measurement error in carbon emissions σ_e is identified from the standard deviation of carbon intensity.

Baseline Estimates. Panel A of Table 2 reports my baseline parameter estimates, which are broadly in line with Errico et al. (2023) and Terry (2023). The estimated persistence of the sales process is high with $\hat{\rho} \approx 0.93$. Moreover, the ratio of earnings noise observed by managers, $\frac{\hat{\sigma}_\varepsilon^2}{\hat{\sigma}_\varepsilon^2+\hat{\sigma}_\nu^2} \approx 0.57$, suggests moderate information asymmetries. Managers incur quantitatively significant private cost from carbon emissions. The perceived private cost amount to about 14.9% of the mean physical marginal cost of carbon abatement $\int 2\psi q_{i,t}^2/e_{i,t}^3 dF(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t}) \approx 1.41$. In response, the board of directors chooses moderately large short-term incentives with $\hat{\theta}_\pi \approx 0.24\%$. Thus, missing analyst's targets is as costly for managers as a one-time loss of 0.24% of mean production profits.

Model Fit. Panel A of Table 2 compares the data moments with the simulated moments implied by my baseline parameter estimates. In summary, the model fits the data reasonably well. The mean carbon intensity in the data is about 0.1746, while it is 0.2366 in the model. The standard deviations of the forecast error, sales growth, profitability, and carbon intensity are closely reproduced by the model. The model is able to match all signs of the targeted correlations, which is difficult due to the coexistence of slightly negative and positive correlations. Moreover, the magnitudes of the correlations generally fit well. For example, the correlation between profitability and carbon intensity is -0.1029 in the data, while it is -0.1272 in the model. Finally, the model fits the local moments associated with the probability of hitting analysts' profit targets and the bunching pattern at the zero forecast error threshold.

5.2 The Quantitative Impact of Short-Termism

I use the estimated model to run counterfactual simulations and compare various quantities in an economy with short-term incentives $\theta_\pi^* > 0$ to an economy without short-termism. As outlined above, managers' perceived private cost of carbon emissions amount to 14.9% of the mean physical cost of carbon abatement. Short-term incentives increase the marginal cost of carbon abatement via the expected marginal loss in compensation due to a higher probability of missing analysts' profit targets, which can be estimated by $-\theta_\pi^* \int q_{i,t} \frac{\partial}{\partial e_{i,t}} \mathbb{P}_\nu \left(\Pi_{i,t} < \Pi_{i,t}^f \right) dF$ $(e_{i,t-1}, q_{i,t}, \varepsilon_{i,t})$. Relative to the average physical cost of carbon abatement, short-termism increases the marginal cost of carbon abatement by 6.9%, which may be interpreted as an economically meaningful carbon subsidy. In total, boards only partially reverse managers' private incentives because managers have private information about profit noise, and thus short-termism also causes value-destroying cuts in carbon abatement when managers are close to targets.

I compare carbon emissions and firm profits in my estimated model with optimal short-term incentives $\hat{\theta}_\pi \approx 0.24\%$ to a counterfactual economy with no short-termism. I find that eliminating short-termism from managers' contracts reduces firms' profits by 0.43% and carbon emissions by 2.19%. At the aggregate level, short-termist carbon emissions amount to about 142 million tons of CO_2 when benchmarked against the level of aggregate emissions in the U.S. economy in 2022. This amount is equivalent to total U.S. aviation emissions in 2022.

The average firm in my sample earns $\$1015$ million in annual profits while emitting 2.39 million tons of CO_2. Thus, each ton of carbon dioxide saved by eliminating short-termist incentives costs about $\$84$ in 2017 USD. Rennert et al. (2022) estimate that the social cost of carbon ranges from $\$42$ to $\$397$, with the preferred estimate being $\$178$ in 2017 USD. Since

Table 3—SUBSAMPLE ANALYSES

	Optimal Short-Term Incentives, θ_π^* (%)	Carbon Abatement Cost Increase (%)	Δ Firm Profits (%)	Δ Carbon Emissions (%)
Baseline estimates	0.24	6.90	−0.43	−2.19
Full sample	0.41	12.65	−0.55	−4.02
Before Paris Agreement	0.26	11.42	−0.89	−3.35
Post Paris Agreement	0.19	5.90	−0.43	−1.88
Low carbon intensity sample	0.59	14.45	−0.29	−2.14
High carbon intensity sample	0.69	12.40	−1.54	−3.90
Young CEOs	0.14	7.68	−0.46	−2.13
Old CEOs	0.23	6.53	−0.44	−2.02

Notes: The table reports the quantitative impacts from conducting various model robustness checks. Optimal Short-Term Incentives, θ_π^* (%), are the firm value maximizing short-term incentives chosen by the board of directors. Carbon Abatement Cost Increase (%) is the mean percentage increase in carbon abatement cost due to short-term incentives $\theta_\pi > 0$. Δ Firm Profits (%) is the counterfactual percentage change in firm profits when short-term incentives are removed from managers' contracts ($\theta_\pi = 0$). Similarly, Δ Carbon Emissions (%) reports the counterfactual percentage change in carbon emissions in an economy without short-termism.

the social cost of carbon tends to be higher than the implicit cost of removing short-term incentives, short-termism is likely to be welfare-reducing at the aggregate level.

5.3 Robustness of SMM Results

This section presents a range of additional robustness analyses. First, I estimate the structural model on different subsamples. Second, I compute the quantitative effects of counterfactually varying the baseline parameter estimates by one standard error up and down. Third, I extend the baseline model to account for private firms.

