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

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October 14, 2019

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 agremeent 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.

*We thank seminar participants at Imperial College Business School, and Harjoat Bhamra, Patrick Bolton, Charlie Donovan, Chris Hansman, and Harrison Hong for comments and useful conversations.

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1 Introduction

There is mounting evidence that global warming is an urgent issue. We now have credible forecasts of imminent physical changes to the planet, as well as forecasts of the associated long-term repercussions of these physical changes for economic and financial stability.[1] These dire warnings led, in December 2015, to 196 nations signing 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, barely a year away from the first ratification deadline in 2020, most signatory countries are falling short of required targets,[2] and the world's second largest emitting country has announced its intention to withdraw from the agreement.[3]

Faced with a diminishing global emphasis on coordinated climate regulation, an important factor to assess is how important and effective such regulation is to firms' actual carbon abatement actions. If firms are already taking action on abatement, and their strategies are not much affected by announcements of climate regulation such as the Paris agreement, 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 begin by collecting and analyzing micro-data from firms' voluntary

[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.

disclosures. Using these data, we uncover significant and striking variation in firms' reported beliefs about climate regulation, their plans for abatement, and their actions on reducing their carbon footprint in the years leading up to and following the Paris announcement. 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. We find that firms' beliefs about climate regulation events strongly influence their planned and actual abatement activities. We also find that both 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 regulation, leading us to conclude that such 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 ESG ratings of firms. 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' 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 group 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 does *not* report plans. The two sets of firms differ in several other ways. The firms that report plans are larger and more profitable, and they also have a greater propensity than firms that do not report plans 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, the average firm steadily downgraded its expectations over the impact of future regulation and progressively increased its 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 the pre-Paris announcement period. These patterns change dramatically in 2016, the year following the announcement of the Paris agreement. 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. Firms that report plans for future abatement reduction react *far more* to the Paris announcement than firms that do not report such plans, despite the fact that their beliefs are revised *far less*. Put differently, firms reporting plans 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 after the announcement of the agreement, and yet, these firms with plans react more to the announcement than those who do not report them. This puzzling observation that beliefs don't directly map to actions in the same way before and after the announcement of the Paris agreement is an important target for any model, and suggests that subtle economic forces are at play.

To better understand and rationalize the patterns in the data, therefore, we begin by building a simple dynamic model of firms' emissions reduction activities. In the model, a single 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 associated with any such adjustment. 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.

This simple model predicts an upward-sloping term structure of planned abatement (i.e., abatement rates increase up to levy imposition), as the costs of abatement are incurred in the present, but the levy is only incurred at the terminal date, meaning that its impact is diminished by discounting at any intermediate date. Moreover, because of the existence of adjustment costs, the optimal abatement rates are concave in the intensity of the levy for each maturity prior to the regulation event.

We calibrate this simple model to the data on the average firm that reports plans for future abatement, feeding the model with firms' reported beliefs about future climate regulation to generate predicted plans and actions at each date. 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 the 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 model, we therefore introduce a second firm into the economy, to capture the behavior of firms that do not report plans for future emissions reduction. Our aim is to understand whether there are strategic interactions between these two groups of firms (those that do and do not report plans) 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 one of the firms.

Having added these two ingredients, 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.

This more complex model yields several predictions that are closer to the observed data. First, the reputational externality generates an amplified reaction by firms to changes in the levy, with the informed firm (in the data, those with plans) reacting more than the uninformed one (those without) because of its leadership position in equilibrium. Second, to the extent that the less informed firm 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 impacts of climate regulation relative to the basic model—and different across the two groups of firms.

The remainder of this paper is structured as follows: in the remainder 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. 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 concludes.

1.1 Related Literature

Our work fits into a fast-growing literature on climate economics and finance. A part of this literature has focused on the impact of externalities on firms' optimal responses to regulatory policy. For example, 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. In related work, Pindyck (2007) and Pindyck (2013) make use of the real options framework pioneered by Dixit et al. (1994) to quantify the delay induced by policy uncertainty on the optimal timing of abatement. Fowlie (2009) and Belaouar et al. (2011) study firms' strategic responses to a carbon levy, and a carbon emissions market, respectively, in the presence of imperfect competition. And Shive and Forster (2019) look at the impact of corporate governance externalities on firms' emissions, finding that publicly listed firms tend to pollute more, and attributing this finding to these firms facing increased pressure from short-term investors. In contrast with several of these studies, our work focuses on empirical evidence that is mainly drawn from large public firms, and in our theoretical work, we highlight the importance of strategic interactions between firms to explain the dynamics of aggregate abatement actions.

