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Abstract

We use data from the Carbon Disclosure project (CDP) to measure firms' beliefs about climate regulation, their plans for future abatement, and their current actions on mitigating carbon emissions. These measures vary both across firms and time in a manner that is especially pronounced around the Paris climate change agreement announcement. A simple dynamic model of carbon abatement with a firm exposed to a certain future carbon levy, facing a trade-off between emissions reduction and capital growth, and convex emissions abatement adjustment costs cannot explain the data. A more complex two-firm dynamic model with both information asymmetry across firms and reputational concerns fits the data far better. Our findings imply that firms' abatement actions depend greatly on their beliefs about climate regulation, and that both informational frictions and reputational concerns can amplify responses to climate regulation, increasing its effectiveness.

JEL Classification: G31, G38, Q52, Q54

Keywords: climate change, climate regulation, Carbon Emissions, Dynamic Models, information asymmetry, reputation, abatement

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Climate Regulation and Emissions Abatement: Theory and Evidence from Firms' Disclosures*

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July 1, 2020

Abstract

We construct measures of firms' beliefs about climate regulation, plans for future abatement, and current actions on emissions mitigation, using Carbon Disclosure Project data. These measures vary significantly around the Paris climate change agreement announcement. A dynamic model of a representative firm exposed to a future carbon levy, trading-off emissions reduction against capital growth, and facing convex emissions abatement adjustment costs cannot explain these patterns. A two-firm model with cross-firm information asymmetry and reputational externalities does far better. Our findings imply that abatement is strongly affected by firms' beliefs about climate regulation, with cross-firm interactions amplifying the effectiveness of regulation.

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1 Introduction

Climate change and its consequences for economic and financial stability looms large even as we deal with current events—lending urgency to calls for action on global warming.[1] Faced with these warnings, in December 2015, 196 nations signed a coordinated agreement at the United Nations Framework Convention on Climate Change (UNFCCC) in Paris, to limit greenhouse gas emissions to a level consistent with global temperatures rising less than 2° Celsius. The agreement also determined a five-year window within which countries could meet and renew the so-called Nationally Determined Contributions (NDCs). Yet, as we approach the first ratification deadline in 2020, most signatory countries are falling far short of required targets,[2] and the world's second largest emitting country has announced its intention to withdraw from the agreement.[3]

How important is coordinated climate regulation to firms' carbon abatement actions, and through what channels does such regulation affect firms? If firms' actions on abatement are not much affected by high-level climate regulation announcements such as Paris, or indeed by announcements of pull-backs from these commitments, then perhaps there is less cause for concern. If, on the other hand, firms' expectations about future climate regulation are an important determinant of their abatement activities, then we should be significantly more concerned about these recent trends to dilute or reverse coordinated climate regulation.

In this paper, we pursue a bottom-up approach to identify how firms' carbon abatement activities respond to, and are influenced by their beliefs about, future climate regulation. We first analyze comprehensive micro-data from firms' voluntary disclosures about these activities. In the years leading up to and following the Paris announcement, we uncover significant and striking variation in firms' self-reported beliefs about the intensity of climate regulation, and their current as well as future planned abatement actions. We then build a set of dynamic models of firms' emissions abatement activities to better understand which combination of model ingredients can best rationalize the patterns we find in the data. Finally, we match the model-implied dynamics of firms' emissions abatement choices to the data up to and just following the

[1]For example, see Carney (2015).

[2]Information on the Nationally Determined Contributions (NDCs) can be found at *https://unfccc.int/process/the-paris-agreement/nationally-determined-contributions/ndc-registry*.

[3]In June 2017, U.S. President Donald Trump announced his intention to withdraw from the agreement, with the final decision to be made in November 2020.

Paris announcement, calibrating key parameters such as the adjustment costs associated with emissions abatement actions, and the extent to which firms respond to one anothers' actions. These calibrated parameters contribute to the fast-growing literature on climate finance which seeks to quantify the impact of climate regulatory risk on realized emissions and firm value. We validate these estimated parameters as well as the model in an out-of-sample exercise, which predicts firms' abatement actions from firms' revised beliefs following U.S. President Trump's subsequent announcement to pull back from the Paris agreement.

Our work reveals that firms' reported beliefs about climate regulation events strongly influence their planned and actual abatement activities. Moreover, cross-firm reputational externalities and cross-firm information asymmetry about the stringency of the regulatory policy are important model ingredients needed to match the patterns and magnitudes of the movements that we observe in the data. These ingredients amplify firms' reactions to climate regulatory announcements, leading us to conclude that climate regulation can have substantial effects on firms' abatement actions.

Our sample comprises North American public firms that voluntarily disclose environmental information through the Carbon Disclosure Project (CDP) between 2011 and 2017. We verify the accuracy of these data using third-party sources (such as Bloomberg and Thomson Reuters) who produce external audits and ratings of firms' ESG activities. The CDP data comprise three important dimensions, namely, firms' self-reported beliefs about the horizon and impact of future climate regulation; firms' plans for future carbon emissions abatement; and finally, data on firms' emissions abatement actions to date, which reflect the actual changes in their carbon footprints.

In our empirical work, we compare the dynamics of firms' reported beliefs about the intensity of future climate regulation with their carbon abatement actions to date. We first document that there are important cross-sectional differences between two groups of firms in the data. One set comprises firms that publicly report plans for future emissions reduction in addition to reporting their beliefs about the intensity of future climate regulation, and current actions on abatement. The other set comprises firms that report beliefs and current abatement actions, but do not report plans for future abatement. The two sets of firms differ in several other ways. The plan-reporting firms are larger and more profitable, more emissions intensive, and also have a greater propensity than non-plan-reporting firms to a) engage with policymakers, and b) provide direct funding to climate regulatory activities.

We find that between 2011 and 2015, prior to the Paris announcement, all firms, on average, steadily downgraded their expectations over the impact of future regulation and progressively increased their actual carbon footprint. However, this tendency is more muted for the firms that consistently report plans for future emissions reduction—they exhibit more constant emissions reduction over this pre-Paris-announcement period. These patterns change dramatically in 2016, the year after the Paris announcement. In that year, all firms report upwardly revised beliefs over the impact of climate regulation, and sharply increase carbon abatement over the year from 2016 to 2017. Once again, we see heterogeneity in these responses. Plan-reporting firms react *far more* to the Paris announcement than non-plan-reporting firms, despite the fact that plan-reporting firms revise their beliefs about future regulation intensity *far less*. Put differently, plan-reporting firms have *more* extreme reactions to the climate regulation event, despite being *less* surprised by the announcement of the agreement. Indeed, the reported plans of these firms in the year *prior* to the Paris announcement forecast their actual emissions reduction rates even *after* the Paris announcement, intensifying the puzzle about their more extreme reactions to the announcement. This puzzling observation on the heterogeneity in responses to the Paris announcement, alongside the fact that reported beliefs don't map similarly to observed actions before and after the announcement are important targets for any model, and together suggest that subtle economic forces are at play.

To better understand and rationalize the patterns in the data we first build a simple dynamic model of a representative firm's emissions reduction activities. In the model, the polluting firm produces output in each period using capital stock in place, with carbon emissions proportional to produced output. The firm is exposed to a future climate regulation event in the form of a carbon levy. At any time period prior to the regulation event, the firm can abate or increase emissions by reducing or increasing its level of polluting capital, but it is subject to standard convex adjustment costs. The firm's optimal policy balances the tradeoff between output growth and emissions reduction. Since the carbon levy only makes its appearance at the terminal date, the firm discounts the cost of regulation to the present, and sets an optimal abatement profile beginning in the current period—i.e., its abatement action—and then for every period leading up to the date of the levy.

We take this simple model to the cross-sectional average of plan-reporting firms' reported disclosure data, feeding the model with the average of reported beliefs about future climate regulation to generate predicted plans and actions at each date, allowing the model to calibrate the expected terminal levy, the productivity of polluting capital, and the emissions adjustment costs. We set the date of the imposition of the carbon levy to 2020, the first ratification deadline of the Paris agreement, which is also the most frequent deadline for planned emissions reduction reported by the firms in the data. We find that the resulting dynamics of abatement actions implied by this model are excessively smooth, and fail to capture the substantial increases in abatement seen in the data around the Paris announcement. The bottom line is that this simple model fails to capture the underlying economic forces that are at work in the data.

To improve the performance of the model, we therefore introduce a second firm into the economy, to capture the behavior of non-plan-reporting firms. Our aim is to understand whether there are strategic interactions between these two groups of firms (those that do and do not report plans for future emissions reduction) that can rationalize the large aggregate responses to the Paris announcement. The first ingredient we add to the basic model is a reputational externality which connects each firm's profits to the abatement actions of the other firm—i.e., a firm's profits from having higher levels of polluting capital are reduced to the extent that the other firm abates emissions at the same time. This conjecture is partly motivated by the recent spike in attention paid to indicators of firms' Environmental, Social, and Governance (ESG) activities, and the ensuing relative performance evaluation of firms along this dimension. We also add a second ingredient to the model to help rationalize the data on firms' reported beliefs. This is an information asymmetry across firms, modelled by assuming that the true intensity of the carbon levy is the sum of a (constant) public component that is visible to both firms, and a signal which is only visible to plan-reporting firms.

In the enriched model, we solve for equilibrium of a dynamic Stackelberg leadership game where the informed firm (the leader) has a first-mover advantage over the uninformed firm (the follower). The leader firm also exercises commitment power by announcing its optimal abatement plan before the game is played. The leader maximizes profits, internalizing the follower's reaction to its actions, including actions arising from any inferences that the follower draws about the leader's private signal from the leader's announced abatement plan.

We take this more complex model to the data, allowing additionally for the size of the reputational and informational externalities to be structurally estimated. Our first finding from this model is that firms' actions are consistent with an expected prior about the carbon levy of roughly 85$/mt CO_2e. This estimate falls in the range estimated by the extensive literature on the social cost of carbon (see, e.g., Tol (2011)), and is far higher than the current implied market levy[4].

Turning to the other aspects of the more richly parametrized model, as we might expect, it yields predictions that are closer to the observed data—although it is worth pointing out that this is not just mechanical, since the model now needs to fit the average disclosures of *both* plan-reporting and non-plan reporting firms. First, the reputational externality generates an amplified reaction by firms to changes in the levy, with the leader (i.e., plan-reporting, in the data) firm reacting more than the follower (non-plan-reporting) firm because of its leadership position in equilibrium. Second, to the extent that the follower puts a lower weight on the signal inferred from the leader's announced abatement plan, the leader's reaction to the common component of the levy is greater. Finally, if reputational externalities are highest in the short-run and decline over time, a belief that the carbon levy will be sufficiently high can generate a declining time-path of abatement, i.e., the model predicts that firms will optimally abate a large share of their polluting capital immediately. Put together, these predictions generated from the extended model help to better fit the observed dynamics of firms' abatement plans and actions before and after the announcement of the Paris agreement. They help to explain why the reactions to the Paris announcement are both high—the new model ingredients result in substantial amplification of the short-term impacts of climate regulation relative to the basic model—and different across the two groups of firms. The amplification increases in the size of the carbon levy. We evaluate the optimal path of carbon emissions generated by the calibrated models for a time horizon of ten years and two policy scenarios corresponding, respectively, to distributed levies (i.e., applied at each time period) of roughly 90$/mt$CO_2$e and 300$/mtCO_2e. Comparing these cases, the augmented model predicts, in the most stringent case, an even more substantial amplification of the firm's baseline reaction to the policy in the short run.

In a final exercise, to validate these estimated parameters as well as our conclusions from the model, we acquire data to extend our sample through 2019, to evaluate the impacts of Trump's announcement in June 2017 to pull back from the Paris agreement. We show that firms' reported

[4]For example, the price of carbon allowances currently traded in the European cap and trade market average around 30$/mt$CO_2$e.

beliefs about the intensity of future climate regulation following Trump's announcement drop sharply, with larger reported belief updates seen for plan-reporting firms. At the same time, we see that firms report revisions to their expected horizons of emissions abatement, which are pushed further into the future. We feed these reported beliefs from the extended sample into the model with parameters fixed at their estimated values in the pre-2017 period, and demonstrate that the complex model that we estimate is well able to capture the patterns seen in emissions abatement in the out-of-sample period. This helps to provide confidence in our parameter estimates and the more complex model with cross-firm interactions that we develop.

The remainder of this paper is structured as follows: in the rest of this section, we discuss some of the academic literature that is related to our work, and highlight our contributions to this literature. Section 2 introduces the CDP dataset, validates the disclosure data using external sources, and describes the construction and measurement of the empirical evidence. In Section 3, we describe and solve the simple dynamic abatement model with an atomistic firm, and calibrate it to the data. Section 4 introduces, solves, and calibrates the more complex two-firm model, and discusses the differences between this model and the simple model. Section 5 describes our out-of-sample exercise, and Section 6 concludes. An online appendix contains more detailed descriptions of the underlying data and our constructed measures, detailed model derivations, and auxiliary exercises.

1.1 Related Literature

Our work fits into the fast-growing literature on climate economics and finance that studies the interplay between corporate environmental regulation and firm behavior.

Our finding that firm priors about the carbon levy appear to be far higher than the current market-implied levy supports work in Barnett et al. (2020) that quantifies the negative impact of climate-related uncertainty. Our estimate suggests that the resolution of uncertainty associated with a climate policy announcement leads to firms internalizing a carbon levy far higher than the one observed in the market. Perhaps more importantly given that carbon prices will need to be raised substantially to meet the 2° target established at the Paris agreement (see, e.g. Nordhaus (2018)), to the extent that our estimates are credible, this result indicates that raising the carbon levy substantially may not come as a shock to firms given their implied priors.

An important strand of this literature focuses on the effects of imperfect regulation on firms' investment and production choices. For example, Fowlie (2009), Martin et al. (2014), and more recently Bartram et al. (2019) show theoretically and empirically how imperfect competition, information asymmetry and financial constraints respectively interact with an incomplete regulatory framework to alter firms' response to the policies. Relatedly, Aghion et al. (2016) use evidence from the auto industry and a model to show that informational frictions significantly influence the clean innovation path of regulated firms, while Pindyck (2007) and Pindyck (2013) quantify the delay induced by policy uncertainty on the firm's optimal timing of abatement. Externalities studied in these papers generally result in policy outcomes that are worse than those in the baseline frictionless, competitive scenario. In contrast with these studies, the reputational and informational externalities that we study in our setting make regulatory policy *more* effective: this is because the externality that we model can serve to augment a firm's profits relative to the baseline scenario—this in turn makes the regulation event not just a risk for the firm to hedge against, but also a potential *opportunity* for the firm to increase its value. Previous academic literature has also investigated the profitability of climate regulation in the context of market-based environmental policies (see, for example, Bushnell et al. (2013)).

The reputational externality that we model also connects our work to the empirical and theoretical literature on the effect of herding and information externalities on firms' investment choices (see, for example, Chamley and Gale (1994), Leary and Roberts (2014) and Décaire et al. (2019)). Grenadier (1999) investigates the role of information externalities in combination with payoff externalities, and in more recent work, Grenadier et al. (2014) focuses on the specific interaction of information and reputation externalities. To our knowledge, our model is the first one to assess the interaction of these externalities in the specific context of emissions reduction, and our empirical work provides evidence to support the importance of these forces in this context.

In our work, we compare firm-level disclosures of their beliefs about the risk of climate regulation, their actual emissions patterns and, importantly, their plans for future emissions reduction. By so doing, we study how signals of climate regulation risk impact firms' beliefs and actions across different maturities, another novel feature of our framework. We find that firms are highly responsive to signals of future regulation, and in line with our findings, previous literature including Engau and Hoffmann (2009) and Bui and De Villiers (2017) shows that firms update their climate management strategies in response to changes in environmental policy risk. In related works, Zingales and Shapira (2017) and Barrage et al. (2020) outline that large public firms act strategically and internalize the costs of pollution even in the absence of specific regulations in place. Relatedly, Shive and Forster (2019) investigates the impact of corporate governance externalities on firms' environmental behavior, finding that publicly listed firms tend to pollute more. The paper attributes this finding to listed firms facing increased pressure from short-term investors. In contrast, our work focuses on empirical evidence mainly drawn from large publicly listed firms, and explores the heterogeneity in these firms responses to a major regulatory announcement.

There is also extensive empirical work on the determinants of corporate engagement in sustainability practices. Several papers show evidence that aligns with our findings in this paper. Among others, Artiach et al. (2010), Martin et al. (2012), and Luo et al. (2012) document a positive association between climate engagement and firm productivity, while Ovtchinnikov et al. (2019), Zhang et al. (2019), and Heitz et al. (2019) point out that political connections and proximity to policymakers also help to explain corporate engagement in environmental activities.

Finally, our work also relates to the fast-growing literature on corporate sustainability ratings, ESG, and firm value. Drawing from information collected from the CDP dataset, Matsumura et al. (2014) show that higher ESG disclosure scores are associated with higher firm value. Engle et al. (2019) show that hedging strategies against negative climate-change news that rely on the use of ESG ratings data outperform alternative approaches, while Bolton and Kacperczyk (2019) show that firms with higher total CO2 emissions earn higher returns. Recent work such as Dyck et al. (2018), Hoepner et al. (2018), and Krueger et al. (2020) shows that institutional investors are highly concerned with firms' exposure to climate risks, and engage actively with them in the management of ESG practices, while Hong and Kacperczyk (2009) show that "sinning" firms are shunned by such investors. Relatedly, Hartzmark and Sussman (2019) studies announcements of mutual funds' sustainability ratings, and argues that investors reacted by reallocating capital to funds in a manner that reveals their preferences for sustainability—providing confirming evidence for the existence of a reputational externality in a different setting to ours.

2 Data

2.1 Carbon Disclosure Project (CDP) Data

We employ detailed data on firms' voluntary disclosures from the Carbon Disclosure Project (CDP) (https://www.cdp.net/en), an international, not-for-profit organization providing a system for companies to measure, disclose, manage, and report environmental information. CDP sends out detailed questionnaires to a large set of firms each year, and we obtain the annual responses to these questionnaires from 2011 to 2017. These data provide information rarely available in SEC-mandated 10-K annual reports, and information that is only occasionally provided by voluntary firm CSR reports.