Subsample Analyses. I conduct the structural estimation on various subsamples and compute the quantitative impacts on carbon emissions and firm profits of counterfactually removing short-termism ($\theta_\pi = 0$). The key results are summarized in Table 3. As described in the data section, Trucost imputes missing data on carbon emissions using a nearly deterministic function of firm fundamentals such as sales and assets (Aswani et al., 2024). Since my structural estimation requires observing variation in carbon emissions that is not deterministically related to firm fundamentals, I exclude all imputed data points from my baseline sample. When I estimate the model using the full sample including imputed data points, the quantitative effects become larger. Detailed results are presented in Table C.5 of the Online Appendix. The board of directors continues to impose moderate short-term incentives of $\theta_{\pi}^{*} = 0.41\%$, which leads to an average increase in perceived carbon abatement cost of 12.65% (baseline sample: 6.90%). Removing these short-term incentives reduces firm profits by 0.55% (baseline sample: -0.46%) and carbon emissions by 4.02% (baseline sample: -2.19%).

Next, I estimate the model separately before and after the 2015 Paris Agreement. Detailed results can be found in Tables C.6 and C.7. Because of the increased attention to climate change, one might expect the quantitative impact of short-termism to be smaller in the post Paris Agreement sample. The results are consistent with this idea, as eliminating short-term incentives from managers' contracts has a quantitatively larger impact on carbon emissions in the before than in the post Paris Agreement sample (-3.35% vs. -1.88%).

I also estimate the model separately for firms above and below the median carbon intensity (detailed results in Tables C.8 and C.9). Cuts in carbon abatement investments should be more useful for profit manipulation when these investments are costly, i.e., for high carbon intensity firms. Consistent with this idea, I find that optimal short-term incentives are lower in the low-carbon-intensity sample ($\theta_{\pi}^{*} = 0.59\%$) than in the high-carbon-intensity sample ($\theta_{\pi}^{*} = 0.69\%$). In addition, the quantitative effects are more pronounced in the high carbon intensity sample. For example, without short-term incentives, firm profits decrease by 1.54% for high carbon intensity firms, while they decrease by only 0.29% for low carbon intensity firms. Similarly, carbon emissions decrease by 3.90% for high carbon intensity firms and 2.14% for low carbon intensity firms.

Finally, I split the sample by CEO age and estimate the model separately for CEOs above and below the median age. Again, I leave the detailed results to the Online Appendix (tables C.10 and C.11). Optimal short-term incentives are 0.14% for young CEOs and 0.23% for old CEOs. The counterfactual effects of eliminating short-termism on carbon emissions are -2.13% and -2.02%, respectively. The lower optimal degree of short-termism for young CEOs is not due to a lower disutility from carbon emissions. In fact, young CEOs appear to care slightly more about carbon emissions than old CEOs ($\phi_e = -0.2553$ vs. $\phi_e = -0.2359$), but they manage firms for which the future cost of carbon α are higher and thus the extent of the agency conflict is smaller.

Table 4—PARAMETER ROBUSTNESS

	Optimal Short-Term Incentives, θ_π^* (%)	Carbon Abatement Cost Increase (%)	Δ Firm Profits (%)	Δ Carbon Emissions (%)
Baseline estimates	0.24	6.90	−0.43	−2.19
High persistence of sales, ρ	0.24	6.90	−0.43	−2.19
Low persistence of sales, ρ	0.24	6.90	−0.43	−2.19
High std of sales shock, σ_z	0.24	6.89	−0.43	−2.19
Low std of sales shock, σ_z	0.24	6.90	−0.42	−2.19
High std of observed profit shock, σ_ε	0.24	6.67	−0.43	−2.11
Low std of observed profit shock, σ_ε	0.24	6.90	−0.47	−2.19
High std of unobserved profit shock, σ_ν	0.29	8.63	−0.43	−2.64
Low std of unobserved profit shock, σ_ν	0.24	6.90	−0.43	−2.19
High private cost of managers, ϕ_e	0.23	6.82	−0.43	−2.17
Low private cost of managers, ϕ_e	0.24	6.90	−0.41	−2.19
High cost of carbon abatement, ψ	0.24	6.91	−0.43	−2.19
Low cost of carbon abatement, ψ	0.24	6.90	−0.43	−2.19
High future cost of carbon, α	0.24	6.87	−0.43	−2.18
Low future cost of carbon, α	0.24	6.90	−0.43	−2.19
High std of measurement error in carbon emissions, σ_e	0.24	6.90	−0.43	−2.18
Low std of measurement error in carbon emissions, σ_e	0.24	6.90	−0.43	−2.19

Notes: The table reports the quantitative impacts from individually changing the estimated parameters from Panel A of Table 2 by one standard error. Optimal Short-Term Incentives, θ_π^* (%), are the firm value maximizing short-term incentives chosen by the board of directors. Carbon Abatement Cost Increase (%) is the mean percentage increase in carbon abatement cost due to short-term incentives $\theta_\pi > 0$. Δ Firm Profits (%) is the counterfactual percentage change in firm profits when short-term incentives are removed from managers' contracts ($\theta_\pi = 0$). Similarly, Δ Carbon Emissions (%) reports the counterfactual percentage change in carbon emissions in an economy without short-termism.

Parameter Robustness. In Table 4, I vary the baseline parameter estimates by one standard error up and down. Across all experiments, I find some moderate variation in the quantitative impact of short-termism, but the main conclusion from the baseline analysis remains unchanged.