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 model, asymmetric information over climate policy motivates cross-firm learning. This, coupled with the reputational externality amplifies firms' responses to climate policy above the magnitude predicted in a baseline model with perfect information.

Finally, our work also adds to the growing literature on corporate social responsibility and ESG. For example, Hong and Kacperczyk (2009) considers the effect of social norms on stock prices. More recently, Dyck et al. (2018) and Hoepner et al. (2018) provide theoretical and empirical evidence on the active role of large institutional investors on firms' environmental decisions. In the context of ESG, 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. Finally, recent work by Hartzmark and Sussman (2018) on announcements of mutual funds' sustainability ratings argues that investors reacted by reallocating capital to funds in a manner that reveals their preferences for sustainability—providing evidence for the existence of a reputational externality in a different setting.

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".[4] 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 publicly available sources.

2.2 Sample Construction

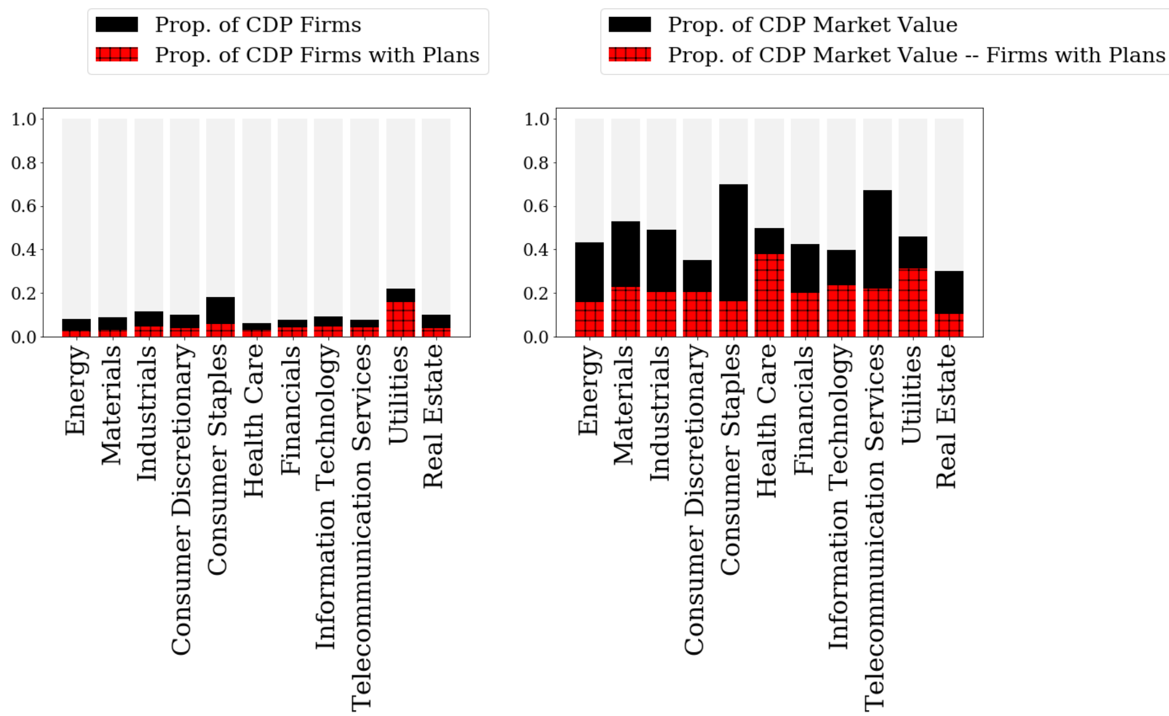
To construct our dataset, we match the CDP data to the CRSP COMPUSTAT North America merged database, comprising 5,991 public firms with complete data over the 2010–2017 accounting period. To ensure that we can measure firms' changing actions and revisions of their beliefs about regulatory risks, we require 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 left 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

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

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.



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 right 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.[5]

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. 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. 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**	**95^{th} perc.**
Market Value* ($ bn)	22.2	23.7	18.9	3.4	23.1
Total Assets* ($ bn)	36.3	45.5	32.7	8.4	52.2
Total Liabilities* ($ bn)	25.1	31.9	22.2	5.8	36.3
Income B. E. Items* ($ bn)	1.1	1.2	0.9	0.3	2.1
Liabilities to Assets Ratio*	0.6	0.6	0.6	0.6	0.9
WACC*	8.1	7.7	8.6	8.4	14.1
Altman Z-Score*	3.9	3.9	3.8	3.7	13.0
ESG Score (1)$^{+}$	38.5	39.1	37.6	18.7	51.3
ESG Score (2)$^{+}$	66.7	67.9	64.8	47.2	81.9
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

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

(i.e., reporting to CDP) is close to the 95^{th} percentile firm in both the size and earnings 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, but a similar liabilities-to-assets ratio, and a slightly lower probability of bankruptcy.[6]

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. The size and performance of firms can affect their incentives to disclose emissions reduction plans, as firm size can bring enhanced scrutiny and pressures to disclose.[7]

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.[8] 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

[6]As implied by the Altman (1968) Z-score, an indicator of the probability of a company entering bankruptcy within the next two years, based on financial ratios obtained from 10-k reports.