In this paper, we focus our attention on three particular sets of firm disclosures in these questionnaires, namely, (i) firms' self-reported measures of their current carbon emissions (henceforth referred to as their *actions*), (ii) firms' forecasts of the future impact of environmental regulation on their operations (henceforth referred to as their *beliefs*), and (iii) firms' self-reported targets for future emissions reductions (henceforth referred to as their *plans*). We describe how we convert the raw data from CDP into the specific measures that we use in our empirical analysis later in this section, but first describe the construction of our sample below.

While it does provide detailed information on firms' environmental activity, we should mention here that the CDP dataset does have several major limitations. First, firms self-report to CDP, meaning that the data comprise a selected subsample of the CRSP COMPUSTAT universe (see, for example, Luo et al. (2012)). More specifically, firms in the dataset are substantially larger than the average firm in the universe. While this does introduce concerns about external validity, it is worth noting that these firms comprise a substantial fraction (25%) of the total emissions reported in the US. Second, since the information reported in CDP is voluntary and not subject to third party auditing, it is potentially subject to "greenwashing".[5] We are therefore careful to assess the validity of the disclosures in CDP on firms' carbon footprint, their beliefs about the expected impact of regulation, and their reported plans for future abatement using a range of internal and external data. This includes two different datasets (Bloomberg and Thomson Reuters) of third-party verified indicators of firms' sustainability collected from

[5] Greenwashing is the use of marketing to portray an organization's products, activities or policies as environmentally friendly when they are not.

publicly available sources.

2.2 Sample Construction

To construct our dataset, we match the CDP data to the CRSP COMPUSTAT North America merged database, comprising 5,991 public firms with complete data over the 2010–2017 accounting period. To ensure that we can measure firms' changing actions and revisions of their beliefs about regulatory risks, we require that firms in CDP report *both* current carbon emissions and their forecasts of the future impacts of regulation for at least two consecutive years in the dataset. Firms also have the option of self-reporting their targets for future emissions reductions (i.e., their plans), and we keep firms who both reported and do not reported their plans in the *previous year*, a distinction that we later return to during our analysis of the data. When we match the CDP data to the CRSP COMPUSTAT sample after applying these filters, the sample comprises a total of 445 unique North American public firms, with between 226 and 365 firms reporting in any given year between 2011 and 2017.

The top panel of Figure 1 shows the fraction of firms in the CRSP COMPUSTAT North America universe that are in our final merged sample of firms. Each bar represents a broad GICS industry. The fractions of firms reporting and not reporting future emissions reductions plans are represented in red and black respectively. Relative to the CRSP COMPUSTAT universe, there are more firms in the merged sample in Consumer Staples, Materials, and Utilities, and fewer Financial and Health Care firms, though these differences are not substantial. Firms that report plans for future emissions reduction are overrepresented in Utilities, though this is the exception rather than the rule—a roughly similar number of firms report and do not report plans in each industry.

The bottom panel of the figure shows that despite the number of firms in the left panel comprising less than 20% of the total number of firms, the firms in the merged sample account for 30% to 60% of the total *market capitalization* across all industries, meaning that firms that report to CDP are substantially larger than the average firm in the universe. It is also worth noting here that the total emissions covered by our sample in 2017 is 1,603 MMT of CO_2, which represents roughly 25% of the total emissions produced in the United States in 2017.[6]

[6] See *https://www.epa.gov/ghgemissions.*

Figure 1
Sector Composition and Market Capitalization

Summary statistics of the CRSP/COMPUSTAT North America universe and the CDP subsample. The left histogram summarizes the proportion of CDP firms in the CRSP/COMPUSTAT North America universe at the GICS two digit level, the right histogram summarizes the proportion of total market value (MKVALT from CRSP/COMPUSTAT as of 2016) represented by these firms. Black (red) bars refer to the total of CDP firms (subset of CDP firms that disclose plans for at least one previous reporting period) in our sample.

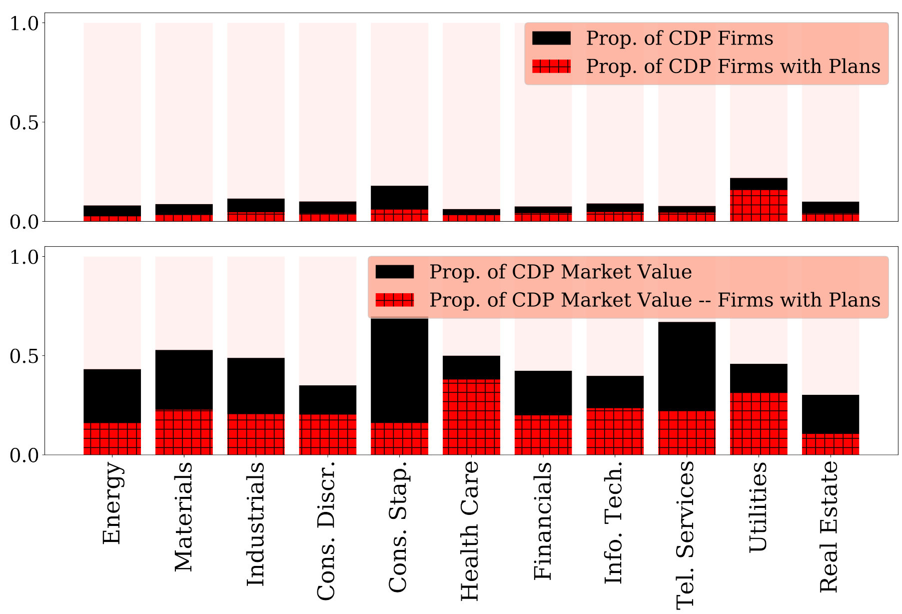


Table 1
Financial and Sustainability Indicators: Summary Statistics

Summary statistics (mean and 95^{th} percentile) of the CRSP/COMPUSTAT North America universe compared with the CDP subsample over the 2010–2016 accounting period. The column Plan (No Plan) refers to the subset of CDP firms that disclose plans for at least one previous reporting period (never disclose plans). Market Value (MKVALT), Total Assets (AT), Total Liabilities (LT) and Income Before Extraordinary Items (IB) are provided by CRSP/COMPUSTAT. Return on Operating Assets (ROA) is computed as Income/(Total Assets - Total Liabilities), expressed in percentage terms. Weighted Average Cost of Capital (WACC) and Altman Z-Score are provided by Bloomberg Equities. Environmental, Social and Governance (ESG) disclosure scores are provided by Bloomberg ESG Data Service (1) and Asset 4 ESG (2) respectively. Emissions are collected from CDP disclosures (as detailed later in the section and in the appendix). Emissions intensity is computed as Emissions/Total Assets, expressed in $\frac{\text{mtCO}_2\text{e ml}}{\$\text{ bn}}$. All variables are collected at the annual level.* indicates that the variable has been winsorized between the 1^{st} and the 99^{th} percentiles of the pooled distribution. $^{+}$ indicates that statistics are computed over a subset of the entire sample.

Variable	CDP **Mean**	Plan **Mean**	No Plan **Mean**	CRSP/COMPUSTAT **Mean**	CRSP/COMPUSTAT **95^{th} perc.**
Market Value* ($ bn)	21.8	26.0	18.3	3.5	23.1
Total Assets* ($ bn)	37.9	46.9	30.3	7.4	52.2
Total Liabilities* ($ bn)	25.9	32.1	22.2	20.6	36.3
Income B. E. Items* ($ bn)	1.2	1.4	1.0	0.2	2.1
Liabilities to Assets Ratio*	0.6	0.6	0.6	0.7	0.9
ROA*	13.7	14.7	13.0	4.2	72.5
WACC*$^{+}$	8.2	7.8	8.4	8.4	14.1
Altman Z-Score*$^{+}$	3.9	3.9	3.8	3.7	13.0
ESG Score (1)$^{+}$	38.6	40.0	37.3	17.8	51.3
ESG Score (2)$^{+}$	66.8	68.7	65.1	50.6	81.9
Emissions (mtCO_2e ml)	5.4	6.4	4.5	-	-
Emissions Intensity	1.7	2.1	1.4	-	-
Unique Firms	445	172	273	5,991	

Table 1 shows pooled means of a selected set of characteristics from CRSP COMPUSTAT, Bloomberg and Thomson Reuters. The average firm in the merged sample (i.e., reporting to CDP) is close to the 95^{th} percentile firm in the size distribution of the CRSP COMPUSTAT universe. The firms in the merged sample also have substantially higher average income than the average firm in the CRSP COMPUSTAT universe, as well as a higher Return on Operating Assets (ROA), but a similar liabilities-to-assets ratio, and a slightly lower probability of bankruptcy.[7]

[7] As implied by the Altman (1968) Z-score, an indicator of the probability of a company entering bankruptcy

There is also an interesting distinction between the firms with and without plans for future emissions reduction. Firms which report such plans are on average larger, have higher income, substantially lower cost of capital, and lower probability of bankruptcy, than firms which do not report these plans. Moreover, plan-reporting firms have greater emissions intensity (as measured by their higher emissions-to-capital ratio) than non-plan-reporting firms. The size, performance, and emissions intensity of firms can affect their incentives to disclose emissions reduction plans, as increases in these attributes can make firms more visible with the attendant enhancement in scrutiny and pressures to disclose.[8]

To verify the CDP disclosures, we also acquire, for a subset of firms, their Environmental, Social, and Governance (ESG) rating scores from two separate sources, namely, Bloomberg ESG Data Service and Thomson Reuters Asset 4 ESG, who independently assess firms' performance on carbon emissions.[9] The percentage of firms in CRSP COMPUSTAT that also have Bloomberg (Thomson Reuters) ESG scores is 37% (27%). Coverage of CDP-reporting firms in our sample, however, is substantially higher (93% in Bloomberg, 92% in Thomson Reuters). Interestingly, across both providers, the externally generated ESG rating scores are not hugely higher for firms in CDP than for the average firm in the universe—this raises the possibility that a certain degree of "green-washing" might motivate firms to report. We are careful, therefore, to consider this factor, and to attempt to validate the CDP data along the dimensions which we are interested in, as we describe more fully below.

2.3 Firms' Actions, Beliefs, and Plans

In this section, we discuss how we use the CDP data to construct three measures that summarize important dimensions in the context of climate risk mitigation, namely, firms' climate mitigation *actions* to date, reflected in their actual changes in carbon footprints; their *beliefs* about the

within the next two years, based on financial ratios obtained from 10-k reports.

[8]Moreover, size and performance can also be related to incentives to disclose through common determinants of these variables. For example, firms in CDP have substantially higher fractions of institutional ownership than firms in the universe (82% vs 64%), and we find that firms with plans have slightly higher fractions of ownership than firms without (82 vs 81%). Institutional ownership has been associated both with higher firm value (e.g., McConnell and Servaes, 1990), as well as with pressures for firms to consider environmental issues (e.g., Hoepner et al. (2018) and Dyck et al. (2018)). The CDP selection bias is also documented in Luo et al. (2012).

[9]Despite multiple controversies on ESG rating methodologies (see, for example, Christensen et al. (2019)), we find that the two ESG disclosure scores are strongly correlated in our sample. Asset 4 ESG also makes available a range of environmental specific indicators—such as the Emissions Reduction (ER) score and the total carbon footprint—which we use later in our analysis.

risk of climate-related regulation; and finally, their *plans* for future carbon footprint mitigation activities. We begin by describing the measures that we construct, and discuss how we validate these metrics by using a range of internal and external data, including third-party verified indicators of firms' sustainability collected using publicly available sources. Then, we show that firms' plans help to predict their subsequent actions, and we uncover interesting variation along both belief and action dimensions, which we subsequently attempt to rationalize using a theoretical model.

2.3.1 Actions

We measure firm's actions as the annual changes in their reported carbon emissions. Specifically, we define firm i's *abatement rate* between time t and $t+1$ as:

$$x_{i,t,t+1} = -\left(\frac{Emissions_{i,t+1} - Emissions_{it}}{Emissions_{it}}\right), \tag{1}$$

where the variable $Emissions_{it}$ measures firm i's direct emissions from production (scope 1) as well as indirect emissions from consumption of purchased energy (scope 2),[10] as reported in CDP in each reporting year t. We exclude from the study other self-reported indirect emissions from the production of purchased materials, product use etc. (scope 3) as the disclosure quality is low (see, for example, Bolton and Kacperczyk (2019)). In the appendix we report how carbon emissions disclosures in CDP compare with third-party estimates provided by Thomson Reuters—to summarize, we obtain consistent figures across the two datasets for the majority of firms in the sample.[11]

2.3.2 Beliefs

In CDP, firms are queried about their exposures to three broad types of risks. The first type is risk arising from likely changes in the physical climate, the second is risk arising from changes in consumer tastes and macroeconomic conditions, and the third is risk arising from future environmental/greenhouse gas emissions regulation. We focus on this third type of risk given

[10] Disclosures of carbon emissions in CDP follow the Greenhouse Gas Protocol Corporate Standard classification.

[11] For example, in 2017, we are able to match a total of 150 firms out of the 365 firms to the Asset 4 ESG dataset. These firms are spread across sectors. For 85% of these matched firms, we find perfect matches between the two datasets, or discrepancies below 10% of the Asset 4 ESG value. For the remaining observations, CDP disclosures are lower than the Asset 4 ESG estimates, especially in pollution intensive sectors such as Energy and Utility.

our interest in the responses of firms to climate regulation events. In CDP, almost 90% of the reporting firms state that they associate climate regulation events with an increase in their operational costs, which in turn may lead to a reduced capacity to conduct "business as usual" operations.

In each reporting year t, firms provide the following pieces of information about the expected impact of a future climate regulation event:

1. A horizon T at which the environmental regulation event is expected to occur.

2. The likelihood of the event q occurring, ranging between *exceptionally unlikely, very unlikely, unlikely, about as likely as not, more likely than not, likely, very likely, virtually certain* and *unknown*, to which we assign numerical values of 0.01, 0.1, 0.25, 0.5, 0.6, 0.75, 0.9, 0.9, and 0.5 respectively for the purposes of quantitative analysis.

3. The expected magnitude of the impact of the event $\tilde{\Lambda}$, which ranges between *low, low-medium, medium, medium-high,* and *high*, to which we assign values 1, 2, 3, 4, and 5 respectively, as well as *unknown* responses, which we simply replace with the sector-specific mean of the impact in each reporting year.

To convert these reported data to our measure of beliefs, we define the expected discounted impact of the regulation event reported by firm i in year t as:

$$\Lambda_{i,t} = \beta^{T_{it}-t}\tilde{\Lambda}_{it}q_{it}. \tag{2}$$

In equation (2), β is a discount rate set equal to 0.93, which is the weighted average cost of capital of the representative firm in the CDP sample.[12] In the appendix, we show the frequency of responses of $\tilde{\Lambda}_{it}$ at each horizon T_{it}, and the average expected impact (i.e., the $t-$pooled cross-sectional average of $\tilde{\Lambda}_{it}$) reported over the 2011 to 2017 period. The plot shows that the reported event horizon T_{it} ranges between zero years and over ten years from the date of reporting, and varies considerably across firms. Moreover, the expected impact of the event $\tilde{\Lambda}_{it}$ increases, on average, with the time horizon of the event T_{it}. In the appendix, we also regress Λ_{it} on firms' current carbon footprint and current market value, as well as a set of

[12]We take the full sample mean (2010–2016 accounting period) of the Weighted Average Cost of Capital (WACC) from Bloomberg Equity.

dummy variables to soak up industry, time, and firm headquarter-specific variation. We find that firms' self-reported beliefs about the future risks of climate regulation increase significantly with their current carbon footprint, though it decreases with firm size, controlling for the level of emissions.

In addition to these more structured quantitative assessments, firms also report unstructured text about the *specific form* of climate regulation that they expect. This text information varies with firms' location and industry, as well as varying across time. We provide more detail in the appendix about these unstructured text disclosures, but highlight here that firms' two most frequently stated types of anticipated climate regulation are, as one might expect, i) a carbon tax/levy, and ii) a cap and trade system. Firms also refer to renewable energy and energy efficiency programmes as a third category of potential climate regulation. These text disclosures partly motivate our modelling choice, described later, of regulation in the form of a carbon levy.

2.3.3 Plans

We use firms' self-reported emissions reduction targets to construct a proxy for planned future emissions abatement. We note here that some firms report these targets, while others do not, a distinction on which we focus in our subsequent work reported below. The firms that *do* report targets report the following information in each year t:

1. A maturity T by or before which the target is planned to be achieved.

2. The total percentage of carbon emissions in year t that the firm plans to reduce between year t and the target year T, which we denote as $\hat{x}$.

We assume a constant emissions reduction rate between each reporting year t, and the stated target year T, which gives us a present discounted abatement rate (i.e., a *plan* for abatement) for each firm i:

$$plan_{i,t} = \frac{1}{T_{it} - t} \sum_{\tau=t+1}^{T_{it}} \beta^{\tau-t} \hat{x}_{it}. \qquad (3)$$

where the first timing of abatement $\tau = t+1$ refers to one year after the year of reporting[13].

[13]It is worth noting that CDP questionnaires are released in October of each reporting year, while firms' responses are submitted in June or July of the same year, with exceptions of later submissions. Planned emissions reduction, as reported from firms in the second-half of the year, refer to the year ahead onwards.

In the appendix, we plot and summarize the various reported components of the abatement plan in (3). The most frequently reported target horizon is between 1 and 5 years, though some firms report far longer horizons, up to 25 years ahead. Once again, the longer the stated horizon, the greater the reported $\hat{x}$, on average across firms and reporting years.

In the appendix, we also attempt to externally validate these estimates. We do so by once again relying on the subset of reporting firms that are also tracked by Thomson Reuters in their Asset 4 ESG dataset. We plot the environmental score that feeds into the ESG rating (a measure of firms' environmental commitment) in Thomson Reuters against our measured $plan_{i,t}$, and find a strong positive relationship between the two variables.