Private Firms. In my counterfactual analysis, I focus on publicly traded firms because, for these firms, analysts' short-term profit targets provide a readily observable measure of short-termism. Thus, I implicitly assume that public firms are a reasonable proxy for all U.S. firms. However, private firms are subject to less stringent reporting requirements and less analyst coverage than public firms. Nevertheless, survey evidence shows that private firm executives feel almost as much pressure to meet short-term earnings targets as their public firm peers (Graham et al., 2005). In the case of private firms, short-term pressures do not come from external pressures from analysts, but may come from internal goals set by private investors. For example, private equity investors are likely to set short-term targets to monitor managers. Similarly, lenders to private companies, such as banks, generally do not have infinite horizons. In summary, the nature of short-term incentives may be different for private and public firms, but both are likely to have their own versions of short-termism.

To further address the concern that my baseline estimates overstate the impact of short-termism on carbon emissions due to the presence of private firms, I extend my model to feature an exogenous mass of private firms m_{pr}. In particular, I make a conservative assumption and assume that there are no short-term incentives for private firms. When $m_{pr} = 0$ the model nests the baseline model, and when $m_{pr} = 1$ short-termism is absent in the economy. The quantitative analysis including private firms is complicated by the fact that carbon emissions for private firms are not available and so the appropriate mass of private firms in the model is difficult to calibrate. However, U.S. Census data shows that the share of total sales generated by private firms in the U.S. economy is 13.75% during my sample period. Assuming relative carbon intensities for public vis-a-vis private firms, I calculate the mass of private firms m_{pr} in the model to match the real-world carbon emission shares for public and private firms under each scenario.

In Table 5, I examine the quantitative impact of including private firms under several conservative scenarios, ranging from assuming that private firms are as carbon-intensive as public firms to assuming that private firms are twice as carbon-intensive as public firms. For example, if private firms are as carbon-intensive as public firms, the mass of private firms in the model is $m_{pr} = 13.97\%$.[14] In this case, the effect of short-termism on carbon emissions is only slightly muted (-1.88% versus -2.19% in the baseline model). As private firms become more carbon intensive, the mass of private firms in the model increases mechanically. In an extremely conservative scenario where private firms are twice as carbon intensive as public firms, the mass of private firms is as high as 24.51%. Nevertheless, I find that the estimates remain quantitatively meaningful, since carbon emissions in the economy fall by 1.65% when short-term incentives are removed from managers' contracts.

[14] The mass of private firms in the model is greater than the share of revenue accruing to private firms because private firms have lower carbon emissions than public firms due to the lack of short-term incentives.

Table 5—ALLOWING FOR PRIVATE FIRMS: QUANTITATIVE IMPACTS

	Optimal Short-Term Incentives, θ_π^* (%)	Carbon Abatement Cost Increase (%)	Δ Firm Profits (%)	Δ Carbon Emissions (%)
Baseline estimates	0.24	6.90	-0.43	-2.19
Private firms, same intensity	0.20	5.93	-0.37	-1.88
Private firms, +10%	0.20	5.85	-0.37	-1.86
Private firms, +25%	0.20	5.73	-0.36	-1.82
Private firms, +50%	0.19	5.55	-0.35	-1.76
Private firms, +100%	0.18	5.21	-0.33	-1.65

Notes: The table reports the quantitative impact of allowing private firms in the model. The first row documents the baseline estimates, while the remaining rows document the quantitative impact of short-termism under different scenarios. Carbon emissions data for private firms are not available. Based on U.S. Census data, I estimate that private firms account for 13.75% of total sales between 2005 and 2020. Assuming relative carbon intensities for public and private firms, I calibrate the mass of private firms m_{pr} in the model to match the real-world carbon emission shares for public and private firms under each scenario. I examine various conservative scenarios, ranging from assuming that private firms are equally carbon-intensive to up to twice as carbon-intensive as private firms. Quantitative impacts are calculated as the average across private and public firms, with weights of m_{pr} and $1 - m_{pr}$ for private and public firms, respectively.

6 Conclusion

I examine how corporate short-termism affects carbon emissions. I show that firms that just meet analysts' targets have about 4.3 to 4.99 percentage points higher carbon emissions growth than firms that just miss. Motivated by these reduced-form facts, I develop a quantitative model with endogenous carbon emissions and short-term incentives for managers. I estimate the model by SMM using data on forecast errors, firm fundamentals, and carbon emissions. The model generally matches the moments in the real data well. I run counterfactual simulations and find that removing short-term incentives from managers' contracts reduces firms' profits by 0.43% and carbon emissions by 2.19%. At the aggregate level, short-termist carbon emissions amount to about 142 million tons, or as much as total U.S. aviation emissions in 2022. My estimates imply that each ton of carbon dioxide saved by eliminating short-term incentives costs about $\$84$. As most conventional estimates of the social cost of carbon are significantly higher, my analysis suggests that short-termism is welfare-reducing via the carbon emissions channel.