[7]Moreover, size and performance can also be related to incentives to disclose through variables that simultaneously affect both. 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).

[8]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.

"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 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:

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

where the variable $Emissions_{it}$ measures firm i's total emissions from both owned and controlled sources (Scope 1) as well as from purchased energy (Scope 2),[9] as reported in CDP in each reporting year t. In the appendix we report how carbon emissions disclosures in CDP compare with third-party estimates provided by Thomson Reuters—

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

to summarize, we obtain consistent figures across the two datasets for the majority of firms in the sample.[10]

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 our interest in the responses of firms to climate regulation events. In CDP, almost 90% of the reporting firms state that they associate environmental 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.

[10]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.

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.[11] 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 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.

2.3.3 Plans

Finally, 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. 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 $\tilde{e}$.

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

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:

$$plan_{i,t} = \frac{1}{T_{it} - t} \sum_{\tau=t+1}^{T_{it}} \beta^{\tau-t} \tilde{e}_{it}. \tag{3}$$

where the first timing of abatement $\tau = t + 1$ refers to one year after the year of reporting[12]. 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 $\tilde{e}$, 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.

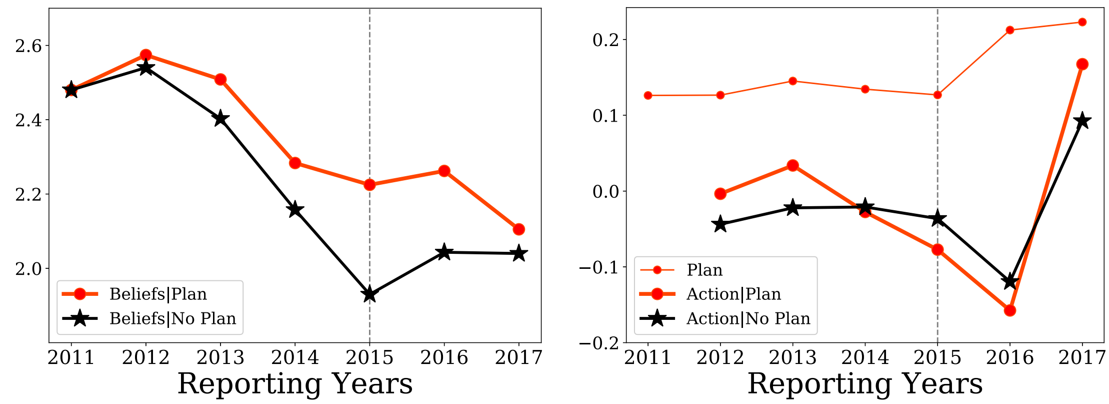
2.4 Patterns in Firms' Actions, Beliefs, and Plans

Figure 2 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., $e_{t,t+1} = \frac{1}{N_t} \sum_{i=1}^{N_t} e_{i,t,t+1}$. In each plot, rather than showing the unconditional average across all firms, we plot the averages separately

[12]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.

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.



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.[13]

The left-hand panel shows that beliefs about future climate regulation exhibit a decreasing trend between 2011 and 2015 for all firms. The firms without plans show a more pronounced downward slope in beliefs than the firms with plans. 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

[13]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. In the appendix, we will reintroduce this distinction to test an additional prediction provided in the theoretical setting.

the firms with and without plans—firms without plans display a much sharper upward belief revision than those with plans between these periods.[14]

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 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 counterintuitive 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.

To better understand the underlying source of these intriguing patterns, in the next section we build a dynamic model of firms' carbon emissions reductions.

[14] 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.