2.4 Patterns in Firms' Actions, Beliefs, and Plans

Figure 2
Beliefs, Plans, and Actions

The left plot shows the belief metric as in (2) against reporting years in the CDP questionnaires. The red-circle (black-star) line refers to firms that disclose (do not disclose) plans in the same reporting year. The right plot shows abatement rates and plans as in (1) and (3) respectively against reporting years in the CDP questionnaires. The red-circle (black-star) line refers to abatement rates for firms that disclose (do not disclose respectively) plans in the previous reporting year. The red thin line at the top of the right-hand panel shows plans for future emissions abatement.

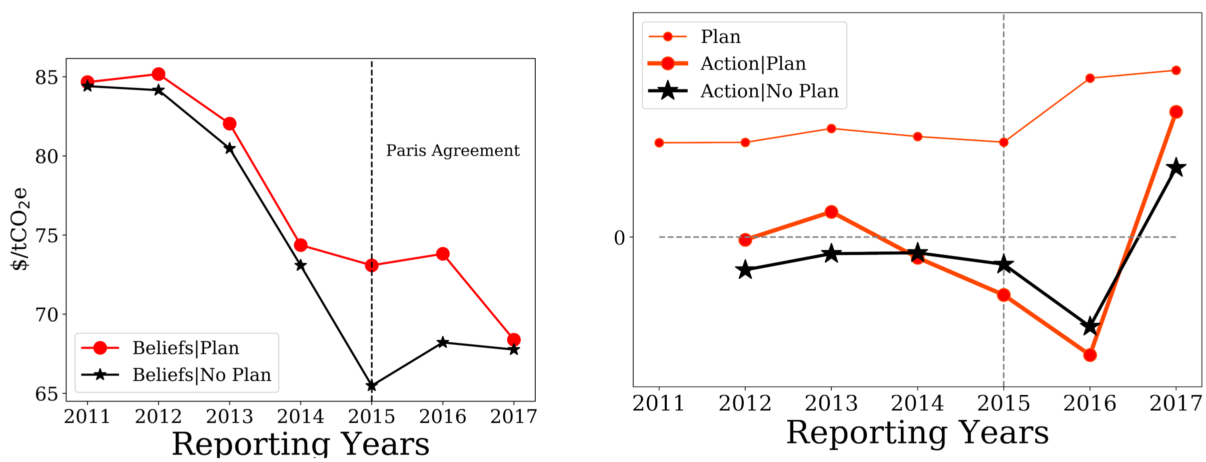


Figure 2 plots the beliefs and actions of firms across our sample period. The left-hand panel of the figure plots beliefs averaged across firms in each reporting period, i.e., $\Lambda_t = \frac{1}{N_t}\sum_{i=1}^{N_t}\Lambda_{i,t}$, where N_t is the number of firms reporting in each year t, while the right-hand panel plots firms' actions, i.e., $x_{t,t+1} = \frac{1}{N_t}\sum_{i=1}^{N_t} x_{i,t,t+1}$. In each plot, rather than showing the unconditional average across all firms, we plot the averages separately for the firms that do report plans (in red), and those that do not report plans (in black). In the right-hand plot, we also show a thin red line, which plots the average planned abatement rate $plan_t = \frac{1}{N_t} \sum_{i=1}^{N_t} plan_{i,t}$ for those firms that report plans.[14]

As described earlier, we construct our measure of beliefs using firms' qualitative responses about the expected impact of future climate regulation. This means that the economic magnitude of these extracted beliefs is not meaningful unless we are able to assign values to them in a sensible fashion. To do so, we now make use of the theoretical model that we develop in the next section—which we explain more fully later. More specifically, the y-axis in the left-hand panel of Figure 2 shows beliefs expressed as that per-period expected carbon levy which, given as an input to our model, would generate an emissions abatement path consistent with the realized path summarized in the right-hand panel of Figure 2.

Observed beliefs exhibit a decreasing trend between 2011 and 2015 for all firms. Firms that do not report plans exhibit a more pronounced downward slope in beliefs than firms reporting plans for future abatement (firms without plans exhibit a cumulative drop of roughly 20\$/mtCO_2e and those with plans, roughly 10\$/mtCO_2e—this is the drop in the expected carbon levy consistent with firms' actions, derived from the model). This difference is especially pronounced in 2015, the year prior to the announcement of the Paris agreement. In this year, firms with a plan seemingly modulate their belief revisions relative to the firms with plans, who more aggressively downward update their beliefs about future climate regulation. This trend reverses following the Paris agreement, when all firms upwardly revise their beliefs about the expected impact of climate regulation. Once again, this belief revision between 2015 and 2016 exhibits differences between the firms with and without plans—firms without plans display a much sharper upward belief revision than those with plans between these two periods.[15]

The right-hand panel of Figure 2 shows how the current actions of firms on emissions reduction vary over time, once again splitting firms into two groups based on whether they

[14] Note here that we simply ignore at this stage the distinction between the size of the emissions reduction that firms plan, and the horizon over which they choose to implement this emissions reduction. We conflate the two into the rate *plan* in what follows.

[15] In the appendix, we also look at the average stock returns of firms with and without plans in the week surrounding the announcement of the Paris agreement. The results show that while both groups of firms experienced negative returns on average, firms without plans were the ones most strongly affected by the announcement.

do or do not report plans for future emissions reduction. The plots show similar patterns to the dynamics of beliefs—both groups of firms increased their emissions, i.e., reduced their abatement activities, between 2012 and 2016, leading up to the Paris climate change agreement. Perhaps surprisingly given their reported beliefs, firms with plans reduced their abatement activities *more* than firms without plans over this period. Once the Paris agreement is ratified, however, both groups sharply reduce their emissions, i.e., increase their abatement activities, in 2017. And again, perhaps surprisingly, firms with plans increase abatement activities more than firms without reported plans for future emissions reduction.

What is particularly interesting is that the realized spike in emissions reduction was *predicted* by the average firm reporting plans for future emissions reduction. When we inspect the plans themselves, which is the thin red line in the right-hand panel of the figure, it shows that the expected future abatement rate remained steady until 2015, but rose significantly in 2016, predicting the realized spike in emissions reduction in 2017. Importantly, as we show in the appendix, predicted and realized emissions reductions persist once we disaggregate the representative firm's disclosure at the sector level, though there is variation across sectors. It is therefore more likely that the spike observed in the data reveals a reaction to a global shock, such as the Paris agreement announcement, rather than a sector-specific regulatory shock. This, in turn, mitigates concerns about the lack of sector-specific information in our study. To better understand the underlying source of these intriguing patterns, in the next section we build a dynamic model of firms' carbon emissions reductions.

3 A Baseline Dynamic Model of Carbon Emissions Reduction

Our modelling strategy proceeds in two steps. We first begin with a dynamic model of a single representative firm considering its optimal abatement strategy. In a second step, to better model the heterogeneity in responses that we observe across firms with and without plans, we extend the model to a two-firm version with information asymmetry and strategic considerations.

3.1 Setup: Single-Firm Model

The economy exists for $t = 0, \dots T$ time periods, and we model a single firm operating in this economy. At the beginning of each time period t, the firm operates with a stock of polluting capital k_{t-1}, producing a proportional amount of carbon emissions $\xi_{t-1} = \eta k_{t-1}$ (measured at the end of time period $t-1$). The firm can reduce or increase its emissions at a rate x_t. If the firm decides to abate, the capital stock then has the following law of motion:

$$k_t = k_{t-1}(1 - x_t), \tag{4}$$

with corresponding carbon emissions (measured at the end of time period t) of:

$$\xi_t = \eta k_t = \eta k_{t-1}(1 - x_t) = \xi_{t-1}(1 - x_t). \tag{5}$$

Over any time period $t < T$, the firm makes profits π_t from its operations:

$$\pi_t = \omega k_t - \frac{1}{2}\phi x_t^2 k_{t-1}, \tag{6}$$

where ωk_t is the firm's output from a linear production function (ω is a productivity constant), and ϕ is a quadratic adjustment cost parameter that is affected by the rate of emissions reduction or abatement (we simply normalize the cost of incremental investment to zero).

At time $t = T$, a regulation event occurs with certainty, and the firm pays a carbon levy λ for each unit of carbon emissions it produces at that time.[16] As a result, the firm's terminal profits can be expressed as:

$$\pi_T^\lambda = \pi_T - \lambda \xi_T. \tag{7}$$

The optimal abatement profile $\{x_t\}_{0 \le t \le T}$ maximizes the firm's value conditional on a given intensity of the levy, λ:

$$V_0^\lambda = \max_{\{x_t\}_{0 \le t \le T}} \sum_{t=0}^{T-1} \beta^t \pi_t + \beta^T \pi_T^\lambda, \tag{8}$$

[16] In the interests of parsimony and simplicity, we choose to model the carbon pricing mechanism as a tax applied to each unit of emissions produced by the firm. As mentioned in the data section, and as we describe in greater detail in the appendix, the carbon tax is one of the most frequent types of regulation explicitly mentioned by reporting firms in the data.

where β denotes the one-period discount rate of the firm.

For each maturity $0 \leq t < T$, the firm value satisfies the Bellman equation:

$$V_t^\lambda = \max_{x_t}\{\pi_t + \beta V_{t+1}^\lambda\}, \tag{9}$$

with the terminal condition:

$$V_T^\lambda = \pi_T^\lambda. \tag{10}$$

3.1.1 Solving the Model

In the appendix, we show the first order condition of the Bellman equation with respect to x_t. The optimal abatement profile conditional on a given intensity of the levy λ is:

$$x_t^*(\lambda) = \beta\left(x_{t+1}^*(\lambda) - \frac{1}{2}(x_{t+1}^*(\lambda))^2\right) - \frac{\omega}{\phi},\ 0 \leq t < T, \tag{11}$$

and the terminal abatement rate is:

$$x_T^*(\lambda) = \frac{1}{\phi}(\lambda\eta - \omega). \tag{12}$$

3.1.2 Comparative Statics

The comparative statics of the terminal abatement rate x_T^* in (12) are intuitive. The abatement rate increases with the intensity of the levy, λ, as well as with the parameter η, which captures the pollution intensity of the firm. On the other hand, the abatement rate decreases with the productivity of polluting capital, ω. Finally, regardless of whether the model predicts an abatement or an increase in polluting capital (i.e., regardless of whether $x_T^* > 0$ or $x_T^* < 0$), the magnitude of any abatement decreases as the adjustment cost parameter ϕ rises.

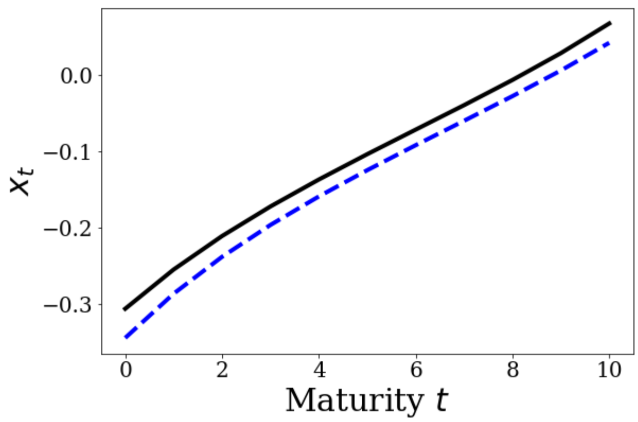
We now outline the key comparative statics of the solution x_t^* in (11). First, we can describe how the abatement rate x_t^* varies with maturity t. Let us assume that the levy λ is such that the model predicts abatement (i.e. $x_t^* > 0$) for some maturity $t < T$, then equation (11) implies that the abatement rate at the subsequent maturity, x_{t+1}^*, satisifies $x_{t+1}^* > x_t^* > 0$. Iterating this argument up to the regulation event T, we get:

$$x_T^* > x_{T-1}^* > \cdots > x_{t+1}^* > x_t^* > 0, \tag{13}$$

that is, an *upward-sloping* term structure of abatement, as seen in Figure 3.

Figure 3
Optimal Abatement Profile

The plot shows the optimal abatement profile $\{x_t^*\}_t$ as a function of the maturity $t = 0, \ldots T$ for two values of the parameter $\lambda = 2.3$ (blue dashed line) and $\lambda = 3.0$ (black thick line) respectively. Other model parameters are: $\phi = 30$, $\omega = 1.0$, $\beta = 0.95$, $\eta = 1.0$, $T = 10$.



This result is intuitive: the benefits to the firm from an additional unit of polluting capital (given by the productivity parameter ω) accrue at the time at which the capital is in place (i.e., any time t before and including the terminal date), while the costs (the levy λ) are always incurred at the terminal date, and hence always discounted more heavily than the benefits. This gap between the present value of costs and benefits shrinks as we approach the terminal date, resulting in the upward-sloping abatement term structure.

Second, we can fix a maturity t, and see how the abatement rate varies as a function of the levy λ. Assume $t = T - 1$. Substituting the terminal condition (12) into (11) and computing the second derivative of x_{T-1}^* with respect to λ, we get:

$$\frac{\partial^2 x_{T-1}^*}{\partial \lambda^2} = -\frac{\beta \eta^2}{\phi^2} < 0. \tag{14}$$

Equation (14) shows that the optimal rate x_{T-1}^* is strictly concave in λ. Equivalently, the firm has a *dampened reaction* to increasing values of the levy. This result holds true if two conditions are satisfied. First, the firm must abate at least some capital in order to control its emissions, and second, abatement of capital must involve convex adjustment costs—these conditions together imply that emissions abatement has convex costs. This result, that the optimal abatement rate is strictly concave in the size of the terminal emissions levy, can be extended by induction to each maturity $0 \leq t < T-1$. The proof of this result is in the appendix.

It is worth noting that in our model, the only way that the firm can hedge against the regulation event at maturity is to scale back its production at each time period. In particular, our model assumes that the emissions intensity η, which controls the amount of emissions generated per one unit of polluting capital, is constant across time periods. A more complex model could introduce the ability of a firm to decrease emissions intensity from η_0 to η_τ at some point in time $0 \leq \tau \leq T$, by replacing the old technology with a new one adapted to cleaner standards. Such a second option would likely require the payment of a lump sum for implementing the technology switch.

While we do not solve this more complex model, we do assess how these two emissions abatement options compare using comparative statics. We begin by assuming that the firm has an initial emissions intensity of $\eta_0 = 0.01\text{mtCO}_2\text{e}/\$$, and that there is a levy of $\lambda = 100\$/\text{mtCO}_2\text{e}$ that needs to be paid after $T = 10$ years. Substituting the optimal abatement rates (11) and (12) into the expression for the firm value in (8), and assuming that $\omega = 25\%$, $\phi = 12$, $\beta = 0.96$, and $k_0 = 1$ \$BN, we find that firm value at time zero $V_0^\lambda = 1.72$ \$BN, a reduction of roughly 45% with respect to a scenario without regulation, in which $V_0^0 = 3.11$ \$BN.

If the firm could instead reduce its emissions intensity of 20% at some point in time between $t = 0$ and $t = T$, so that $\eta_T = 0.008$, then the firm value under this new scenario would be $V_0^{\lambda'} = 1.92$ \$BN, that is, compared with the capital reduction, the firm would save 0.20 \$BN in total (i.e. 20% of its initial capital). This allows us to understand the costs that firms would be willing to pay for such a technology. In NPV terms, the firm would exercise the technology switch at a time τ and a lump-sum investment cost below the threshold $I_\tau = \beta^{-\tau} 0.20$ \$BN.

3.1.3 Single Firm Model Calibration

We calibrate the single firm model to match the average firm in the sample. To do so, we make the following parameter choices:

- We set the discount rate $\beta = 0.93$ to match the inverse of the weighted average cost of capital of the representative firm in the dataset.[17]

- We set the maturity of the regulation $T = 10$ to match the first ratification period of the Paris agreement (December 2020), which is the most frequent target year reported by the firms in the dataset[18]

- We set the initial belief about the intensity of the carbon levy $\lambda_0 = \bar{\lambda}$, where $\bar{\lambda}$ is a parameter to be estimated, and assume that changes in beliefs are a transformed version of the 1 to 5 scale reported in firms' disclosures. That is, we set:

$$\lambda_t - \lambda_{t-1} = m_t \ \sigma^{-1}\big(\frac{\Lambda_t - \Lambda_{t-1}}{m_t}\big) \tag{15}$$

  where for each reporting period t, Λ_t is the reported belief of the representative firm with a plan in the dataset (i.e. $\Lambda_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \Lambda_{i,t}$, with $\Lambda_{i,t}$ as in (2)), $m_t = 1/t$ is a learning parameter, and $\sigma^{-1}(\cdot)$ is the inverse of a sigmoid function.[19] More specifically, we assume that observed revisions are a time-varying function of a regularized signal $\Lambda_t - \Lambda_{t-1} = m_t \ \sigma\big(\tilde{\epsilon}_t\big)$. We do so to account for the fact that firms report beliefs as categorical variables on the same scale between 1 and 5 each period, and to account for the differential updates conveyed by more extreme reported beliefs as time elapses. The recovered signal $\tilde{\epsilon}_t = \sigma^{-1}\big(\frac{\Lambda_t - \Lambda_{t-1}}{m_t}\big)$ is therefore what we use in expression (15).

- We estimate the parameters $\bar{\lambda}$, ω and ϕ to minimize the squared distance between the empirical and model-implied abatement actions and abatement plans:

$$\min_{\bar{\lambda},\omega,\phi} \sum_t \big(x_{t,t+1} - x^*_{t+1}(\lambda_t)\big)^2 + \big(plan_t - plan^*_t(\lambda_t)\big)^2, \tag{16}$$

  where the levy λ_t follows (15), $x^*_{t+1}(\lambda_t)$ is the optimal abatement rate at the shortest maturity, computed as in (11) and conditional on the belief λ_t, and the optimal plan $plan^*_t(\lambda_t)$ is the sum of future discounted optimal abatement rates $plan^*_t(\lambda_t) = \sum_{\tau=t+1}^{T} \beta^{\tau-t} x^*_\tau(\lambda_t)$.

[17] The Weighted Average Cost of Capital (WACC) is from Bloomberg Equity.

[18] Note that the reporting period varies between the beginning of 2011 and the end of 2016.