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For Online Publication

Online Appendix to:

"SHORT-TERMIST CARBON EMISSIONS"

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A Summary Statistics

Table A.1—SUMMARY STATISTICS

	Mean	Median	Std. Dev.	Min	Max
Assets	30,214.93	11,747.59	52,865.78	231.11	532,577.47
Sales	24,127.85	8,608.35	46,060.52	186.29	498,583.18
Market Value	38,218.66	13,226.04	75,718.79	88.89	1,073,390.54
Profits	1,015.32	627.62	1,037.01	-255.80	4,764.76
Carbon Emissions	2.3893	0.6318	4.3577	0.0010	21.0977
Carbon Intensity (Assets)	0.1252	0.0414	0.2364	0.0006	3.2588
Carbon Intensity (Sales)	0.1784	0.0460	0.3778	0.0005	5.0283

Notes: The table shows summary statistics for my baseline sample. Assets, sales, market value, and profits are in millions of dollars. Carbon emissions are in million metric tons of CO_2 equivalents. Carbon intensity is reported in tons per 1000 dollars of assets or sales, respectively. The sample consists of 3,147 observations from 493 firms between 2006 and 2019.

Table A.2—DISTRIBUTION OF FIRMS ACROSS FAMA FRENCH 12-INDUSTRIES

Fama French 12-Industry	Number of Firms
Consumer Non-Durables	50
Consumer Durables	13
Manufacturing	78
Energy	34
Chemicals	46
Business Equipment	106
Telecommunication	13
Utilities	0
Wholesale and Retail	50
Healthcare	42
Finance	0
Other	61

Notes: The table shows the number of firms by Fama French 12-industries.

B Robustness of Reduced-Form Results

B.1 Alternative Forecast Error Measures

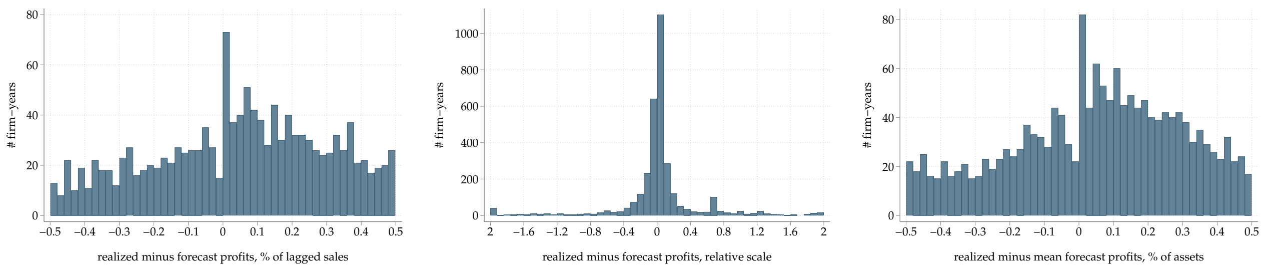

Figure B.1—ALTERNATIVE FORECAST ERROR MEASURES

Notes: The figure plots the histograms of alternative forecast error measures based on the Compustat/IBES/Trucost merged sample, which includes 3,147 observations from 493 firms between 2006 and 2019. Realized profits are fiscal year dollar street earnings. The left panel scales the baseline forecast error by lagged sales instead of assets. Following Terry (2023), the middle panel plots the relative forecast error computed via $2\frac{fe_{it}}{|street_{it}|+|consensus_{it}|}$. The right panel uses the mean across all analysts' earnings forecasts at a four-quarter horizon as the consensus estimate.

B.2 Discontinuity Results for Full Sample

Table B.3—Regression discontinuity results for full sample

	(1)	(2)	(3)
Emissions Growth	CO_2	CO_2/Assets	CO_2/Sales
Mean Change at	2.20	2.36	0.66
0 Threshold (p.p.)	(2.33)	(2.33)	(0.83)
Standardized (%)	5.55	5.84	2.15
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Obs.	10,133	10,133	10,132

Notes: The table reports the estimated mean differences in firms' emissions policy around the zero forecast error threshold. Compared with the baseline estimates, I also include observation for which Trucost imputed carbon emissions based on a proprietary model that depends on firm fundamentals. Standardized values express the point estimates in terms of the standard deviation of the outcome variable. Column (1) compares the growth rate of carbon emissions, column (2) carbon emissions scaled by assets, and column (3) carbon emissions scaled by sales for firms that just beat and firms that just missed the consensus earnings forecast. Estimates are obtained using local linear regression with a triangular kernel and optimal Calonico, Cattaneo, and Farrell (2020) bandwidth. Standard errors are clustered by firm and robust t-statistics are shown in parentheses.

B.3 Discontinuity Results By Emissions Scope

Table B.4—Regression discontinuity results by emissions scope

	(1)	(2)	(3)
	CO_2	CO_2/Assets	CO_2/Sales
Panel A: Scope 1 Emissions			
Mean Change at	9.71	10.18	9.64
0 Threshold (p.p.)	(2.83)	(2.84)	(2.74)
Standardized (%)	15.36	15.82	15.20
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Obs.	3,147	3,147	3,147
Panel B: Scope 2 Emissions			
Mean Change at	4.41	4.81	3.97
0 Threshold (p.p.)	(2.11)	(2.15)	(1.89)
Standardized (%)	9.52	10.11	8.69
Fixed Effects	Firm, Year	Firm, Year	Firm, Year
Obs.	3,147	3,147	3,147

Notes: The table reports the estimated mean differences in firms' emissions policies around the zero forecast error threshold. Compared with the baseline estimates, I estimate the discontinuity for Scope 1 and Scope 2 emissions separately. Standardized values express the point estimates in terms of the standard deviation of the outcome variable. Column (1) compares the growth rate of carbon emissions, column (2) carbon emissions scaled by assets, and column (3) carbon emissions scaled by sales for firms that just beat and firms that just missed the consensus earnings forecast. Estimates are obtained using local linear regression with a triangular kernel and optimal Calonico, Cattaneo, and Farrell (2020) bandwidth. Standard errors are clustered by firm and robust t-statistics are shown in parentheses.