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 ηk_{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:

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

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. As a result, the firm's terminal profits can be expressed as:

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

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

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

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:

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

and the terminal abatement rate is:

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

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:

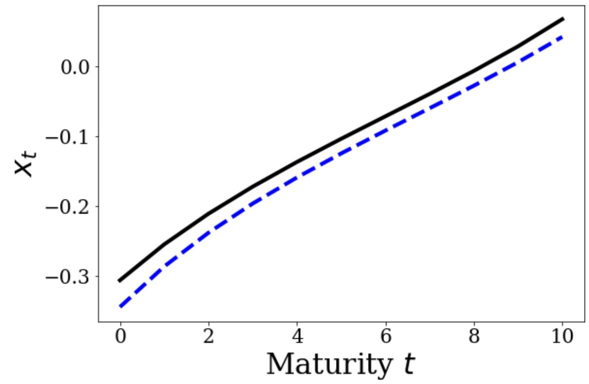
$$x_T > x_{T-1} > \cdots > x_{t+1} > x_t > 0, \tag{13}$$

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

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

Figure 3
Optimal Abatement Profile

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



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.

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 productivity constant $\omega = 0.71$ to match the asset turnover ratio of the representative firm in the dataset.[15]

- 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.[16]

- We set the maturity of the regulation $T = 2020$ as the first ratification period of the Paris agreement, which is the most frequent target year reported by the firms in the dataset. Note t then varies within the reporting period, i.e., $t = \{2011, \ldots, 2016\}$

- Finally, we estimate the parameters η and ϕ to minimize the squared distance between the empirical and model-implied abatement actions and abatement plans:

$$\min_{\eta,\phi} \sum_{t} \big(e_{t,t+1} - x_{t+1}(\Lambda_t)\big)^2 + \big(plan_t - \hat{x}_t(\Lambda_t)\big)^2, \tag{15}$$

  where $\Lambda_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \Lambda_{i,t}$ is the belief of the representative firm *with a plan* in the dataset, $x_{t+1}(\Lambda_t)$ is the optimal abatement rate at the shortest maturity, computed as in (11) and conditional on the belief Λ_t, and the plan $\hat{x}_t(\Lambda_t)$ is the sum of future discounted abatement rates $\hat{x}_t(\Lambda_t) = \sum_{\tau=t+1}^{T} \beta^{\tau-t} x_\tau(\Lambda_t)$. 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 $x_{t+1} = -\big(\frac{\eta_{t+1}-\eta_t}{\eta_t}\big)$, which allows for a direct comparison with the relative change in realized emissions $e_{t,t+1}$, measured

[15] We compute the asset turnover ratio ratio as Sales Turnover Net divided by Total Assets from CRSP/COMPUSTAT. The asset turnover ratio, also known as the total asset turnover ratio, measures the efficiency with which a company uses its assets to generate sales.

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

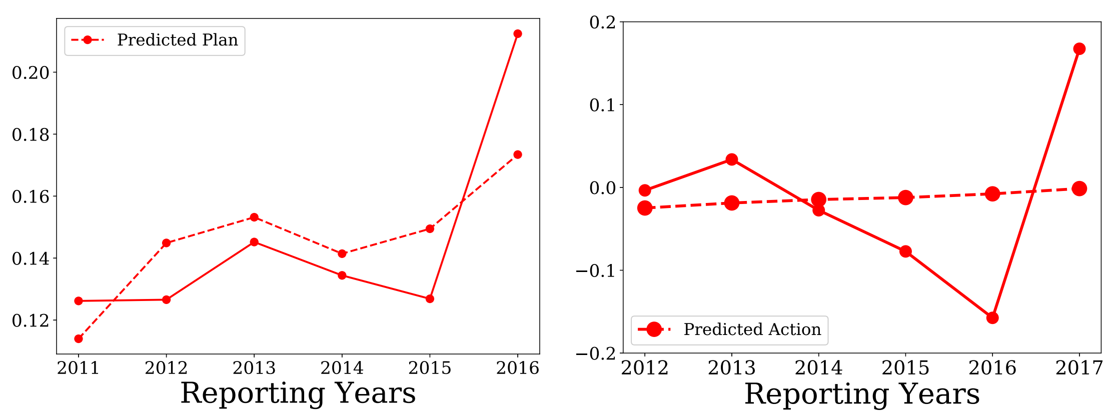
as in (1) for the representative firm with plans in the dataset. In the same way, the model-implied abatement plan $\hat{x}_t(\Lambda_t)$ also allows for a direct comparison with the measured abatement plan $plan_t$ in (3), reported by the representative firm at year t and anticipating relative changes in emissions from year $t+1$ onwards.

The left-hand panel of Figure 4 compares empirical and model-implied abatement plans on average across the sample period. 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.

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.