[19] Further details are provided in the final section of the Appendix, but this is assuming a simple update of the prior assuming Bayesian learning in each period.

It is worth recalling that, from the specification of the firm's emissions in (5) and the capital stock dynamics in (4), we have that $x^*_{t+1} = -\big(\frac{\xi_{t+1}-\xi_t}{\xi_t}\big)$, which allows for a direct comparison with the relative change in realized emissions $x_{t,t+1}$, measured as in (1) for the representative firm with plans in the dataset. In the same way, the model-implied abatement plan $plan^*_t(\Lambda_t)$ also allows for a direct comparison with the measured abatement plan $plan_t$ in (3), reported by the representative firm at year t and anticipating relative changes in emissions from year $t+1$ onwards. Finally, we normalize the emissions intensity $\eta = 1$[20], while we will discuss its economic meaning below.

As reported in Table 2, we estimate parameters $\bar{\lambda} = 2.64$ and $\omega = 0.28$. In relative terms, the baseline model therefore estimates that the gross benefit from an additional unit of polluting capital, evaluated at each time period, is roughly 11% of its terminal cost (i.e. $\omega/\bar{\lambda} = 0.11$).

In terms of magnitudes, we note that the productivity constant ω is roughly twice the Return on Operating Capital observed for the representative firm with plans in the dataset (i.e., equal to 14.7% as summarized in Table 1).

For a normalized emissions intensity $\eta = 1$ mtCO_2e/\$, the model estimates an initial levy of $\bar{\lambda} = 2.64$ \$/mtCO_2e. If one had to use a realistic value for the emissions intensity ($\eta \approx 0.002$ mtCO_2e/\$ from Table 1), the estimated levy would be $\bar{\lambda} \approx 1,320$ \$/mtCO_2e, incurred at maturity T, which in turn corresponds to an equivalent per-period levy of $\bar{\lambda}^{eq} \approx 87$ \$/mtCO_2e at each time t.[21]

Despite the growing literature dedicated to the topic, there is still large uncertainty about the social costs of climate change, and the economic implications of carbon policies (see, for example, Nordhaus (2014)). Recent work by Barnett et al. (2020) attempts to quantify the limitations of such uncertainty in terms of discounts applied to the social cost of carbon (SCC), showing that uncertainty-adjusted SCC are substantially lower than average estimates predicted by a set of models in the literature. In a review by Tol (2011), the average of SCC estimates across over 300 published articles is over 150\$/mtCO_2e, while the mode of the distribution is below 50\$/mtCO_2e. We contribute to this literature using our simple model, which predicts that the representative disclosing firm's actions are consistent with an expected policy of roughly

[20]The emissions intensity enters in the model only at maturity, as $\eta\lambda$. Therefore, the parameters λ and η cannot be uniquely identified in the estimation.

[21]The equivalent levy is simply measured by $\lambda^{eq} = \frac{\beta^T \bar{\lambda}}{\sum_{t=1}^{10} \beta^t}$, for the discount rate $\beta = 0.93$.

90\$/mtCO_2e, well above the 30\$/mtCO_2e implied levy currently traded in the European cap and trade market.[22] Adding support to the study in Barnett et al. (2020), our estimates suggest that the resolution of uncertainty following a climate policy announcement makes firms internalize a carbon levy which is far higher than that observed in the market. But perhaps more importantly, to the extent that our estimates are credible, the policy implication is that raising the levy substantially might not come as a shock to firms given these implied priors.

Finally, we note that the parameter $\phi = 16.2$, which controls the capital adjustment cost is slightly higher the standard estimates provided by production-based asset pricing models (see, for example, Liu et al. (2009), where $\phi \approx 12.5$).

Figure 7 shows the optimal emissions path $\{\xi_t(\lambda^{eq})\}_{t=1,\ldots 10}$ generated by the estimated model parameters for two values of the per-period levy, namely, $\lambda^{eq} = 87$ \$/mtCO_2e (dashed red line) and $\lambda^{eq} = 300$ \$/mtCO_2e (dashed blue line) respectively, assuming initial emissions $\xi_0 = 1$. As the figure shows, increasing the levy from 87 to 300 \$/mtCO_2e generates an additional 63% decrease in emissions (from the 25% decrease under a 87 \$/mtCO_2e levy). Moreover, consistent with the theoretical predictions of the model, the figure shows that most of the abatement occurs at later maturities, when the time horizon approaches the regulation event.

To assess the predictive quality of the model, the left-hand panel of Figure 4 compares empirical and model-implied abatement plans on average across the sample period, while the right-hand panel compares the model-implied actions with observed abatement actions on emissions reduction. In both plots, the model-implied moments are dashed lines, while the solid lines show the patterns in the data.

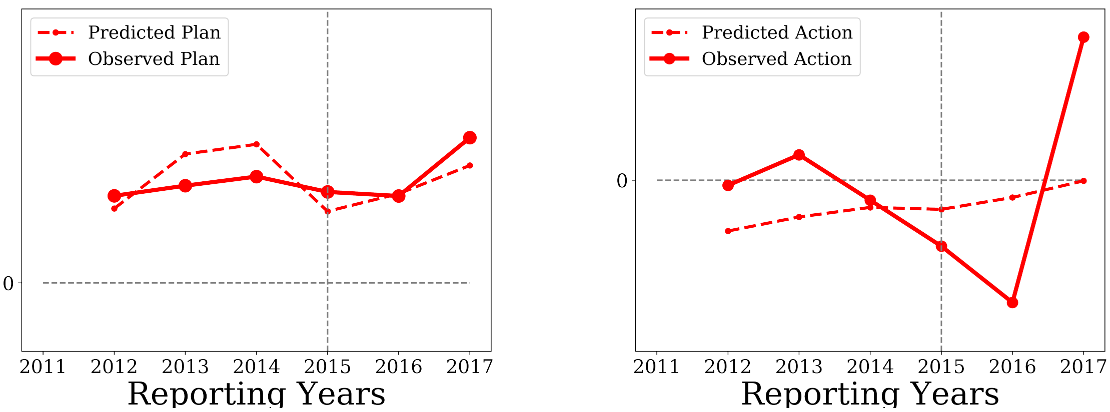
The model-implied abatement plans and actions vary for two reasons. The first is that the impending regulation event gets closer as time passes and $T - t$ falls. The second is that we feed the model the reported beliefs over the timing and intensity of the levy, i.e., the model takes as an input Λ_t reported in the data.

The left-hand panel of Figure 4 shows that the model captures the dynamics of plans reasonably well, once the beliefs have been inputted into the model. While there is an issue of magnitude, which might be expected given the simplicity of the model, the broad pat-

[22] Information on the current pricing of carbon in the EU emissions trading scheme (EU ETS) can be found at $https://ec.europa.eu/clima/policies/ets_en$.

Figure 4
Model-Implied and Observed Moments

The left plot compares the model-implied and observed abatement plan against reporting years in CDP. The right plot compares the model-implied and observed abatement rate against reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments. Model parameters are reported in the first column of Table 2.



terns are roughly similar to the data. However, the right-hand panel of the figure shows that model-predicted abatement actions miss important dynamics in the data on the average firm's abatement actions. Moreover, the data that we match only comprises the firms who do report plans, rather than the firms that do not, and as we showed in Figure 2, firms with and without plans exhibit noticeable differences in behavior. To attempt to better explain the patterns in the data, we therefore move to a model with two firms, which we describe in the next section.

4 A Leader-Follower Model of Carbon Emissions Reduction

To improve the predicted dynamics of the model, and to more broadly capture the patterns observed in the data, we introduce a *second* firm in the market to represent the firms that *do not report* plans for emissions reduction. Throughout this section, we denote by l (for *leader*) and f (for *follower*) the firms with and without plans for emissions reduction respectively, and we derive l and f's optimal abatement profiles in an extended Stackelberg leadership equilibrium where l (the firm reporting its plans) announces commitment to an abatement plan before the

Stackelberg game is played, rationally anticipating the abatement choices of the competitor, while f (the firm not reporting its plans) infers information from the leader's announcement, and takes the abatement choices of the leader as given.

4.1 Setup: Two-Firm Model

We add strategic considerations to the environment as follows:

1. In each time t, we augment the baseline profit function in ((6)) with a *payoff externality* that makes firm l and firm f's profits depend *symmetrically* on the other firm's actions.

$$\pi_t^l(x_t^f) = \omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_{t-1}^l - \gamma_t x_t^f (k_t^l - k_{t-1}^l), \tag{17}$$

$$\pi_t^f(x_t^l) = \omega k_t^f - \frac{1}{2}\phi(x_t^f)^2 k_{t-1}^f - \gamma_t x_t^l (k_t^f - k_{t-1}^f), \tag{18}$$

   when γ_t is a positive parameter, it can be interpreted as a *reputation externality*, in that a firm's profits are reduced in any period t in which the *other* firm abates emissions. γ_t can also be thought of the degree of attention paid by society to firms' abatement activity, manifested in relative performance evaluation along this dimension[23]. The dynamics of media attention to firms' ESG scores has been increasing, even relative to attention paid to general climate change issues. Some evidence to back up this assumption can be seen in Figure 5, which documents the frequency of articles in Dow Jones newswire on selected keywords.

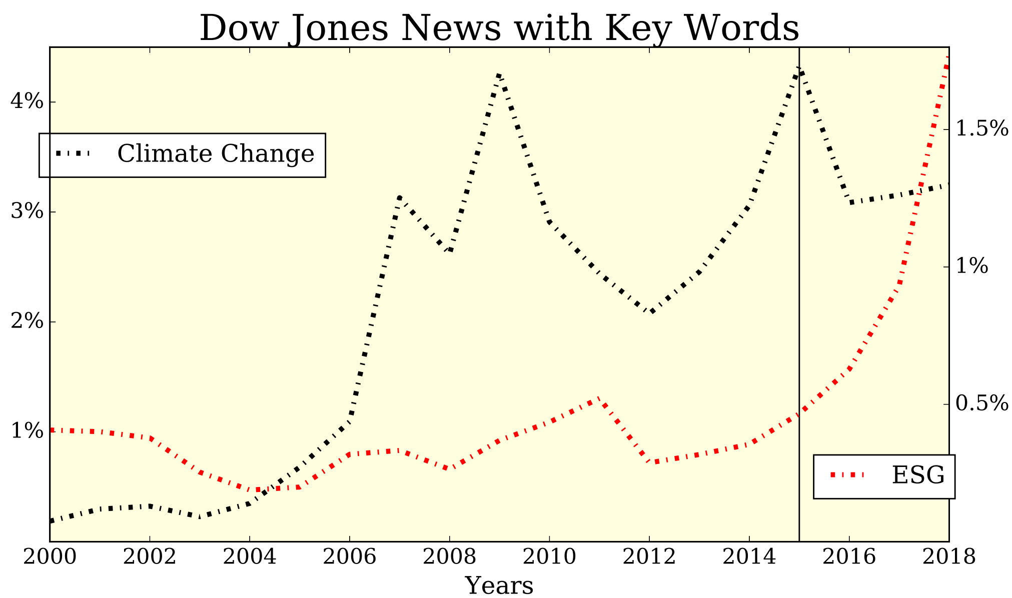
2. We also introduce an asymmetry in the degree of *information* over the intensity of the levy. Specifically, we assume that only firm l receives information about the true intensity λ of the levy, which we now model as:

$$\lambda = \bar{\lambda} + \tilde{s}. \tag{19}$$

[23]Put in these terms, it is worth noting that we could simply set $\gamma_t = \gamma$, that is, a constant time-path of attention paid by society to firms' abatement activity, and still get all of the results developed in this section. However, as we discuss later, allowing for a non-constant time-path improves the fit of the model, and more importantly, provides additional interesting predictions about the time-path of firms' abatement plans.

Figure 5
Historical Environmental Media Coverage

The figure shows the time-series of the percentage of Dow Jones articles containing the words *"Climate Change"* (black dotted line) and *"ESG"* (red dotted line) in headlines or lead paragraphs as recorded from the Factiva database between 2000 and 2018.



> In contrast, firm f can only observe the expected value $\bar{\lambda}$ of the levy. This second assumption requires further justification, which we attempt to provide in the appendix. We summarize a few of these arguments below.

First, in our data, firms with plans have lower financial leverage and higher profitability, on average, than firms with plans. A plausible assumption here is that attention is a scarce resource, and attention paid by the firm to financial stakeholders takes away from sustainability activities that are more likely to appeal to other stakeholders. If this is the case, then less profitable firms will need to spend more time focusing on the needs of financial stakeholders. In contrast, more profitable firms will pay more attention to the details of climate regulation, appeal to non-financial stakeholders by activities such as publishing plans, and potentially have more precise forecasts. Moreover, we find that plan-reporting firms are on average more carbon intensive than firms with no plans. This makes them more exposed to the climate regulation (this can also be seen in firms' own disclosures of climate regulation risk in 2). This also, we believe, gives them greater incentives to focus on the details of regulation.

Second, we find direct evidence from the CDP disclosures that firms with plans are different in another relevant manner to firms that do not reporting plans. In particular, firms with plans have a greater propensity to a) engage with policymakers, and b) provide direct funding to climate regulatory activities. This proximity to the policy process is another channel supporting the second assumption made above (see, for example, recent works in Ovtchinnikov et al. (2019), Zhang et al. (2019), and Heitz et al. (2019)).

In the model, when we make these two assumptions, as a result of its superior information over the levy, firm l has a strong advantage over firm f, because it can commit to an abatement plan before the game is played. This naturally leads to describing our third assumption:

3. Assume that firm l publicly announces its abatement plan before the game is played.[24] In this case, firm f would in turn attempt to extract information from the leader's announcement, rationally updating its belief (using Bayes' rule) over the levy as:

$$\bar{\lambda} + \rho\tilde{s}^{-1}, \tag{20}$$

where $\tilde{s}^{-1}$ is the signal that the follower f *infers* from the leader's announced plan, and $\rho \in [0, 1]$ is the precision weight on the inferred signal,[25] which controls the size of the *information externality* from the leader to the follower firm.

Given these three assumptions, when deciding its optimal course of action and announcement, firm l will internalize firm f's reaction to both its revelation and its actions, and firm f's corresponding inferences about the signal $\rho\tilde{s}$. In contrast, firm f takes firm l's actions as given, and reacts to the announcements and actions of the leader l.

In what follows, we derive the optimal abatement profiles of the two firms in such a setting, which can be interpreted as a specific equilibrium of an extended duopoly game (as the one formalized in Hamilton and Slutsky (1990)) where firms can announce the timing of their moves

[24]That is, assume some net benefit to public reporting. In reality, firms voluntarily report their plans to CDP, rationalizing the existence of such a net benefit.

[25]To formalize this further, we could assume that there is noise in the observation of the plan so that the inferred signal $\tilde{s}^f = \tilde{s} + 1/\rho\tilde{\epsilon}$, with $\tilde{\epsilon}$ drawn from a standard normal distribution. This would then imply that the leader does not observe the follower's belief $\bar{\lambda} + \rho\tilde{s}^f$, but instead has a belief over the follower's belief, i.e., $\mathbb{E}[\bar{\lambda} + \rho\tilde{s}^f] = \bar{\lambda} + \rho\tilde{s}$. However, to eliminate unnecessary complexity, and since we only attempt to match the average beliefs of firms with and without plans in the dataset, we simply assume that $\tilde{\epsilon} = 0$.

before the game is played. Before we proceed, we discuss two additional assumptions that we make about model structure.

First, we simply exclude *cheap talk* Stackelberg duopoly equilibria in our setting (see, for example, Hämäläinen and Leppänen (2017)). More specifically, we assume that the leader can only truthfully report its abatement plan to the follower. One way to justify this choice is to assume that, as in reality, the informational quality of the announcement is subject to a high degree of third-party scrutiny.

Second, we do not endogenize the timing of the actions in the game, meaning that we do not formally prove optimality of the leadership equilibrium. However, we do show in the appendix that a simultaneous equilibrium with no plan revelation by the leader does a worse job of describing the patterns in the data, even when we allow for different adjustment costs of emissions abatement as a more traditional source of heterogeneity in the observed patterns of beliefs and actions across firms.

Having described these caveats, we now move to discussing equilibrium in the two-firm model.

4.2 Equilibrium Abatement Profiles.

Holding fixed the model parameters $\{\phi, \beta, \eta, \omega, \bar{\lambda}, \tilde{s}, \rho\}$, and the maturity of the regulation event T, for any time $t \leq T$ and payoff externality $|\gamma_t| \leq \frac{\phi}{\sqrt{2}}$, the optimal abatement profiles x_t^l and x_t^f satisfy:[26]

- Firm f (follower):

$$x_t^{*,f} = w_t x_t^{*,l} + \beta\Big(x_{t+1}^{*,f} - w_{t+1} x_{t+1}^{*,l} - \frac{1}{2}(x_{t+1}^{*,f})^2\Big) - \frac{\omega}{\phi}, \tag{21}$$

with $w_t = \frac{\gamma_t}{\phi}$, and,

$$x_T^{*,f} = w_T x_T^{*,l} + \frac{\eta}{\phi}\big(\bar{\lambda} + \rho\tilde{s}\big) - \frac{\omega}{\phi}. \tag{22}$$

[26]The upper bound on the magnitude of the strategic parameter γ_t is a requirement that we impose to get well-defined abatement plans and actions. This can be thought of as a bound on the size of the reputation externality.

- Firm l (leader):

$$x_t^{*,l} = \frac{\beta}{(1-2w_t^2)}\Big(x_{t+1}^{*,l}(1-w_{t+1}^2 - w_t w_{t+1}) + x_{t+1}^{*,f}(w_t - w_{t+1})\dots \\ \dots - \frac{1}{2}((1-2w_{t+1}^2)(x_{t+1}^{*,l})^2 + w_t(x_{t+1}^{*,f})^2)\Big) - \frac{\omega(1+w_t)}{\phi(1-2w_t^2)}, \tag{23}$$

and

$$x_T^{*,l} = \frac{\eta}{\phi}\Big(\bar{\lambda}\frac{1+w_T}{1-2w_T^2} + \tilde{s}\frac{1+\rho w_T}{1-2w_T^2}\Big) - \frac{\omega(1+w_T)}{\phi(1-2w_T^2)}. \tag{24}$$

The derivation of these expressions are in the appendix.