B.4 Bandwidth Choice

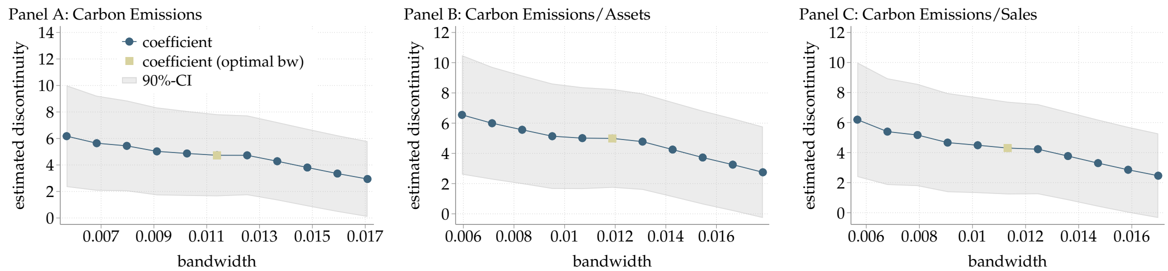

Figure B.2—REGRESSION DISCONTINUITY RESULTS FOR VARIOUS BANDWIDTH CHOICES
Notes: The figure plots the estimated discontinuity in carbon emissions growth for firms just hitting analysts' forecasts as a function of different bandwidth choices (on the horizontal axis). Panel A compares the growth rate of carbon emissions, Panel B carbon emissions scaled by assets, and Panel C carbon emissions scaled by sales for firms that just beat and firms that just missed the consensus earnings forecast. I estimate Equation (2) using a local linear regression discontinuity with triangular kernel and a bandwidth ranging between 0.5 and 1.5 times the optimal bandwidth according to Calonico et al. (2020). The square represents the estimated discontinuity when using the optimal bandwidth that is considered in the main specification. The 90% confidence bands take clustering at the firm level into account.

C Appendix to Quantitative Model

C.1 Computational Details

Preliminaries. I use a three-dimensional grid to capture the state variables of the model, i.e., past emissions e_{-1}, unmanipulated sales q, and observable profit noise ε. I discretize the exogenous processes for q and ε using the Tauchen algorithm (Tauchen, 1986). I use seven grid points for q and ten for ε, resulting in a transition matrix of dimension 70×70. The grid for e_{-1} is not fixed, but is determined endogenously, similar to the endogenous grid method introduced by Carroll (2006).

Numerical Algorithm. I implement the following inner-outer-loop structure to find the stationary equilibrium of the model:

1) [Outer Loop] Guess short-term incentives θ_π

   (a) [Inner Loop] Guess emissions forecast function $e^f(q)$, implying profit forecasts $\Pi^f(q)$.

   (b) Compute the implied emissions policy by managers $e(q, \varepsilon)$ by directly solving the time-*t* decision of managers:

$$\max_{e_t} -\psi \left(\frac{q_{i,t}}{e_{i,t}} \right)^2 - q_t \theta_\pi \mathbb{P}_\nu \left(\Pi_t < \Pi_t^f \right) + \phi_e e_t - \frac{1}{R} \alpha e_t$$

   (c) Check whether the forecast function $e^f(q)$ is consistent with the emissions policy function according to $e^f(q) = \mathbb{E}_\varepsilon \left[e(q, \varepsilon) \mid q \right]$. If so, the policy $e(q, \varepsilon)$, profit forecasts $\Pi^f(q)$, the value function $V_F(e_{-1}, q, \varepsilon)$, and the stationary distribution F implied by θ_π are computed. If not, update the guess for forecasts and return to 1(a).

2) Compute the implied mean firm value objective of boards given θ_π via (16)

3) If the board objective is optimized, optimal short-term incentives θ_π^* are computed. If not, update guess of θ_π and return to 1(a). I use Brent's algorithm to solve the board objective.