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 patterns 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.

$$\pi_t^l(x_t^f) = \omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_{t-1}^l - \gamma_t x_t^f (k_t^l - k_{t-1}^l), \tag{16}$$

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

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[17]. 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:

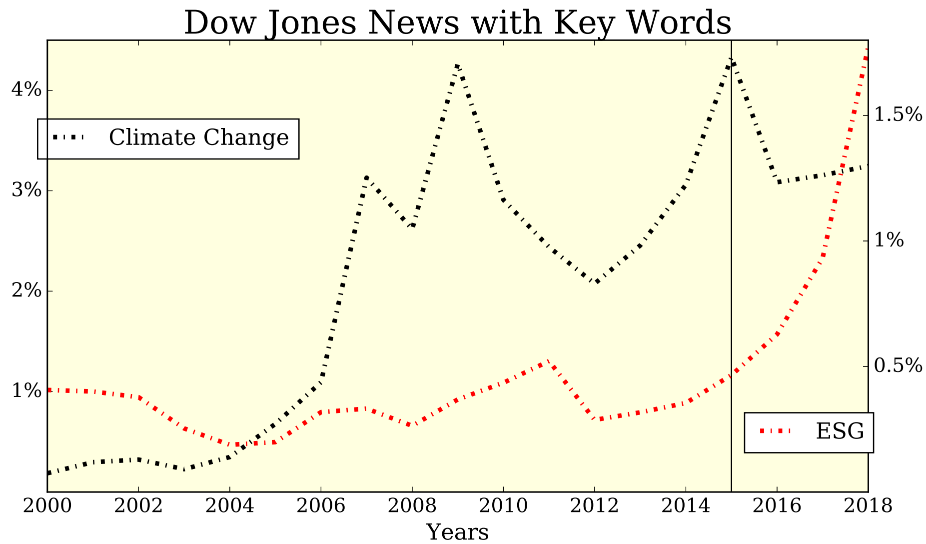
$$\lambda = \bar{\lambda} + \tilde{s}. \tag{18}$$

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.

[17]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.



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.

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.

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.[18] In this case, firm f would in turn attempt to extract information from firm l's announcement, rationally updating its belief (using Bayes' rule) over the levy as:

$$\bar{\lambda} + \rho\tilde{s}, \tag{19}$$

where $\rho\tilde{s}$ is the signal that the follower f infers from the leader's announcement and $\rho \in [0, 1]$ is the precision weight on the inferred signal,[19] which controls the size of the *positive 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 before the game is played. Before we proceed, we discuss two additional assumptions that we make about model structure.

[18] 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.

[19] 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 $\tilde{\epsilon} = 0$.

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 in that alternative model for both heterogeneity in firms' beliefs over the levy, as well as different adjustment costs of emissions abatement.

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 $\{\phi, \beta, \mu, \omega, \bar{\lambda}, \tilde{s}, \rho\}$, 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:[20]

- Firm f (follower):

$$x_t^f = w_t x_t^l + \beta\Big(x_{t+1}^f - w_{t+1} x_{t+1}^l - \frac{1}{2}(x_{t+1}^f)^2\Big) - \frac{\omega}{\phi}, \tag{20}$$

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

$$x_T^f = w_T x_T^l + \frac{\eta}{\phi}\big(\bar{\lambda} + \rho\tilde{s}\big) - \frac{\omega}{\phi}. \tag{21}$$

[20]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):

$$x_t^l = \frac{\beta}{(1-2w_t^2)}\Big(x_{t+1}^l(1-w_{t+1}^2 - w_t w_{t+1}) + x_{2,t+1}(w_t - w_{t+1})\dots \\ \dots - \frac{1}{2}((1-2w_{t+1}^2)(x_{t+1}^l)^2 + w_t(x_{t+1}^f)^2)\Big) - \frac{\omega(1+w_t)}{\phi(1-2w_t^2)}, \tag{22}$$

and

$$x_T^l = \frac{\eta}{\phi}\Big(\bar{\lambda}\frac{1+w_T}{1-2w_T^2} + \tilde{s}\frac{1+\rho w_T}{1-2w_T^2}\Big) - \frac{\omega(1+w_T)}{\phi(1-2w_T^2)}. \tag{23}$$

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 $\{\phi, \beta, \mu, \omega, \bar{\lambda}, \tilde{s}, \rho\}$ 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., $t \leq T$.[21]

[21] 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.