4.3 Comparing the Single-Firm and Two-Firm Models

We now compare the equilibrium abatement rates in the expressions above in the previous subsection with the baseline solution established in (11) and (12). We first state the following proposition:

- **Proposition** *At T, the date of the regulation event, for any given set of model parameters $\{\phi, \beta, \eta, \omega, \bar{\lambda}, \tilde{s}, \rho\}$ and payoff externality $|\gamma_t| \leq \frac{\phi}{\sqrt{2}}$, the leader firm l's reactions to changes in the expected carbon levy $\bar{\lambda}$ are larger than those of follower firm f.*

  - **Corollary** *When the payoff externality $\gamma_t \in (0, \frac{\phi}{\sqrt{2}})$, then the leader and follower firm reactions to the levy are both greater than their corresponding reactions in the baseline (i.e., single-firm) model with no cross-firm payoff externalities.*

The proof of this proposition can be found in the appendix. There, we also identify a sufficient condition under which the proposition can also be extended to shorter maturities, i.e., $t \leq T$.[27]

To develop intuition, we begin by discussing the corollary, which is easy to verify—starting from the explicit expressions for the terminal abatement rates in (22) and (24), one can easily derive that the parameter $\bar{\lambda}$ has a higher marginal effect on $x_T^{*,l}$ and $x_T^{*,f}$ than on the baseline solution x_T^* in (12). The intuition is that the cross-firm reputational externalities makes firms

[27] Due to the presence of convex adjustment costs, the result does not necessarily hold for shorter maturities $t \leq T$. However, as we show in the appendix, Proposition 1 holds at shorter maturities t for the subset of model parameters $\{\phi, \beta, \mu, \omega, \bar{\lambda}, \tilde{s}, \rho\}$ and γ_t that generate negative abatement rates (i.e., $x_{t+1}^{*,l}, x_{t+1}^{*,f} < 0$) in equilibrium. Importantly, this inequality is almost always satisfied in the data.

endogenously increase their reaction to changes in the policy, because the way the model is set up in equations (17) and (18), firms have incentives *to act alike* provided that γ_t is *positive*. More specifically, when γ_t is positive, firms find more costly to act such that $x_T^{*,f} x_T^{*,l} < 0$. This tendency towards similarity amplifies their actions relative to the "atomistic" optimum which is unencumbered by such externalities.

The proposition says that as the leader internalizes the marginal effect of the parameter $\bar{\lambda}$ on the follower's abatement choice, it reacts *more* than the follower to variations in $\bar{\lambda}$. Why is this the case? Inspecting equations (17) and (18), we can see that they bear a resemblance to the expressions that one might get from a traditional Stackelberg duopoly, with a modified "demand function of abatement."[28] Essentially, since firm profits respond to (own and other firm) abatement negatively in a similar way that price responds to demand in the traditional Stackelberg model, the leader firm has an incentive to grab "abatement market share" in a similar way to the traditional Stackelberg model, since it has a first-mover advantage.

Another important observation that emerges from the terminal abatement rates in (22) and (24) is that, because the follower learns from the leader's plans (recall (20)), the leader endogenously puts more weight on the expected component of the levy, $\bar{\lambda}$, than on the private component of the levy, $\tilde{s}$. This is because the leader internalizes the follower's reaction to the private signal only partially, to the extent that the follower can learn, i.e., to the extent of $\rho\tilde{s}$. In contrast, the leader fully internalizes the follower's reaction to movements in the expected levy $\bar{\lambda}$, because both the follower and the leader fully observe $\bar{\lambda}$.

Together with the results stated in Proposition 1, this property predicts interesting relationships between the leader's and the follower's reactions and variations in the true value of the levy. For example, think of a situation in which there are shocks to both $\bar{\lambda}$ and $\tilde{s}$ which are equal, but opposite in sign, meaning that the total levy λ remains unchanged. Since the leader firm overweights $\bar{\lambda}$ changes over changes in $\tilde{s}$, and reacts more to changes in $\bar{\lambda}$ than the follower firm, the prediction from the model is that the leader will react more than the follower to this shock ex-post, even though the leader knows that the change in λ is zero. This prediction

[28] To see this, note that we can rewrite the firms' terminal profits as:

$$\pi_T^i(x_t^{-i}) \approx (\eta(\bar{\lambda} + \rho\tilde{s}) - \frac{\phi}{2}(x_T^i - 2w_T x_T^{-i}))x_T^i - \omega x_T^i \tag{25}$$

with $i = l, f$ and $-i = f, l$ respectively.

wouldn't hold in an environment in which there were payoff externalities as in this model, but no information asymmetry across the two firms.

In the appendix, we describe an additional feature of the model, and prove a second Proposition 2 there as well. The proposition allows us to understand how the abatement term structure is affected by changes in the time-path of γ_t. While we leave the details to the appendix, in intuitive terms, Proposition 2 states that when the reputation parameter γ_t decreases monotonically and sufficiently quickly with time, the equilibrium solutions in (21) and (23) can support an inverted term-structure of abatement, i.e., abatement can decrease over time rather than increase, as in the baseline model. This is because a decreasing time-path of the reputational externality (which might be induced by a sudden increase in attention to climate change which gradually revert back to the mean) introduces an additional cost associated with carbon emissions that accrues more aggressively at the (current) time at which the capital is in place. As we discuss in the appendix, Proposition 2 can help to reconcile the observed differences between firms' reported abatement plans and actions before and after the announcement of the Paris agreement.

4.3.1 Two-Firm Model Calibration

We conclude this section by calibrating the two-firm model to the data. We begin with the same set of calibrated parameters β and T, while we estimate the remainder of the parameters to satisfy the following minimization problem:

$$\min_{\rho,\gamma,g,\bar{\lambda},\omega,\phi} \sum_t \left(x^l_{t,t+1} - x^{*,l}_{t+1}(\lambda^l_t)\right)^2 + \left(plan_t - plan^*_t(\lambda^l_t)\right)^2 + \left(x^f_{t,t+1} - x^{*,f}_{t+1}(\lambda^f_t)\right)^2. \tag{26}$$

In equation (26), for the purposes of estimation, we specify the sign and magnitude of the payoff externality for each maturity s and reporting year t assuming a simple exponential functional form, i.e., $\gamma_{s,t} = \gamma e^{-g(s-t)}$. The strategic parameter ρ identifies the size of the positive information externality in the model.[29] The beliefs λ^l_t and λ^f_t follow the dynamics

$$\lambda^l_0 = \bar{\lambda}, \quad \lambda^l_t - \lambda^l_{t-1} = m_t\, \sigma^{-1}\Big(\frac{\Lambda^l_t - \Lambda^l_{t-1}}{m_t}\Big) \tag{27}$$

[29]To preserve consistency with Bayes rule, we impose a zero lower-bound on the value of this parameter.

and respectively

$$\lambda_0^f = \bar{\lambda}, \quad \lambda_t^f - \lambda_{t-1}^f = m_t \, \sigma^{-1} \Big(\frac{\Lambda_t^f - \Lambda_{t-1}^f}{m_t} \Big) \tag{28}$$

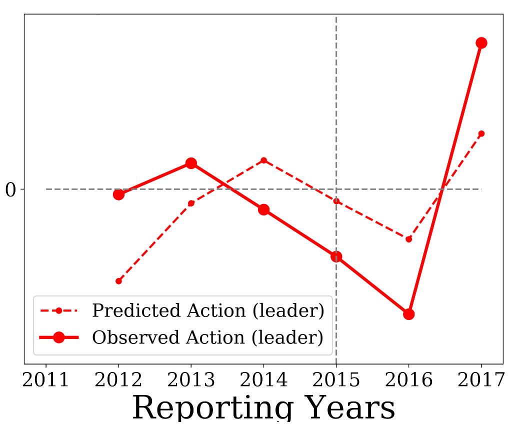
where Λ_t^l and Λ_t^f are computed as described in (2) using the CDP data, and refer to the beliefs inferred from the data for firms with and without plans in the dataset. Finally, for each reporting year t the leader's private signal about the levy $\tilde{s}_t$ is extracted from the leader's and the follower's beliefs as:

$$\tilde{s}_t = \lambda_t^l - \lambda_t^f. \tag{29}$$

Figure 6 summarizes the results of the calibration; the list of input parameters is reported in

Figure 6
Model-Implied and Observed Moments

The left plot compares the model-implied and observed abatement actions for the leader firm against reporting years in CDP. The right plot compares the model-implied and observed actions for the follower firm against reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments. Model parameters are reported in the second column of Table 2.



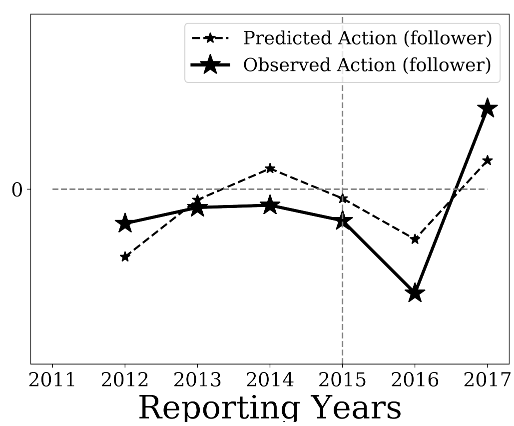


Table 2. The left and right-hand panels in Figure 6, show that the more complicated two-firm model with cross-firm externalities and leader-follower dynamics does result in a better ability to capture the observed dynamics of abatement in the data. A few features are worth discussing in this context.

First, Figure 6 shows that introducing the strategic parameters γ, g, and ρ improves the fit of the model.

Table 2

Calibration Results

The table reports the calibration results for the single-firm (column I) and two-firm (columns II) models respectively. The first set of parameters are calibrated on the representative firm reporting in CDP. The second set of parameters is estimated so that to minimize the sum of squared distances between observed and model-implied abatement rates and actions in the baseline and two firm models (eq. 16 and 26 respectively). The third set of parameters is estimated so that to minimize the sum of squared distances between observed and model-implied abatement rates and actions in the two-firm model (eq. 26).

Parameters	I	II
T	10.0	10.0
β	0.93	0.93
ϕ	16.2	27.0
$\bar{\lambda}$	2.64	2.60
ω	0.28	0.19
ρ	0.00	0.17
g	0.00	0.41
γ	0.00	17.9

Second, the parameter $\rho = 0.17$ that minimizes the squared distance between observed and model-implied moments reveals that to match the dynamics, we need to assume a positive information externality across firms, which results in the leader firm overweighting the observable component of the levy.

Third, the parameters $\gamma = 17.9$ and $g = 0.41$ show that the data are consistent with the presence of a positive reputation externality, whose size decreases with time. As discussed earlier, in the appendix, we show that when γ_t is positive and satisfies a decreasing condition of this type, the model can generate a downward sloping term-structure of abatement, i.e., firms will find it optimal to abate the most at the shortest maturities. This feature can clearly be seen in the simulation exercise reported in Figure 7 and we discuss it in greater detail below.

As reported in Table 2, the estimated parameters are $\bar{\lambda} = 2.60$ and $\omega = 0.19$. In relative terms, the model estimates that the gross benefit from an additional unit of polluting capital, accrued at each time period is roughly 8% of its terminal cost (i.e. $\omega/\bar{\lambda} = 0.08$). In terms of economic magnitudes, the productivity constant ω estimated in the two-firm model is closer to the Return on Operating Capital observed for the representative firm with plans in the dataset, while the parameter ϕ is higher than the reference estimates for capital adjustment costs in the literature. At the same time, the parameter $\bar{\lambda} = 2.60$ implies a per-period levy of $\bar{\lambda}^{eq} \approx 85$ \$/mtCO_2e, as opposed to $\bar{\lambda}^{eq} \approx 87$ \$/mtCO_2e from the baseline model, meaning that the inferences on firms' priors about the levy are very similar from this model.

In addition to the baseline parameters, the model estimates an additional time-varying benefit (cost) from abating (increasing) emissions, which is controlled by the reputation externality term $\gamma e^{-gt} x_t^f x_t^l$. For example, assume that at $t = 0$ the follower firm abates emissions by an amount $x_0^f = 1\%$, then for a corresponding abatement (increase) in emissions $x_0^l = \pm 5\%$, the leader firm faces an externality term $\pm\gamma x_0^f x_0^l = \pm 0.009$, which accounts for almost 5% of the output-capital ratio ω. Finally, the estimated rate of decay of this externality $g = 0.41$ implies that the impact of the externality becomes negligible after $t = 2$ or 3 time periods (years in our setup), depending on the magnitude of the competitor's abatement rate.

Figure 7 shows the optimal emissions path for the leader firm $\{\xi_t^l(\lambda^{eq})\}_{t=1,\ldots 10}$ generated by the estimated model parameters for two values of the levy in input, $\lambda^{eq} = 87$ \$/mt CO2 (thick red line) and $\lambda^{eq} = 300$ \$/mt CO2 (thick blue line) respectively, assuming initial emissions

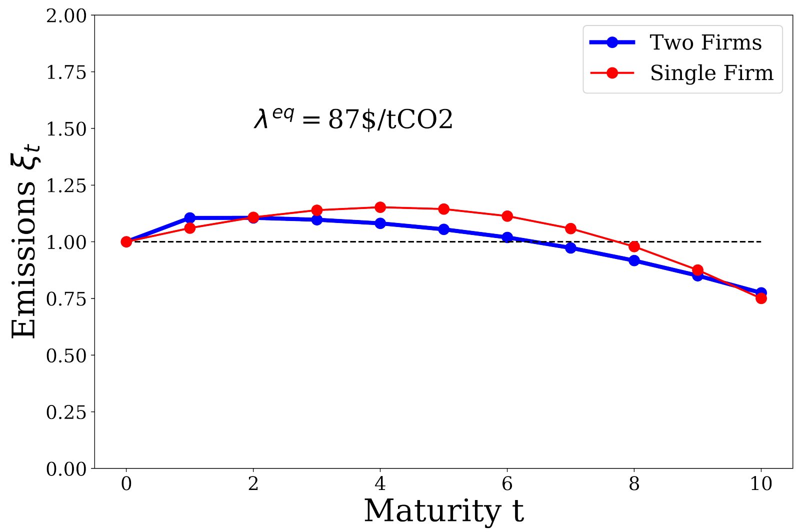
$\xi_0 = 1$.[30] Here, increasing the levy from 87 to 300 \$/mtCO_2e generates an additional 66% decrease in emissions (from the 23% decrease under a 87 \$/mtCO_2e levy), which is a slight amplification in the aggregate response to the policy relative to what is predicted by the baseline model.

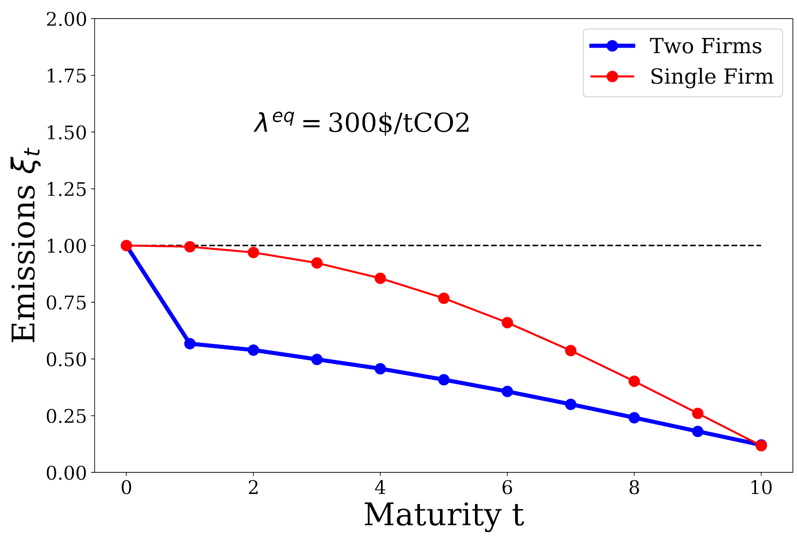
Importantly, however, under the most stringent policy, the two-firm model predicts a substantial amplification of the firm's baseline reaction to the policy in the short run. Consistent with the theoretical predictions of the two-firm model, under a positive and time-decreasing payoff externality, firms decreases in emissions in this extended model primarily occur at the shortest maturity, which is arguably better for the environment.

[30] To permit comparison with the single firm model, we assume that the signal $\tilde{s} = 0$

Figure 7
Optimal Emissions Path

The plots show the optimal path of carbon emissions at each time period as generated from the baseline model (red) and two-firm model (blue) respectively. Left and right plots refer to the emissions generated by the models when the levy parameter $\bar{\lambda} = 2.64$ and $\bar{\lambda} = 9.14$ respectively, which correspond to an equivalent per-period levy of $\bar{\lambda}^{eq} = 87\$/\mathrm{mtCO_2e}$ and $\bar{\lambda}^{eq} = 300\ \$/\mathrm{mtCO_2e}$ respectively, as specified in Section 4. The remainder of model parameters in input are reported in Table 2.