C.2 Identification of Other Model Parameters

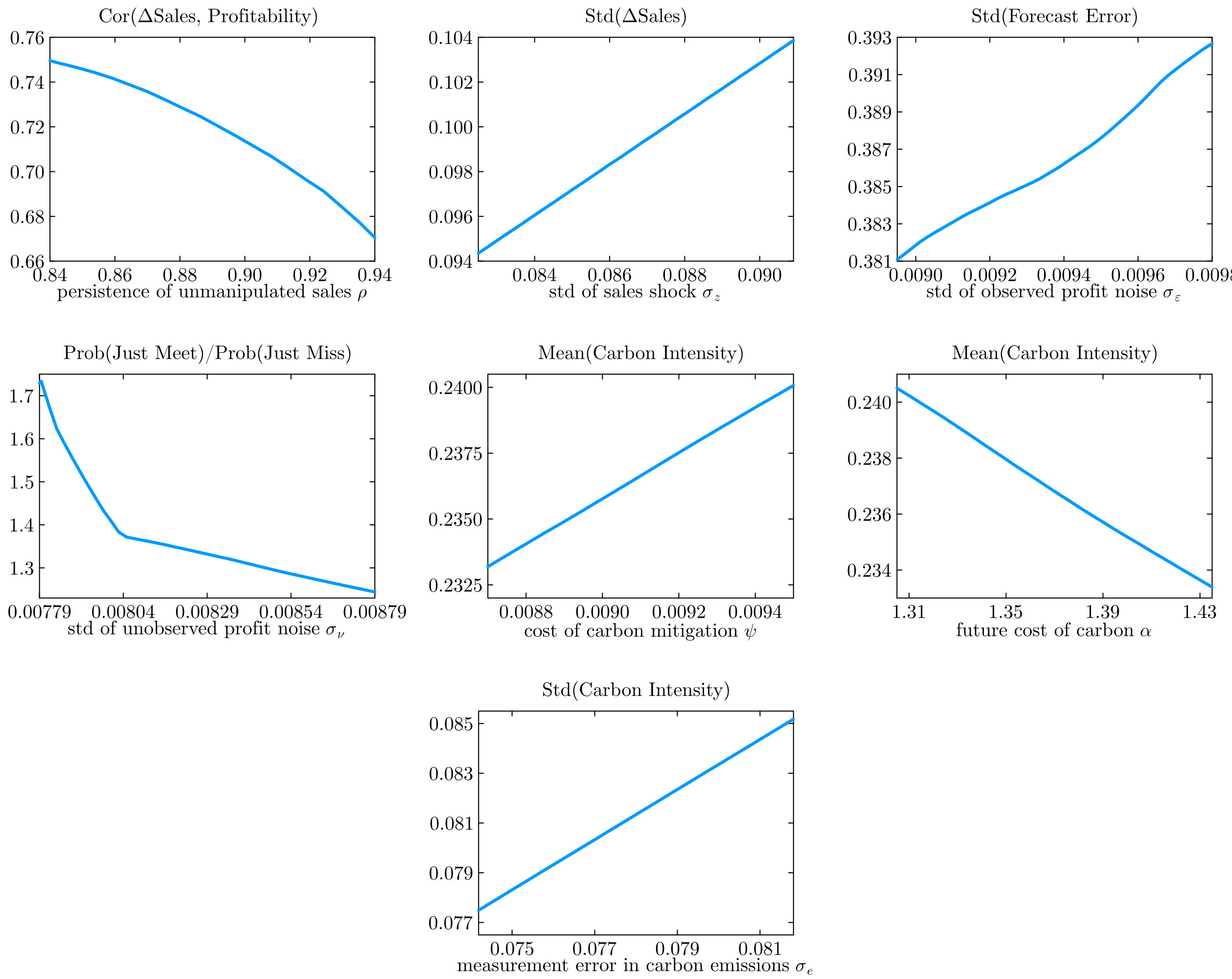

Figure C.3—Identification of other model parameters

Notes: The figure plots selected, smoothed moments used for estimating the remaining parameters. I vary the parameter values above and below their estimated value.

C.3 Supplemental Tables

Table C.5—Model robustness: full sample

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.8143	0.0007
Std of sales shock	σ_z	0.2887	0.0066
Std of observed profit shock	σ_ε	0.0060	0.0037
Std of unobserved profit shock	σ_ν	0.0091	0.0044
Private cost of managers	ϕ_e	-1.0617	0.0001
Cost of carbon abatement	ψ	0.0019	0.0000
Future cost of carbon	α	4.9721	0.0002
Std of measurement error in carbon emissions	σ_e	0.0302	0.0059
Panel B: Targeted moments	**Data**	**Model**	**t-stat**
Mean carbon intensity	0.1273	0.0933	3.10
Std of forecast error	0.4352	0.2939	53.46
Std of sales growth	0.1540	0.3121	-34.19
Std of profitability	0.3439	0.1798	0.02
Std of carbon intensity	0.0720	0.0399	2.10
Correlation of sales growth, profitability	0.1696	0.7983	-6.88
Correlation of sales growth, carbon intensity	-0.0884	-0.1324	2.11
Correlation of profitability, carbon intensity	0.0970	-0.2836	4.44
Correlation of profitability, forecast error	0.1331	0.0649	4.43
Correlation of carbon intensity, forecast error	0.0021	-0.0105	0.34
Correlation of sales growth, forecast error	0.1489	0.0406	20.74
Prob of meeting forecast	0.5653	0.5797	-11.27
Prob. of just meeting to prob. of just missing	1.5288	1.4893	14.23
Panel C: Quantitative Impacts			
Optimal short-term incentives, θ_π^*			0.41%
Mean carbon abatement cost increase from short-termism			12.65%
Δ Firm profits without short-termism			-0.55%
Δ Carbon emissions without short-termism			-4.02%

Notes: The table reports the SMM results based on the full sample including imputed and non-imputed carbon emissions. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ_π^*, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Table C.6—Model robustness: before 2015 Paris agreement