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 (21) and (23), 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 endogenously increase their reaction to changes in the policy, because the way the model is set up in equations (16) and (17), 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 (16) and (17), 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."[22] 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 (21) and (23) is that, because the follower learns from the leader's plans (recall (19)), 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

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

$$\pi_T^i(x_t^{-i}) \approx (\eta(\bar{\lambda} + \rho\tilde{s}) - \frac{\phi}{2}(x_T^i - 2w_T x_T^{-i}))x_T^i - \omega x_T^i \tag{24}$$

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

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 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 (20) and (22) 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 baseline parameters ω, β, and T outlined in the single-firm setting (i.e., in equation (15)), and find parameters to satisfy the following minimization problem:

$$\min_{\eta,\phi,\rho,\gamma,g} \sum_t \left(e^l_{t,t+1} - x^l_{t+1}(\Lambda^l_t)\right)^2 + \left(plan_t - \hat{x}^l_t(\Lambda^l_t)\right)^2 + \left(e^f_{t,t+1} - x^f_{t+1}(\Lambda^f_t)\right)^2. \tag{25}$$

In equation (25), 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.[23] The beliefs Λ^l_t and Λ^f_t 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:[24]

$$\tilde{s}_t = \Lambda^l_t - \Lambda^f_t. \tag{26}$$

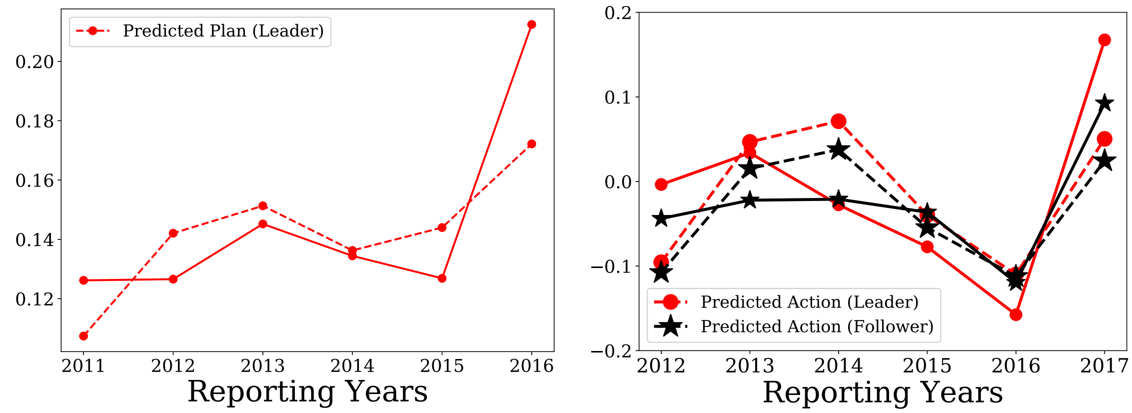
Figure 6 summarizes the results of the calibration; the list of input parameters is reported in Table 2. The left and right-hand panels in Figure 6, show that the more complicated two-firm model with cross-firm externalities and leader-follower dynamics does result in a better ability to capture the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

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

[24]It would also be possible to specify the estimated private signal as $\tilde{s}_t = \frac{\Lambda^l_t - \Lambda^f_t}{(1-\rho)}$; to simplify, we assume here that beliefs are announced simultaneously by both firms ex-ante, but that actions are determined by ex-post beliefs for the follower firm.

Figure 6
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, red-circle (black-star) lines refer to the subset of firms that disclose (do not disclose respectively) plans in the previous reporting year. Model parameters are reported in the second column of Table 2.



First, Table 2 shows that introducing the strategic parameters γ, g, and ρ improves the fit of the model.

Second, the parameter $\rho = 0.2$ 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 $\gamma = 9.05$ and $g = 0.19$ 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. In the appendix, we attempt to verify this prediction by constructing a reported term-structure of future abatement using the plans of firms who report them in the CDP dataset. We find only mixed support for this prediction in the plans data.

Finally, in terms of economic magnitudes, we compute the present discounted value

Table 2
Calibration Results

The table reports the calibration results for the single-firm (column I) and two-firm (columns II) models respectively. Squared errors refer to the sum of squared distances between observed and model-implied abatement rates and actions. Cost of the levy refers to the discounted payment of the levy at maturity, i.e. $\beta^T \Lambda \eta_T$, divided by firm value V^Λ. Firm value refers to the expression in (8) where the operating profits are specified as in (16). Results are reported for the leader firm only and are relative to the levy Λ reported by the leader in the last year of observation.

Parameters	I	II
ω	0.71	0.71
β	0.93	0.93
ϕ	24.9	17.3
η	1.98	0.79
ρ	0.00	0.20
g	0.00	0.19
γ	0.00	9.05
Fitting Error	0.061	0.038
Cost of the Levy	0.18	0.14

of the loss arising from the levy incurred by firms. For the average firm reporting an abatement plan in the CDP data, using the belief reported in the last year of observation, the levy accounts for roughly 18% of firm value in the single-firm model. In contrast, this reduces to roughly 14% of firm value in the two-firm model. The contrast between the two figures shows that the reputational externality causes the leader firm to increase current abatement, in turn resulting in a lower expected cost of regulation.

4.4 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.