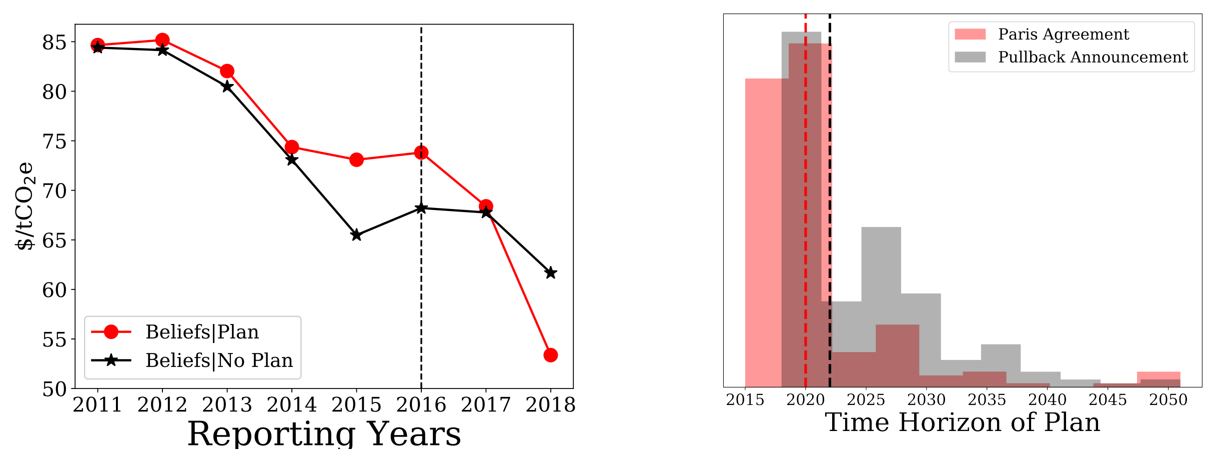


5 Out of Sample Predictions

One way to evaluate the quality of the model's predictions is to assess the quality of its out-of-sample predictions. We therefore extended and processed the CDP dataset after estimating the model up to 2017, to include U.S. public firms' responses for the years 2018 and 2019.[31] This period is particularly interesting, as it allows us to evaluate the impact on firms' responses of a regulatory shock that goes in the opposite direction to those used to fit the model, namely, U.S. President Donald Trump's announcement to pull back from the Paris Agreement, which occurred in June 2017.

Figure 8
Extended Beliefs

The plot shows the belief metric as in (2) against reporting years in the extended CDP questionnaires. The red-circle (black-star) line refers to firms that disclose (do not disclose) plans in the same reporting year.



The left-hand panel of Figure 8 shows beliefs computed from the extended CDP dataset that we use as input variables to our out-of-sample evaluation exercise. As can be seen in the figure, in the year following Trump's pull-back announcement, all firms significantly downgrade their expectations of the impact of climate policy regulation. In contrast with the patterns

[31]Over these two years, CDP implemented a set of changes to make the questionnaires more aligned with the recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD), which was established in 2016. In the appendix we report the major changes to the responses and format arising from these changes and how they affected the measures that we compute. We also describe in the appendix a few adjustments to the data that we needed to implement to conduct the out-of-sample exercise.

previously observed, however, firms reporting plans for future emissions abatement now appear to revise their beliefs about the intensity of future climate regulation far more extensively than those not reporting plans in response to the announcement. According to the model, the expected impact of climate regulation disclosed by plan-reporting firms decreases by more than 15$/mt$CO_2$e relative to their prior estimates, reaching an equivalent per period levy of roughly 55$/mt$CO_2$e.

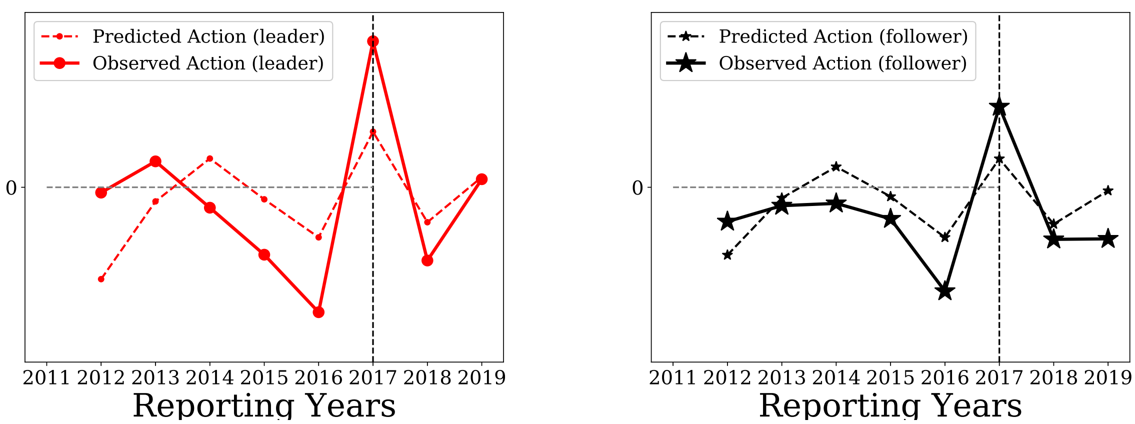
The right-hand panel of Figure 8 shows another interesting observation from the new disclosure data, which is the change in the distribution of firms' reported time horizon T over which they expect to reduce emissions. Following Trump's pull-back announcement, in addition to their changing beliefs about the intensity of regulation, firms also seem to change the expected time horizon over which climate regulation is expected to come into effect, by a median value of 2 years.

To conduct the out-of-sample exercise, we use the beliefs reported in the right panel of Figure 8 to generate emissions abatement plans and actions from the two-firm model. We also fix all parameter values at the levels reported in the second column of Table 2, estimated over the period from 2011 to 2017, except for the time horizon T, which we alter from 10 years to 12 years to account for the evidence seen in Panel B of Figure 8 on firms' extended time horizons.

The left- and right-hand plots in Figure 9 respectively show predicted and realized actions for the leader (plan-reporting) and follower (non-plan reporting) firms for each reporting year in the dataset. The vertical dashed line in the figures indicates the beginning of the out-of-sample forecasting period. The model does a reasonable job of capturing the realized drop in emissions reduction predicted by the downward revision in beliefs following the pull-back announcement for both leader and follower firms, and correctly predicts a larger response for the leader firm. The model is also able to capture the increase in emissions reduction observed in the final year of reported data, which once again is more pronounced for leader than follower firms in the data. Overall, the out-of-sample exercise helps to increase confidence in the augmented two-firm model's ability to capture the dynamics of reported emissions abatement, given beliefs.

Figure 9
Out-of-sample Prediction

The left plot compares the model-implied and observed abatement actions for the leader firm against reporting years in CDP. The right plot compares the model-implied and observed actions for the follower firm against reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments. Model parameters are reported in the second column of Table 2.



5.1 Conclusions

In this paper, we pursue a bottom up approach to identify the determinants of firms' decision making when faced with climate regulation risk. We begin by bringing new empirical observations to the table, using firms' disclosures to the Carbon Disclosure Project (CDP), which we verify using third-party sources (such as Bloomberg and Thomson Reuters) who produce ESG ratings of firms. We document patterns in firms' beliefs about the climate regulation risks that they face, their plans for future abatement, and their actions to date on mitigating carbon emissions. We find that in the five years prior to the Paris announcement, firms' actions on carbon abatement and their beliefs about climate regulation both gradually reduce. However, firms' actions and beliefs both adjust sharply around the announcement of the Paris climate change agreement in 2016, with the size of these responses depending on whether or not firms pre-announce plans for carbon emissions reduction.

To learn more about the underlying structure that can jointly rationalize these findings, we build two dynamic models of emissions abatement. The first model features an atomistic firm operating with polluting capital, which is exposed to a future climate regulation event of known intensity. To abate emissions, the firm must incur convex capital adjustment costs. We calibrate the model to the data, feeding it with the dynamics of reported beliefs, and comparing the predicted plans and actions from the model with those in the data. While the model can fit the dynamics of abatement prior to the Paris agreement, the reactions to the Paris agreement predicted by this atomistic firm model cannot match the sharp variations observed in the data.

We therefore move to a more complex model, introducing a second firm into the economy, with the goal of understanding whether the amplification we observe in the data can be rationalized by firms strategic responses to one another. Specifically, we introduce a reputation externality in the firms' payoffs, which reduces the profits of a given firm when the other firm abates, and vice-versa. We also introduce an asymmetry in firms' information about the regulation event, with the "leader" firm receiving an informative signal which is learnt by the follower. The leader moves first in the game, and the resulting equilibrium of the model predicts abatement dynamics that more closely match the patterns that we observe in the data, and are well able to capture the patterns observed in abatement following the announcement of the U.S. pullback from the Paris agreement in an out-of-sample test.

There is much work to be done on the economics of climate change and carbon emissions. Our paper contributes to this important agenda by demonstrating that i) climate regulation matters greatly to firms, and ii) to better understand firms' responses to regulation events, it is important to take strategic interactions and information asymmetries between firms into account.

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Climate Regulation and Emissions Abatement: Theory and Evidence from Firms' Disclosures

Online Appendix

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A Data Appendix

We employ detailed data on firms' voluntary disclosures from the Carbon Disclosure Project (CDP). CDP sends out environment-related questionnaires to firms each year, and we obtain firms' responses from 2011 to 2017. In total, over 3,000 publicly listed firms from different sectors and countries respond to the questionnaires. We focus on the CDP subsample of publicly listed North American firms that are also in the balanced firm panel available from the CRSP/COMPUSTAT database between 2010 and 2016.[1] We find a total of 700 CDP firms which match with the selected CRSP/COMPUSTAT sample ,[2] but not all matched firms report all variables necessary for our analysis, and some provide inconsistent disclosures. As detailed below, we clean raw disclosures of climate risks, carbon emissions, and emissions reduction targets in order to get firm-level metrics of beliefs, actions, and plans that survive internal consistency checks, and can be validated against external data. The final dataset (consisting of 445 unique firms that report carbon emissions and regulation risk for *at least* two consecutive years) is reported in the third column of Table 1 below.

[1] We keep only firms in the CRSP/COMPUSTAT North America (Fundamental Annual) dataset with non-missing market value within the 2010–2016 accounting period. We lag the information from CRSP/COMPUSTAT by one year to account for a time window between the filling and the final release of the CDP questionnaires.

[2] Matches are computed at the Ticker level.

Table 1

Selected Disclosures

Number of firms in the CRSP/COMPUSTAT North America universe reporting selected disclosures in the CDP questionnaires between 2011 and 2017. Column (1) is the subset of firms that disclose climate risk (regulation); column (2) is the number of firms that disclose total carbon footprint; column (1)+(2) is the selected dataset: firms that disclose carbon risk, carbon footprint, and report to the dataset for at least two consecutive years. Column (3) is the subset of firms in the selected sample that also disclose emissions reduction plans in the previous reporting year.

	(1)	(2)	(1)+(2)	(3)
Reporting Year	Climate Risk	Footprint	Risk & Footprint	Plans
2011	236	390	**227**	**88**
2012	297	429	**227**	**88**
2013	332	465	**277**	**111**
2014	342	468	**291**	**115**
2015	372	481	**326**	**133**
2016	402	508	**348**	**141**
2017	418	505	**368**	**157**
Total Firms	526	631	445	172

Emissions. Raw disclosures of carbon emissions are from CDP data worksheets that pertain to emissions data For each firm i and reporting year t, we compute emissions as

$$Emissions_{i,t} = Scope1_{i,t} + Scope2_{i,t} \tag{1}$$

Where $Scope1$ denotes direct emissions (e.g. for 2017 we look at the sheet "CC8. Emissions Data") and $Scope2$ denotes indirect emissions (e.g. for 2017 we look at the sheet "CC83a. Emissions Data", summarized in Figure 8). In each reporting year, firms can provide multiple estimates of direct or indirect emissions, i.e., there are different vintages of the data. To avoid overlapping disclosures in the time-series, we select only disclosures of carbon emissions related to the latest accounting year: this can either be one year prior to, or the same year as, the reporting year, depending on the date of submission of the firm's data.

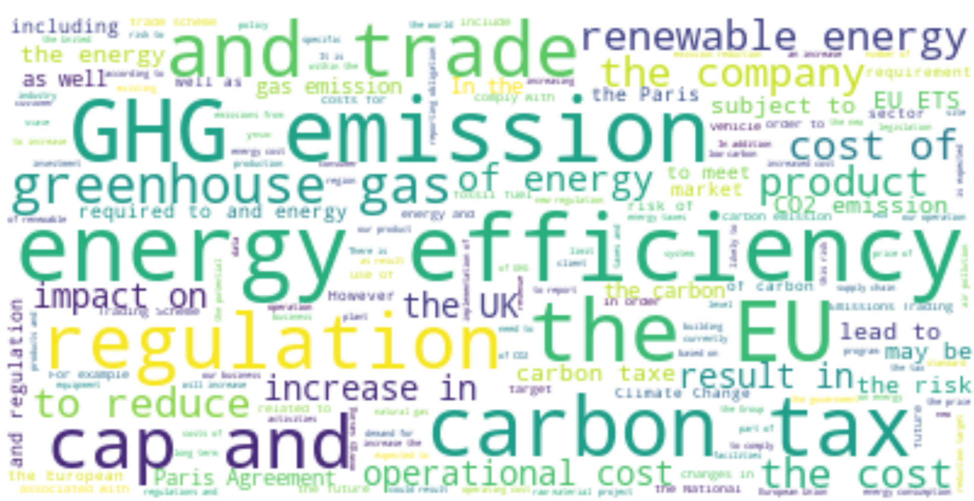
Table 2
Emissions

The table compares sector-level values of CO_2 emissions collected from the CDP questionnaire of 2017 with third party estimates collected from Asset 4 ESG (variable ENERDP023 as of December 2016, see the Asset 4 ESG Dada Glossary for details). Carbon emissions are reported in millions metric tonnes CO_2, and include both Scope 1 (Direct) and Scope 2 (Indirect) emissions. Statistics of the matched sample are reported in bold, statistics on the full CDP sample are reported in the last column.

GIC Sector	**Cumulate Emissions (m tonnes CO_2e)**		
	CDP	Asset 4 ESG	Total CDP
Consumer Discretionary	**39**	**42**	101
Consumer Staples	**52**	**50**	62
Energy	**134**	**150**	150
Financials	**4**	**4**	68
Health Care	**12**	**11**	15
Industrials	**127**	**127**	243
Information Technology	**17**	**11**	39
Materials	**180**	**178**	248
Telecomm. Services	**20**	**20**	21
Utilities	**96**	**136**	470
Real Estate	**2**	**2**	22
All Sectors	684	731	1,638

Beliefs. Raw disclosures of regulation risk are from CDP sheets related to climate change risks (e.g. for 2017 we look at the sheet "CC5.1a" on risks driven by changes in regulation, summarized in Figure 9). Firms' descriptions of the regulation risk they face vary across firms and reporting years in the dataset. The word cloud below highlights some of the most frequent words that appear in the unstructured text field in the pooled dataset in which firms describe the specific regulation risks. As the figure shows, firms refer to several different types of climate regulation. Firms' two most frequently stated types of anticipated climate regulation are, as one might expect, i) a carbon tax/levy, and ii) a cap and trade system. Firms also refer to renewable energy and energy efficiency programmes as a third category of potential climate regulation. These text disclosures partly motivate our modelling choice, described in the paper, of regulation in the form of a carbon levy.

Figure 1
Regulation - Description by Firms



Unlike carbon emissions, risk disclosures always refer to the latest accounting year available. However, firms usually describe multiple types of regulation events as they differentiate, for example, at the plant or business unit levels. For each firm i and reporting year t, we therefore compute the aggregate belief metric as

$$\Lambda_{it} = \sum_{k=0}^{k_{it}} \beta^{T_k - t} \tilde{\Lambda}_k q_k \tag{2}$$

where $k = 0, \ldots k_{it}$ varies over the number of events disclosed by firm i in reporting year t, while $\tilde{\Lambda}_k$ and q_k are the magnitude and likelihood respectively of each event k. Figure 2 below summarizes the frequency of disclosures as well as the expected impact of the event $\tilde{\Lambda}_k q_k$ by event horizon T_k.

Figure 2
Beliefs - Constituents

The right plot shows the average expected impact of the regulation event across different maturities of the regulation event. The left plot indicates the frequency of disclosures across each time horizon as collected from the selected CDP sample between 2011 and 2017.

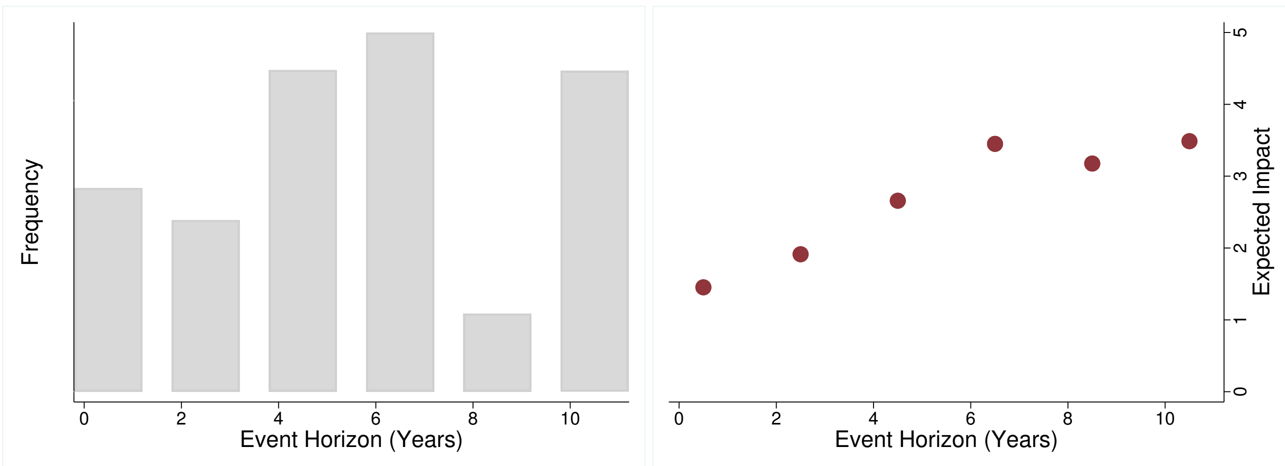


Table 3

Beliefs - Linear Regressions

Linear regressions of beliefs on carbon emissions and market value. Market value is provided by CRSP/COMPUSTAT, carbon emissions are collected from CDP, both the variables are expressed in logarithmic scale. Industry dummies are identified at the GICS industry level, while state dummies are identified at the Head Quarters (HQ) level, both provided by CRSP/COMPUSTAT. Standard errors in square brackets are clustered at the firm-level. *,**,*** indicates statistical significance at the 10%, 5% and 1% level respectively.