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.9197	0.0074
Std of sales shock	σ_z	0.0724	0.0044
Std of observed profit shock	σ_ε	0.0065	0.0063
Std of unobserved profit shock	σ_ν	0.0067	0.0027
Private cost of managers	ϕ_e	-0.3017	0.0016
Cost of carbon abatement	ψ	0.0028	0.0002
Future cost of carbon	α	1.3479	0.0242
Std of measurement error in carbon emissions	σ_e	0.0503	0.0092
Panel B: Targeted moments	**Data**	**Model**	**t-stat**
Mean carbon intensity	0.1715	0.1587	0.55
Std of forecast error	0.2844	0.3033	-2.61
Std of sales growth	0.0959	0.0840	1.71
Std of profitability	0.0227	0.0243	-1.02
Std of carbon intensity	0.0628	0.0510	0.87
Correlation of sales growth, profitability	0.1417	0.6666	-15.11
Correlation of sales growth, carbon intensity	-0.1691	-0.0452	-4.41
Correlation of profitability, carbon intensity	-0.0090	-0.1105	4.40
Correlation of profitability, forecast error	0.1165	0.2698	-10.50
Correlation of carbon intensity, forecast error	0.0591	0.0008	1.26
Correlation of sales growth, forecast error	0.1741	0.0074	3.76
Prob of meeting forecast	0.5829	0.5440	4.75
Prob. of just meeting to prob. of just missing	1.4198	1.3351	5.24
Panel C: Quantitative Impacts			
Optimal short-term incentives, θ^*_π			0.26%
Mean carbon abatement cost increase from short-termism			11.42%
Δ Firm profits without short-termism			-0.89%
Δ Carbon emissions without short-termism			-3.35%

Notes: The table reports the SMM results based on the before 2015 Paris agreement sample. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ^*_π, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Table C.7—Model robustness: post 2015 Paris agreement

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.9357	0.0012
Std of sales shock	σ_z	0.0894	0.0003
Std of observed profit shock	σ_ε	0.0094	0.0000
Std of unobserved profit shock	σ_ν	0.0064	0.0006
Private cost of managers	ϕ_e	-0.2057	0.0029
Cost of carbon abatement	ψ	0.0076	0.0008
Future cost of carbon	α	1.4124	0.0016
Std of measurement error in carbon emissions	σ_e	0.0638	0.0094

Panel B: Targeted moments	Data	Model	t-stat
Mean carbon intensity	0.1799	0.2203	-2.46
Std of forecast error	0.3265	0.4644	-11.44
Std of sales growth	0.1104	0.1010	1.24
Std of profitability	0.0267	0.0416	-4.44
Std of carbon intensity	0.0667	0.0678	-0.07
Correlation of sales growth, profitability	0.0366	0.6807	-8.52
Correlation of sales growth, carbon intensity	-0.1164	-0.0551	-1.45
Correlation of profitability, carbon intensity	-0.1059	-0.1530	0.70
Correlation of profitability, forecast error	0.2470	0.1736	1.46
Correlation of carbon intensity, forecast error	-0.1799	0.0101	-2.39
Correlation of sales growth, forecast error	0.0903	-0.0145	2.01
Prob of meeting forecast	0.5576	0.5884	-13.18
Prob. of just meeting to prob. of just missing	1.5525	1.7397	-15.03

Panel C: Quantitative Impacts	
Optimal short-term incentives, θ^*_π	0.19%
Mean carbon abatement cost increase from short-termism	5.90%
Δ Firm profits without short-termism	-0.43%
Δ Carbon emissions without short-termism	-1.88%

Notes: The table reports the SMM results based on the post 2015 Paris agreement sample. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ^*_π, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Table C.8—MODEL ROBUSTNESS: LOW EMISSIONS SAMPLE

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.8330	0.0171
Std of sales shock	σ_z	0.1003	0.0000
Std of observed profit shock	σ_ε	0.0209	0.0029
Std of unobserved profit shock	σ_ν	0.0053	0.0021
Private cost of managers	ϕ_e	-1.7178	0.1242
Cost of carbon abatement	ψ	0.0001	0.0000
Future cost of carbon	α	7.3371	0.1588
Std of measurement error in carbon emissions	σ_e	0.0043	0.0003

Panel B: Targeted moments	Data	Model	t-stat
Mean carbon intensity	0.0223	0.0259	-5.30
Std of forecast error	0.2389	0.2757	-2.78
Std of sales growth	0.0881	0.1122	-3.06
Std of profitability	0.0252	0.0322	-3.10
Std of carbon intensity	0.004	0.0046	-5.63
Correlation of sales growth, profitability	0.0945	0.6086	-7.76
Correlation of sales growth, carbon intensity	-0.1633	-0.1114	-1.03
Correlation of profitability, carbon intensity	-0.1826	-0.2112	0.53
Correlation of profitability, forecast error	0.0939	0.5675	-26.57
Correlation of carbon intensity, forecast error	0.0112	-0.0203	1.18
Correlation of sales growth, forecast error	0.2273	0.056	4.18
Prob of meeting forecast	0.6092	0.5581	9.70
Prob. of just meeting to prob. of just missing	1.6057	1.3992	5.81

Panel C: Quantitative Impacts	
Optimal short-term incentives, θ_π^*	0.59%
Mean carbon abatement cost increase from short-termism	14.45%
Δ Firm profits without short-termism	-0.29%
Δ Carbon emissions without short-termism	-2.14%

Notes: The table reports the SMM results based on the below median carbon intensity sample. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ_π^*, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Table C.9—MODEL ROBUSTNESS: HIGH EMISSIONS SAMPLE

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.8455	0.0015
Std of sales shock	σ_z	0.0773	0.0016
Std of observed profit shock	σ_ε	0.0137	0.0017
Std of unobserved profit shock	σ_ν	0.0129	0.0006
Private cost of managers	ϕ_e	-0.2664	0.0020
Cost of carbon abatement	ψ	0.0143	0.0004
Future cost of carbon	α	1.0814	0.0016
Std of measurement error in carbon emissions	σ_e	0.0969	0.0200