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 a) climate regulation matters greatly to firms, and b) 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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October 14, 2019

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	**226**	**88**
2012	297	429	**226**	**88**
2013	332	465	**279**	**111**
2014	342	468	**292**	**115**
2015	372	481	**327**	**133**
2016	402	508	**341**	**141**
2017	418	505	**365**	**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"). 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). 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 1 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 1
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.

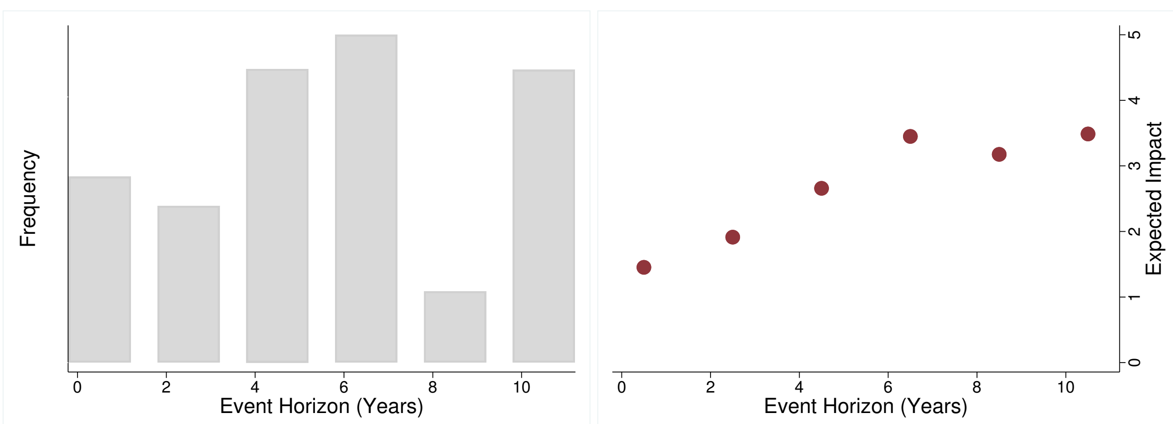


Table 3

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). 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 $t_k \leq t$ 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 2 below summarizes the frequency of disclosures as well as the reduction rate e_k by target horizon T_k.

Figure 2

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.

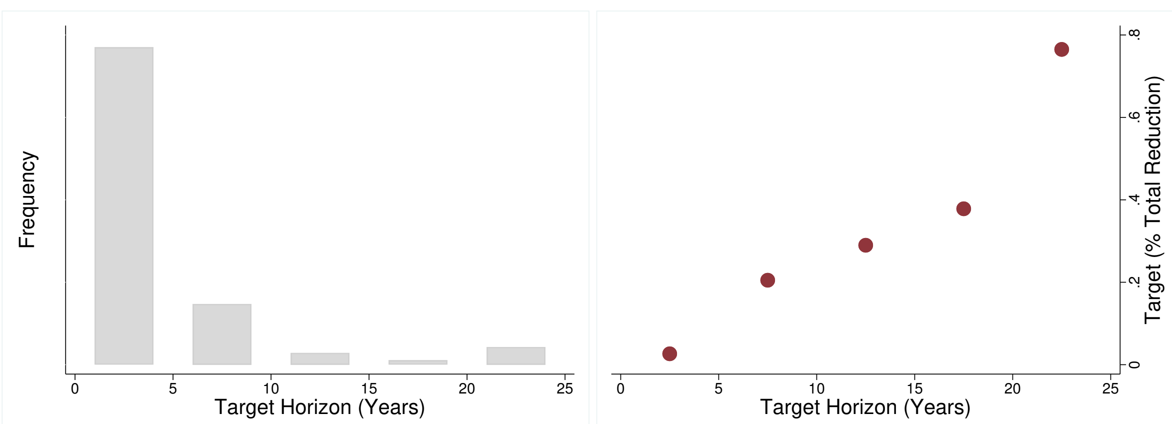


Figure 3
Plans - External Environmental Ratings

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).