Regressor	**Beliefs**			
Emissions	0.15***	0.16***	0.17***	0.16***
	[0.04]	[0.04]	[0.04]	[0.04]
Market Value		-0.13***	-0.11**	-0.13**
		[0.04]	[0.05]	[0.05]
Intercept	0.87***	0.18	0.46	0.52
	[0.27]	[0.33]	[0.34]	[0.37]
Industry dummy?	No	Yes	Yes	Yes
Year dummy?	No	No	Yes	Yes
HQ State dummy?	No	No	No	Yes
$\mathcal{R}^2$	0.04	0.06	0.10	0.18
Firms	445	445	445	445

Plans. Raw disclosures of emissions reduction targets are from CDP sheets related to targets and initiatives (e.g. for 2017 we look at the sheet "CC3.1a" on absolute emissions reduction targets, summarized in Figure 10). As for climate risks, firms can provide multiple targets if they include emissions targets set in previous reporting years that might (or might not) be still active in the current reporting year. For each firm i and reporting year t, we therefore compute the aggregate metric of abatement plans as:

$$plan_{i,t} = \sum_{k=0}^{k_{it}} \frac{1}{T_k - t_k} \sum_{s=t+1}^{T_k} \beta^{s-t} e_k \tag{3}$$

where $k = 0, \ldots k_{it}$ ranges over the total number of targets reported by the firm that are still active in the reporting year t (i.e. $t < T_k$), while $\frac{e_k}{T_k - t_k}$ is the average yearly rate of emissions reduction relative to target k, with $t_k \leq t$ the baseline year of the target. To get rid of inconsistent disclosures, we trim the distribution of the reduction rate e_k so that it lies between $0 \leq e_k \leq 1$. Figure 3 below summarizes the frequency of disclosures as well as the reduction rate e_k by target horizon T_k.

Figure 3
Plans - Constituents

The right plot shows the average emissions reduction target across different target maturities. The left plot indicates the frequency of disclosures across each time horizon as collected from the selected CDP sample between 2011 and 2017.

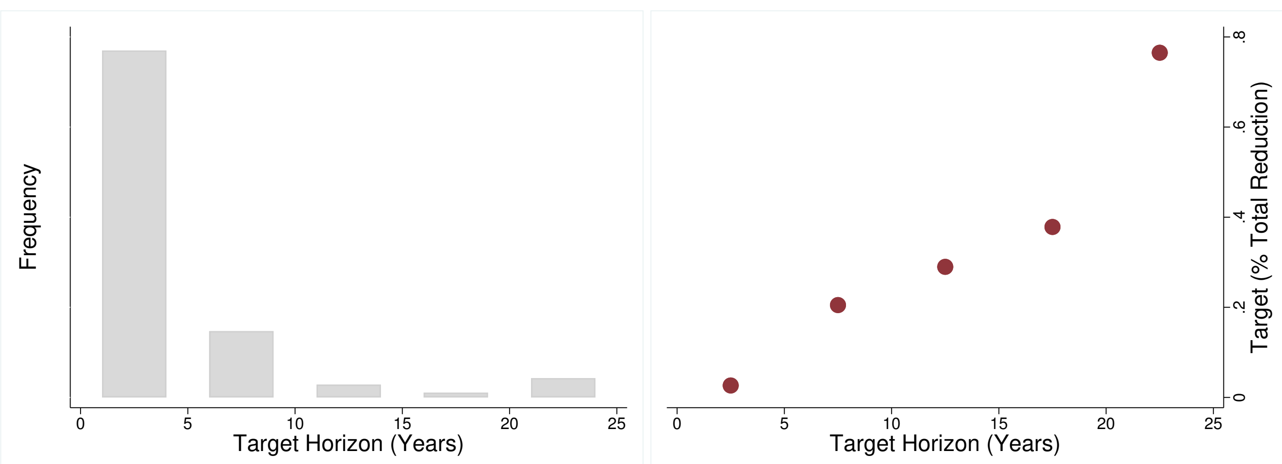


Figure 4
Plans - External Environmental Ratings

The plot shows the environmental (E) scores against equally-sized bins of abatement plans. E scores are constituents of the ESG disclosure score provided by Asset 4 ESG (see the Asset 4 ESG Dada Glossary for details).

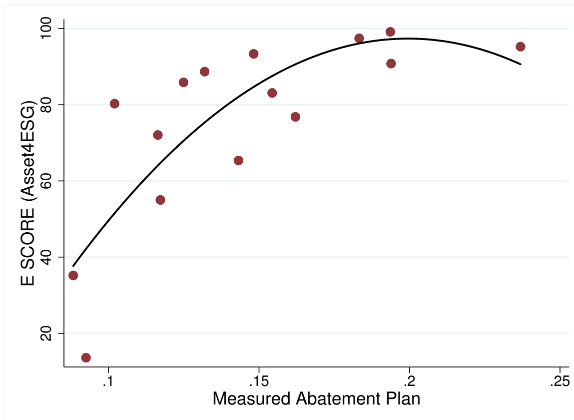


Figure 5
Revisions in Plans and Actions across Industries

The bar plot shows average changes in reported plans and actions across GICS industries. The red bars refer to changes in plans between the years surrounding the Paris agreement announcement. The blue bars refer to changes in actions between the years surrounding the Paris agreement.

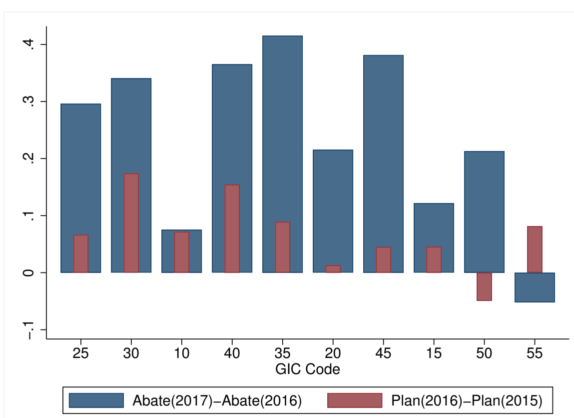
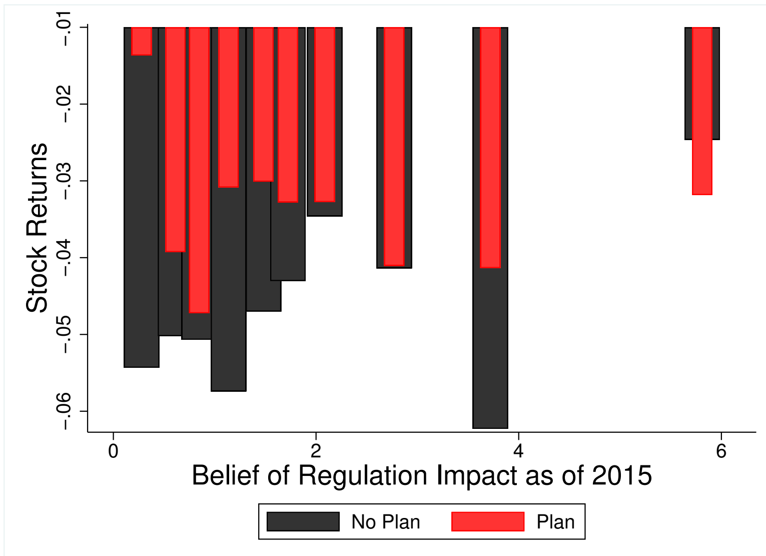


Figure 6

Stock Reaction around Paris Agreement

The plot shows average stock returns around the announcement of the Paris Agreement (Saturday, 12^{th} December of 2015) against equally-sized bins of beliefs relative to the reporting year 2015. Stock returns are relative changes in stock prices (between the last working day preceding the announcement and the first working day following the announcement) as collected from CRSP. The red (black) bars refer to firms in the selected CDP dataset that disclose (do not disclose) targets in the previous reporting year.



B Theory Appendix

B.1 Single Firm Model

Solving the Model. The Bellman equation for the single firm problem reads:

$$V_t = \max_{x_t}\{\omega k_t - \frac{1}{2}\phi x_t^2 k_{t-1} + \beta V_{t+1}\} \tag{4}$$

where the capital stock satisfies:

$$k_t = k_{t-1}(1 - x_t) \tag{5}$$

Deriving (4) with respect to x_t and using (5), we get:

$$-\omega - \phi x_t = \beta \frac{\partial V_{t+1}}{\partial k_t} \tag{6}$$

Deriving V_{t+1} in (4) with respect to k_t, we then get:

$$\frac{\partial V_{t+1}}{\partial k_t} = \omega(1 - x_{t+1}) - \frac{1}{2}\phi x_{t+1}^2 + \beta \frac{\partial V_{t+2}}{\partial k_{t+1}}(1 - x_{t+1}) \tag{7}$$

where we again used (5). Iterating (6) to get $\partial V_{t+2}/\partial k_{t+1}$ and substituting it into (7), we then get:

$$\frac{\partial V_{t+1}}{\partial k_t} = \omega(1 - x_{t+1}) - \frac{1}{2}\phi x_{t+1}^2 + (-\omega - \phi x_{t+1})(1 - x_{t+1}) \tag{8}$$

which after rearrangement gives:

$$\frac{\partial V_{t+1}}{\partial k_t} = \frac{1}{2}\phi x_{t+1}^2 - \phi x_{t+1} \tag{9}$$

now substituting (9) into (6) and solving for x_t, we get:

$$x_t = \beta\Big(x_{t+1} - \frac{1}{2}x_{t+1}^2\Big) - \frac{\omega}{\phi} \tag{10}$$

which proves the result. The expression for the terminal abatement x_T derives directly from the first order condition $\partial \pi_T^\lambda / \partial x_T = 0$, recalling that $\eta_T = \eta k_{T-1}(1 - x_T)$.

Concavity of the abatement rate x_t with respect to λ. We want to show that the inequality

$$\frac{\partial^2 x_t}{\partial \lambda^2} < 0 \tag{11}$$

holds for each maturity $t \in 0, \dots T-1$. Deriving (10) twice with respect to λ, we get:

$$\frac{\partial^2 x_t}{\partial \lambda^2} = \beta\Big(\frac{\partial^2 x_{t+1}}{\partial \lambda^2}(1 - x_{t+1}) - \big(\frac{\partial x_{t+1}}{\partial \lambda}\big)^2\Big), \tag{12}$$

let us start with $t = T-1$. Recalling the expression for the terminal abatement rate $x_T = \frac{\eta\lambda}{\phi} - \frac{\omega}{\phi}$, we get:

$$\frac{\partial^2 x_{T-1}}{\partial \lambda^2} = -\beta\big(\frac{\partial x_T}{\partial \lambda}\big)^2 = -\beta\big(\frac{\eta}{\phi}\big)^2 < 0, \tag{13}$$

which proves the result. Let us now assume that (11) is true for a certain $t = k$. Then, from (12) we have:

$$\frac{\partial^2 x_{k-1}}{\partial \lambda^2} = \beta\Big(\frac{\partial^2 x_k}{\partial \lambda^2}(1 - x_k) - \big(\frac{\partial x_k}{\partial \lambda}\big)^2\Big) < \beta\Big(\frac{\partial^2 x_k}{\partial \lambda^2}(1 - x_k)\Big), \tag{14}$$

that is,

$$\frac{\partial^2 x_{k-1}}{\partial \lambda^2} < 0 \quad \longleftrightarrow \quad x_k < 1, \tag{15}$$

which falls in the range of admissible solutions for x_k.

B.2 Leader-Follower Model

Assumption of asymmetric information In our theoretical framework, the firm that reports plans for future abatement is designated as more informed about the climate policy than the firm that does not report plans. This provides us a rationale for the derivation of the leader-follower equilibrium. This section outlines evidence in favour of this modelling assumption, which is ultimately motivated in the text as a way to rationalize the observed differences in beliefs across the two types of firms.

Table 1 and Figure 2 in Section 3 of the paper summarize differences in characteristics across firms that report and do not report plans for emissions reduction in CDP. As discussed, firms that report plans are overrepresented in the utility sector, which is the sector targeted the most by climate regulation. These firms also have higher market value, more assets, higher income, and lower cost of capital. Using a stakeholder framework, Artiach et al. (2010) suggest a number of hypotheses that relate firms' financial performance to their decisions to invest in corporate sustainability. One hypothesis is that in times of low profitability, firms with high debt will be forced to prioritize financial over societal stakeholders. This makes it more likely that firms with lower leverage and higher income have higher performance along the sustainability or environmental dimension. A second hypothesis is that as firms' financial characteristics also influence their ability to participate in costly sustainability programmes, it is likely that larger firms with lower cost of capital have higher sustainability performance. To the extent that firms with higher propensity to invest in corporate sustainability also manage environmental risks more carefully, it is then likely that their information over these risks is more precise than the other firms in the dataset.

The statistics reported in Table 4 provide more direct support to our assumption, showing that firms that report plans for future emissions abatement are more likely to engage with policymakers and more likely to be involved in lobbying for climate regulation—by providing direct funding to support these activities. Engagement with policymakers, which often constitutes an important dimension of firms' engagement in corporate sustainability, can often provide more direct access to valuable information about future climate regulation (see Ovtchinnikov et al. (2019), Zhang et al. (2019) and Heitz et al. (2019) respectively).

Table 4

Active participation to regulatory policy

Percentage of firms that engage with policymakers and provide fundings to climate regulatory activities as collected from CDP disclosures in 2017. The first (second) column refers to the group of firms that disclose (do not disclose respectively) plans in the previous reporting year.

	Plan	**No Plan**
Engage with policymakers	94%	78%
Provide direct funding	72%	53%
Total Firms	157	208

Solving the leader-follower model. The Bellman equation for the leader-follower model reads:

$$V_t^l = \max_{x_t^l}\{\omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_{t-1}^l + \gamma_t x_t^f x_t^l k_{t-1}^l + \beta V_{t+1}^l\} \tag{16}$$

and:

$$V_t^f = \max_{x_t^f}\{\omega k_t^f - \frac{1}{2}\phi(x_t^f)^2 k_{t-1}^f + \gamma_t x_t^l x_t^f k_{t-1}^f + \beta V_{t+1}^f\} \tag{17}$$

Taking x_t^l as given, x_t^f is first derived following the same steps as in the baseline case with no externalities. It is then simple to show that the optimal abatement rate of the follower satisfies:

$$x_t^f = w_t x_t^l + f_{t+1} \tag{18}$$

with $w_t = \frac{\gamma_t}{\phi}$ and f_{t+1} given by:

$$f_{t+1} = \beta\Big(x^f_{t+1} - w_{t+1}x^l_{t+1} - \frac{1}{2}(x^f_{t+1})^2\Big) - \frac{\omega}{\phi} \tag{19}$$

Now substituting (18) into (16), the leader's Bellman equation reads:

$$V^l_t = \max_{x^l_t}\{\omega k^l_t - \frac{1}{2}\phi(x^l_t)^2 k^l_t + \gamma_t(w_t x^l_t + f_{t+1})x^l_t k^l_{t-1} + \beta V^l_{t+1}\} \tag{20}$$

From the first order conditions with respect to x^l_t, one gets:

$$-\omega - \phi x^l_t + \gamma_t(2w_t x^l_t + f_{t+1}) = \beta\frac{\partial V^l_{t+1}}{\partial k^l_t} \tag{21}$$

Recalling that $w_t = \frac{\gamma_t}{\phi}$, we rewrite the expression in (21) as:

$$-\omega - \phi(1 - 2w_t^2)x^l_t + \phi w_t f_{t+1} = \beta\frac{\partial V^l_{t+1}}{\partial k^l_t} \tag{22}$$

Following the same procedure as in (7) and (8), we get:

$$\begin{aligned}\frac{\partial V^l_{t+1}}{\partial k^l_t} &= \omega(1 - x^l_{t+1}) - \frac{1}{2}\phi(x^l_{t+1})^2 + \gamma_{t+1}x^f_{t+1}x^l_{t+1}\dots\\ &\dots + (1 - x^l_{t+1})\Big[-\omega - \phi x^l_{t+1} + \gamma_{t+1}(x^f_{t+1} + w_{t+1}x^l_{t+1})\Big]\end{aligned} \tag{23}$$

where we used (18) to rewrite $\gamma_{t+1}(2w_{t+1}x^l_{t+1} + f_{t+2}) = \gamma_{t+1}(x^f_{t+1} + w_{t+1}x^l_{t+1})$. After rearrangement, this gives:

$$\frac{\partial V^l_{t+1}}{\partial k^l_t} = \frac{1}{2}\phi(1 - 2w^2_{t+1})(x^l_{t+1})^2 - \phi(1 - w^2_{t+1})x^l_{t+1} + \gamma_{t+1}x^f_{t+1} \tag{24}$$

Putting (24) back into (22) and solving for x^l_t, we finally get:

$$x^l_t = \frac{w_t}{(1 - 2w_t^2)}f_{t+1} + \beta\Big(\frac{(1 - w^2_{t+1})x^l_{t+1} - w_{t+1}x^f_{t+1}}{1 - 2w_t^2} - \frac{(1 - 2w^2_{t+1})}{(1 - 2w_t^2)2}(x^l_{t+1})^2\Big) - \frac{\omega}{\phi(1 - 2w_t^2)} \tag{25}$$

which by substituting the expression for f_{t+1} in (25) gives us the result.
The terminal abatement x^l_T is determined from the first order condition $\partial\pi^l_T/\partial x^l_T = 0$, with:

$$\pi^l_T = \omega k^l_T - \frac{1}{2}\phi(x^l_T)^2 k^l_{T-1} + \gamma_T x^f_T(x^l_T)x^l_T k^l_{T-1} - (\bar{\lambda} + \tilde{s})\eta_T \tag{26}$$

where the follower's terminal abatement given the leader's reads:

$$x_T^f(x_T^l) = w_T x_T^l + \frac{\eta}{\phi}\big(\bar{\lambda} + \rho\tilde{s}\big) - \frac{\omega}{\phi} \tag{27}$$

deriving the expression in (26) with respect to x_T^l and solving for x_T^l, we get:

$$x_T^l = \frac{\eta}{\phi}\Big(\bar{\lambda}\frac{1+w_T}{1-2w_T^2} + \tilde{s}\frac{1+\rho w_T}{1-2w_T^2}\Big) - \frac{\omega}{\phi}\frac{1+w_T}{1-2w_T^2} \tag{28}$$

from which one we also get x_T^f by substituting the expression (28) into (27).