Panel B: Targeted moments	Data	Model	t-stat
Mean carbon intensity	0.3368	0.2944	1.16
Std of forecast error	0.4001	0.4096	-0.66
Std of sales growth	0.1206	0.0876	4.53
Std of profitability	0.0361	0.0394	-1.19
Std of carbon intensity	0.1281	0.0964	1.27
Correlation of sales growth, profitability	0.1626	0.6601	-13.53
Correlation of sales growth, carbon intensity	-0.1427	-0.0485	-3.13
Correlation of profitability, carbon intensity	-0.1069	-0.0737	-0.66
Correlation of profitability, forecast error	0.2315	0.5041	-10.48
Correlation of carbon intensity, forecast error	-0.0278	0.0016	-0.53
Correlation of sales growth, forecast error	0.1028	0.1038	-0.06
Prob of meeting forecast	0.5315	0.5605	-14.77
Prob. of just meeting to prob. of just missing	1.3469	1.2314	9.42

Panel C: Quantitative Impacts	
Optimal short-term incentives, θ_π^*	0.69%
Mean carbon abatement cost increase from short-termism	12.40%
Δ Firm profits without short-termism	-1.54%
Δ Carbon emissions without short-termism	-3.90%

Notes: The table reports the SMM results based on the above median carbon intensity sample. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ_π^*, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Table C.10—MODEL ROBUSTNESS: YOUNG CEOS

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.8972	0.0124
Std of sales shock	σ_z	0.0784	0.0014
Std of observed profit shock	σ_ε	0.0058	0.0009
Std of unobserved profit shock	σ_ν	0.0055	0.0068
Private cost of managers	ϕ_e	-0.2553	0.2032
Cost of carbon abatement	ψ	0.0060	0.0000
Future cost of carbon	α	1.6670	0.0046
Std of measurement error in carbon emissions	σ_e	0.0970	0.0341
Panel B: Targeted moments	**Data**	**Model**	**t-stat**
Mean carbon intensity	0.2070	0.1942	0.30
Std of forecast error	0.3404	0.2897	2.52
Std of sales growth	0.0980	0.0911	1.20
Std of profitability	0.0253	0.0361	-5.95
Std of carbon intensity	0.1071	0.0958	0.28
Correlation of sales growth, profitability	0.0655	0.7371	-10.82
Correlation of sales growth, carbon intensity	-0.2098	-0.0399	-4.25
Correlation of profitability, carbon intensity	-0.1082	-0.0900	-0.18
Correlation of profitability, forecast error	0.2181	0.1315	1.41
Correlation of carbon intensity, forecast error	-0.0873	-0.0102	-0.79
Correlation of sales growth, forecast error	0.1049	0.0091	2.89
Prob of meeting forecast	0.5859	0.5566	6.83
Prob. of just meeting to prob. of just missing	1.5763	1.3236	16.49
Panel C: Quantitative Impacts			
Optimal short-term incentives, θ_π^*			0.14%
Mean carbon abatement cost increase from short-termism			7.68%
Δ Firm profits without short-termism			-0.46%
Δ Carbon emissions without short-termism			-2.13%

Notes: The table reports the SMM results based on the young CEOs sample. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ_π^*, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.

Table C.11—MODEL ROBUSTNESS: OLD CEOS

Panel A: Estimated parameters	Symbol	Estimate	Std. Error
Persistence of sales	ρ	0.9226	0.0008
Std of sales shock	σ_z	0.0658	0.0003
Std of observed profit shock	σ_ε	0.0102	0.0055
Std of unobserved profit shock	σ_ν	0.0079	0.0010
Private cost of managers	ϕ_e	-0.2359	0.0277
Cost of carbon abatement	ψ	0.0060	0.0002
Future cost of carbon	α	1.5930	0.0081
Std of measurement error in carbon emissions	σ_e	0.0969	0.0110
Panel B: Targeted moments	**Data**	**Model**	**t-stat**
Mean carbon intensity	0.1611	0.1965	-1.69
Std of forecast error	0.3020	0.4145	-10.45
Std of sales growth	0.1056	0.0761	3.89
Std of profitability	0.0293	0.0324	-1.13
Std of carbon intensity	0.0610	0.0953	-2.93
Correlation of sales growth, profitability	0.1220	0.6574	-18.78
Correlation of sales growth, carbon intensity	-0.1016	-0.0278	-2.64
Correlation of profitability, carbon intensity	-0.1260	-0.0642	-1.50
Correlation of profitability, forecast error	0.1932	0.3526	-9.81
Correlation of carbon intensity, forecast error	0.0146	-0.0026	0.68
Correlation of sales growth, forecast error	0.1649	0.0586	6.11
Prob of meeting forecast	0.5641	0.5632	0.33
Prob. of just meeting to prob. of just missing	1.4554	1.3307	10.47
Panel C: Quantitative Impacts			
Optimal short-term incentives, θ_π^*			0.23%
Mean carbon abatement cost increase from short-termism			6.53%
Δ Firm profits without short-termism			-0.44%
Δ Carbon emissions without short-termism			-2.02%

Notes: The table reports the SMM results based on the old CEOs sample. Panel A shows the parameter estimates using efficient moment weighting. Panel B documents a comparison of the actual data moments with the simulated moments using the optimal parameter vector $\hat{\theta}_{SMM}$. Model moments use a panel of 1,000 firms and 25 years. Standard errors are clustered by firm. Panel C documents the optimal short-term incentives, θ_π^*, and computes the quantitative impacts of short-termism on the mean carbon abatement cost, firm profits, and carbon emissions.