Proof of the Proposition. From the explicit expression in (28) we get:

$$\frac{\partial x_T^l}{\partial\bar{\lambda}} = \frac{\eta}{\phi}\frac{1+w_T}{1-2w_T^2} \tag{29}$$

and substituting the expression (28) into (27) and deriving x_T^f with respect to $\bar{\lambda}$ we get:

$$\frac{\partial x_T^f}{\partial\bar{\lambda}} = \frac{\eta}{\phi}\big(1 + w_T\frac{1+w_T}{1-2w_T^2}\big) = \frac{\eta}{\phi}\frac{1+w_T-w_T^2}{1-2w_T^2} \tag{30}$$

from which we immediately get:

$$\frac{\partial x_T^l}{\partial\bar{\lambda}} > \frac{\partial x_T^f}{\partial\bar{\lambda}} \quad \forall \quad w_T \neq 0, |w_T| \leq \frac{1}{\sqrt{2}} \tag{31}$$

which recalling that $\gamma_T = \phi w_T$ proves the result.

Proof of the Corollary. Recalling the expression for the terminal abatement rate of the single-firm model, we get:

$$\frac{\partial x_T^l}{\partial\bar{\lambda}} > \frac{\partial x_T}{\partial\bar{\lambda}} \quad \longleftrightarrow \frac{1+w_T}{1-2w_T^2} > 1 \tag{32}$$

and similarly:

$$\frac{\partial x_T^f}{\partial\bar{\lambda}} > \frac{\partial x_T}{\partial\bar{\lambda}} \quad \longleftrightarrow \frac{1+w_T-w_T^2}{1-2w_T^2} > 1 \tag{33}$$

which are both satisfied for $w_T > 0$, $w_T < \frac{1}{\sqrt{2}}$. By induction, it is also possible to show that the result holds for shorter maturities $t < T$ provided the set of model parameters $\{\phi, \beta, \mu, \omega, \bar{\lambda}, \tilde{s}\}$ is such that the optimal abatement rates $x_{t+1}^f|_{\bar{\lambda}}, x_{t+1}^l|_{\bar{\lambda}} < 0$, and the payoff externality $\gamma_t > 0$, $\gamma_t' < 0$.

Consider the case of the leader. Assume $\frac{\partial x_{t+1}^l}{\partial\bar{\lambda}} > \frac{\partial x_{t+1}}{\partial\bar{\lambda}}$ for $t+1$. Deriving (25) with respect to the parameter $\bar{\lambda}$, we get:

$$\frac{\partial x_t^l}{\partial \bar{\lambda}} = \frac{\beta}{1-2w_t^2}\Big[\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}}(1-w_{t+1}^2-w_t w_{t+1}) + \frac{\partial x_{t+1}^f}{\partial \bar{\lambda}}(w_t - w_{t+1})\dots \\ \dots - \Big(\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}}(1-w_{t+1}^2)x_{t+1}^l + \frac{\partial x_{t+1}^f}{\partial \bar{\lambda}} w_t x_{t+1}^f\Big)\Big] \tag{34}$$

Provided that $w_t \geq w_{t+1}$, we get after some computation:

$$\frac{\partial x_t^l}{\partial \bar{\lambda}} > \beta\Big(\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}}(1-x_{t+1}^l) - \frac{\partial x_{t+1}^f}{\partial \bar{\lambda}} w_t x_{t+1}^f)\Big) \tag{35}$$

from which the result follows, recalling that $\frac{\partial x_{t+1}^l}{\partial \bar{\lambda}} > \frac{\partial x_t^l}{\partial \bar{\lambda}}$, $x_{t+1}^l < 0$, $x_{t+1}^f < 0$, and $w_t > 0$.

B.3 Supplementary Results to the Leader-Follower Model

Proposition *For each maturity $t < T$, discount rate β, adjustment cost ϕ and size of the reputation externalities $\gamma_t, \gamma_{t+1} \in (0, \frac{\phi}{\sqrt{2}})$ that verify the following inequality*

$$\gamma_{t+1} \leq \gamma_t \sqrt{1 + 4(\frac{\phi^4(1-1/\beta)}{\gamma_t} + \frac{2\phi^2\gamma_t}{\beta})} \tag{36}$$

there exists a set of model parameters $\{\mu, \omega, \bar{\lambda}, \rho, \tilde{s}\}$ that invert the optimal profile of abatement for the leader firm, that is $x_t^l > x_{t+1}^l > 0$.
Proof. The expression in (25) can be put in compact notation as

$$x_t^l = x_{t+1}^l b_{t,t+1} - a_{t,t+1}(x_{t+1}^l)^2 - c_{t,t+1} \tag{37}$$

where the coefficient of the linear term is $b_{t,t+1} = \beta\frac{(1-w_{t+1}^2-w_t w_{t+1})}{1-2w_t^2}$, the coefficient of the quadratic term is $a_{t,t+1} = \beta\frac{1}{2}\frac{1-2w_{t+1}^2}{1-2w_t^2}$ and the coefficient of the constant term is $c_{t,t+1} = \frac{\omega}{\phi(1-2w_t^2)} - \frac{x_{t+1}^f(w_t - \beta w_{t+1} - w_t x_{t+1}^f)}{(1-2w_t^2)}$. We therefore have that

$$x_t^l > x_{t+1}^l \iff (b_{t,t+1}-1)x_{t+1}^l - a_{t,t+1}(x_{t+1}^l)^2 - c_{t,t+1} > 0 \tag{38}$$

which holds whenever x_{t+1}^l falls in the range

$$x_{t+1}^l \in \Big[b_{t,t+1} - 1 - \frac{\sqrt{(b_{t,t+1}-1)^2 - 4a_{t,t+1}c_{t,t+1}}}{2a_{t,t+1}}, b_{t,t+1} - 1 + \frac{\sqrt{(b_{t,t+1}-1)^2 - 4a_{t,t+1}c_{t,t+1}}}{2a_{t,t+1}}\Big] \tag{39}$$

A sufficient condition for the upperbound

$$b_{t,t+1} - 1 + \frac{\sqrt{(b_{t,t+1}-1)^2 - 4a_{t,t+1}c_{t,t+1}}}{2a_{t,t+1}} \tag{40}$$

to be strictly positive, which in turns implies an inverted order of abatement $x^l_t > x^l_{t+1} > 0$, is that $b_{t,t+1} > 1$. This in turn requires that w_t and w_{t+1} satisfy

$$\frac{(1 - w_{t+1}^2 - w_t w_{t+1})}{1 - 2w_t^2} > \frac{1}{\beta} \tag{41}$$

which solving for $\gamma_t, \gamma_{t+1} \in (0, \frac{\phi}{\sqrt{2}})$ proves the result.

B.4 Calibration and Alternative Setup

In Section 3, when performing the calibration of the baseline model, we specify the dynamics of beliefs λ_t in input as a non-linear transformation of the dynamics of beliefs Λ_t of the representative firm in the dataset, to account for the fact that the latter are extracted from categorical disclosures, and that the firms are learning across reporting periods in the dataset. Specifically, we assume that each observed revision in beliefs is a function of a *regularized* signal $\sigma\big(\tilde{x}_t\big)$ and a time-varying weight m_t, that is

$$\Lambda_t - \Lambda_{t-1} = m_t \; \sigma\big(\tilde{x}_t\big) \tag{42}$$

This specification corrects for the fact that, even if signals $\tilde{x}_t$ are unbounded, firms' disclosures are constrained to fixed categories. The choice $m_t = 1/t$ is a shortcut from Bayesian learning from normally distributed signals[3]. To extract the original signal, we then invert the sigmoid function to get

$$\tilde{x}_t = \sigma^{-1}\big(\frac{\Lambda_t - \Lambda_{t-1}}{m_t}\big) \tag{43}$$

where in particular $\sigma(x) = \frac{2\Delta}{1+e^{-x}} - \Delta$, with $\Delta = \max_t |\Lambda_t - \Lambda_{t-1}|$ the largest revision in reported beliefs in absolute terms, so that $\sigma(x) \in (-\Delta, +\Delta)$ for $x \in (-\infty, +\infty)$.

To conclude the analysis, we show how our calibration results performed in Section 4 change in the case where firms endogenize the payoff externality induced by reputation in a simultaneous

[3]Assuming a signal $\tilde{x} = \theta + \tilde{\epsilon}$ is received at each time t, with ρ_ϵ the precision of the signal and ρ_0 the precision of the prior θ_0. Then for each time t the precision of the prior is $\rho_t = \rho_0 + (t-1)\rho_\epsilon$, and the weight assigned to the signal is $m_t = \rho_\epsilon/(\rho_0 + (t-1)\rho_\epsilon)$. Assuming $\rho_\epsilon = \rho_0$, then $m_t = 1/t$

equilibrium setting, assuming heterogeneous adjustment costs and heterogeneous beliefs over the levy. Specifically, we relax the assumption of asymmetric information across firms, assuming instead that firms are simply endowed with heterogeneous beliefs over the levy. Relaxing this assumption in turn implies that the leader firm has no commitment power over the follower firm, which results in a simultaneous equilibrium where firms act based on their expectations over the competitor's action (and therefore their expectations over the competitor's belief). It is simple to show that the terminal abatement rates in this setting read:

$$x_T^i = \frac{\eta}{\phi_i}\Big(\lambda_i \frac{1+w_{iT}}{(1-w_{iT}^2)}\Big) - \frac{\omega(1+w_{iT})}{\phi_i(1-w_{iT}^2)} \tag{44}$$

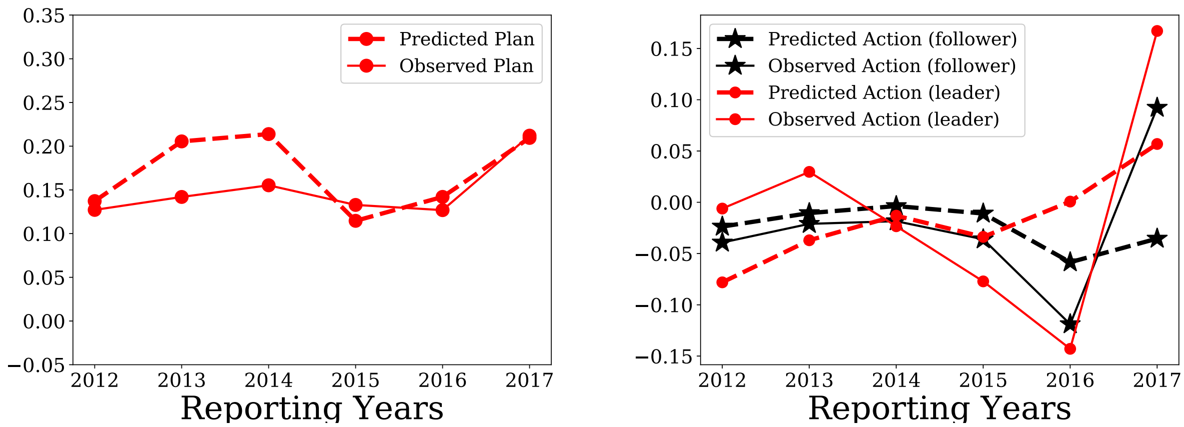
where we let the adjustment cost parameter ϕ_i vary across firms with and without plans to capture fundamental differences across firms with and without plans in the data.

This expression can be compared with the expressions in (28) and (27). Specifically, each firm now amplifies in a symmetric manner the sensitivity of the abatement rate x_T^i with respect to its own belief over the levy, λ_i. However, as we let the adjustment cost ϕ_i vary across firms, the sensitivity parameters $\frac{\eta}{\phi_i}\frac{1+w_{iT}}{(1-w_{iT}^2)}$ will also vary across firms. Figure 7 reports the results of the calibration outlined in Section 3 under the assumption that firms follow the simultaneous game described above. As observed, keeping the hypothesis of the reputation externality allows us to capture variation in the predicted abatement rates, which is an improvement relative to the baseline setting with no externalities. However, by relaxing the assumption of asymmetric information we fail to capture an extra degree of correlation between firms' abatement actions: in particular, firms with plans are predicted to begin reducing emissions one year ahead of firms without plans, reflecting only the dynamics of their own beliefs over the levy. This is not what we observe in the data.

Figure 7

Model Implied and Observed Moments

The left plot compares the model-implied and observed (lagged) abatement plan across reporting years in CDP. The right plot compares the model-implied and observed abatement actions across reporting years in CDP. Thick (dashed) lines refer to observed (model-implied) moments, red-circle (black-star) lines refer to the subset of firms with (without) abatement plans respectively. Input parameters are $\beta = 0.93$, $T = 10$, $\omega = 0.19$, $\bar{\lambda} = 2.70$, $\phi_l = 27.0$, $\phi_f = 22.4$, $\eta = 1$, $\gamma = 24.4$, $g = 0.63$. The parameter ρ is set to 0.



C Out of Sample Predictions

To conduct our out-of-sample validation exercise, we extend the CDP dataset to include U.S. public firms' responses from 2018 and 2019. Over these two years, CDP implemented a set of changes to make the questionnaires more aligned with the recommendations of the Task Force on Climate-Related Financial Disclosures (TCFD), established in 2016. Below, we describe the major changes to the dataset arising as a result of these changes, as well as adjustments that we implemented to our construction of the data as a result of these changes to make the out-of-sample data consistent with our treatment of the in-sample data.

First, regulation risk in the later period is part of a broader classification of climate-related risks, collectively labelled "climate transition risks". These risks include: marked shifts in consumer tastes, reputation risks from negative stakeholder feedback, technology risk due to forced substitution of products and services, and policy risk from new or existing regulations. To preserve continuity with the previous setting, we select firms' disclosures related only to this policy risk component. Second, time horizons of climate-related risks are not tied to numeric ranges as in the earlier data. That is, firms in the later period of the data choose from options: current, short-term, medium-term, and long-term horizons. To preserve continuity with the previous setting, we therefore translate these responses into the time ranges provided by CDP before 2018. More specifically, current horizon is translated into 0 to 1 years from the time of reporting, short-term horizon to 1 to 3 years from reporting, medium-term horizon to 3 to 6 years from reporting, and long-term horizon to beyond 6 years from reporting. Finally, while responses have remained unaltered as far as emissions reduction targets and total carbon emissions are concerned, a number of firms reporting CDP questionnaires in 2018 and 2019 have taken the option to hide their emissions data. As a consequence, of the 368 firms reporting emissions and risks in 2017 (see Table 1), only 137 report emissions in the consecutive year, and 73 of these also report targets. We focus on the data for this reduced number of firms in our out-of-sample exercise.

Figure 8
CDP Sheet - Actions

CDP's 2017 Climate Change Information Request

Emissions

Scope 1 and 2 Emissions Data

CC8.2 Please provide your gross global Scope 1 emissions figures in metric tonnes CO_2e

CC8.3 Please describe your approach to reporting Scope 2 emissions **(CDP 2016 CC8.3, amended)**

Scope 2, location-based	Scope 2, market-based (if applicable)	Comment

CC8.3a Please provide your gross global Scope 2 emissions figures in metric tonnes CO_2e

Scope 2, location-based	Scope 2, market-based (if applicable)	Comment

CC8.4 Are there any sources (e.g. facilities, specific GHGs, activities, geographies, etc.) of Scope 1 and Scope 2 emissions that are within your selected reporting boundary which are not included in your disclosure?

If yes: CC8.4a Please provide details of the sources of Scope 1 and Scope 2 emissions that are within your selected reporting boundary which are not included in your disclosure

Figure 9

CDP Sheet - Beliefs

CDP's 2017 Climate Change Information Request

Risks & Opportunities

CC5. Climate Change Risks

CC5.1 Have you identified any inherent climate change risks that have the potential to generate a substantive change in your business operations, revenue or expenditure? (Tick all that apply)

Please identify the relevant categories:

- Risks driven by changes in regulation
- Risks driven by changes in physical climate parameters
- Risks driven by changes in other climate-related developments

CC6. Climate Change Opportunities

CC6.1 Have you identified any inherent climate change opportunities that have the potential to generate a substantive change in your business operations, revenue or expenditure? (Tick all that apply)

Please identify the relevant categories:

- Opportunities driven by changes in regulation
- Opportunities driven by changes in physical climate parameters
- Opportunities driven by changes in other climate-related developments

For all of the inherent risks and/or opportunities identified, please provide the following details in the table provided in the ORS:

- Risk/Opportunity driver
- Description
- Potential impact
- Timeframe
- Direct/Indirect
- Likelihood
- Magnitude of impact
- Estimated financial implications of the risk/opportunity before taking action
- Methods you are using to manage this risk/opportunity
- Costs associated with these actions

Where inherent risks and/or opportunities have not been identified for any of the categories:

Please explain why you do not consider your organization to be exposed to these risks/opportunities that have the potential to generate a substantive change in your business operations, revenue or expenditure

Figure 10
CDP Sheet - Plans

CDP's 2017 Climate Change Information Request

Management

If "Direct engagement", "Trade associations", "Funding research organizations" or "Other" is ticked:

CC2.3f What processes do you have in place to ensure that all of your direct and indirect activities that influence policy are consistent with your overall climate change strategy?

If "No" is ticked:

CC2.3g Please explain why you do not engage with policy makers

CC3. Targets and Initiatives

Targets

CC3.1 Did you have an emissions reduction or renewable energy consumption or production target that was active (ongoing or reached completion) in the reporting year?**)**

If you have an absolute target:

CC3.1a Please provide details of your absolute target **(CDP 2016 CC3.1a, amended)**

If you have an intensity target:

CC3.1b Please provide details of your intensity target **(CDP 2016 CC3.1b, amended)**

CC3.1c Please also indicate what change in absolute emissions this intensity target reflects

The following details are requested for targets (in Questions CC3.1a and CC3.1b), to be inputted in tables in the ORS:

- Scope
- % of emissions in scope
- % reduction from base year
- Metric denominator (intensity targets only)
- Base year covered by target
- Base year emissions
- Target year
- Is this a science-based target?
- Comment

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