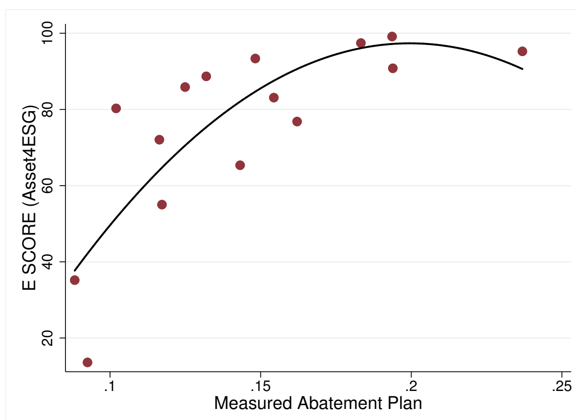
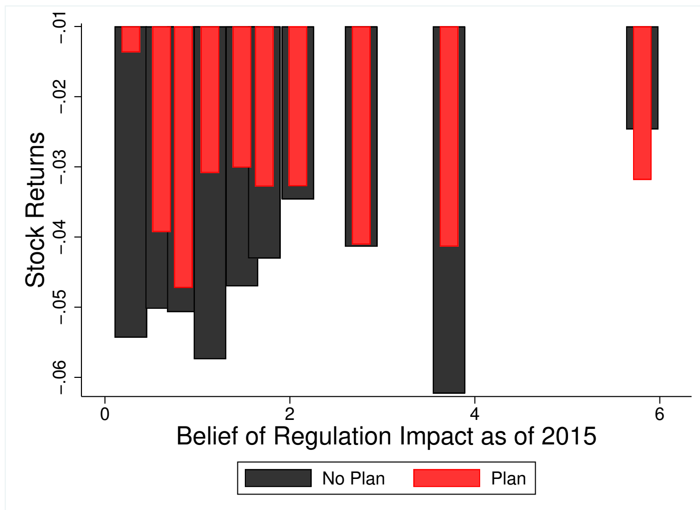


Figure 4

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 $t \in 0, \ldots T-1$. 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 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.

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:

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

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

$$V_t^l = \max_{x_t^l}\{\omega k_t^l - \frac{1}{2}\phi(x_t^l)^2 k_t^l + \gamma_t(w_t x_t^l + f_{t+1})x_t^l k_{t-1}^l + \beta V_{t+1}^l\} \tag{20}$$

From the first order conditions with respect to x_t^l, one gets:

$$-\omega - \phi x_t^l + \gamma_t(2w_t x_t^l + f_{t+1}) = \beta\frac{\partial V_{t+1}^l}{\partial k_t^l} \tag{21}$$

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

$$-\omega - \phi(1-2w_t^2)x_t^l + \phi w_t f_{t+1} = \beta\frac{\partial V_{t+1}^l}{\partial k_t^l} \tag{22}$$

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

$$\begin{aligned}\frac{\partial V_{t+1}^l}{\partial k_t^l} &= \omega(1-x_{t+1}^l) - \frac{1}{2}\phi(x_{t+1}^l)^2 + \gamma_{t+1}x_{t+1}^f x_{t+1}^l \dots\\ &\dots + (1-x_{t+1}^l)\Big[-\omega - \phi x_{t+1}^l + \gamma_{t+1}(x_{t+1}^f + w_{t+1}x_{t+1}^l)\Big]\end{aligned} \tag{23}$$

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

$$\frac{\partial V_{t+1}^l}{\partial k_t^l} = \frac{1}{2}\phi(1-2w_{t+1}^2)(x_{t+1}^l)^2 - \phi(1-w_{t+1}^2)x_{t+1}^l + \gamma_{t+1}x_{t+1}^f \tag{24}$$

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

$$x_t^l = \frac{w_t}{(1-2w_t^2)} f_{t+1} + \beta\Big(\frac{(1-w_{t+1}^2)x_{t+1}^l - w_{t+1}x_{t+1}^f}{1-2w_t^2} - \frac{(1-2w_{t+1}^2)}{(1-2w_t^2)2}(x_{t+1}^l)^2\Big) - \frac{\omega}{\phi(1-2w_t^2)} \tag{25}$$

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

$$\pi_T^l = \omega k_T^l - \frac{1}{2}\phi(x_T^l)^2 k_{T-1}^l + \gamma_T x_T^f(x_T^l) x_T^l k_{T-1}^l - (\bar{\lambda} + \tilde{s})\eta_T \tag{26}$$

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:

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

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

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

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 $x_t^l > x_{t+1}^l > 0$, 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.

Figure **??** compares the observed term-structure of the abatement plan (black-thick line) and the model-implied term-structure of the abatement plan for the single-firm setting (red-dashed line) and leader-follower setting (blue-dashed line) respectively. The observed term-structure of the abatement plan is constructed from the full-sample representative firm with plans in the dataset. Specifically, following the details in the data appendix, we first construct the planned yearly rate of emissions reduction $e_{it,\tau}$ for each firm i, reporting year t, and maturity τ as

$$e_{it,\tau} = \sum_{k=0}^{k_{it}} \frac{e_k}{T_k - t_k} 1_{t<t+\tau\leq T_k} \tag{42}$$

where k_{it} is the total number of active targets reported by firm i at time t. Then, we take the full-sample average of the planned yearly reduction rate

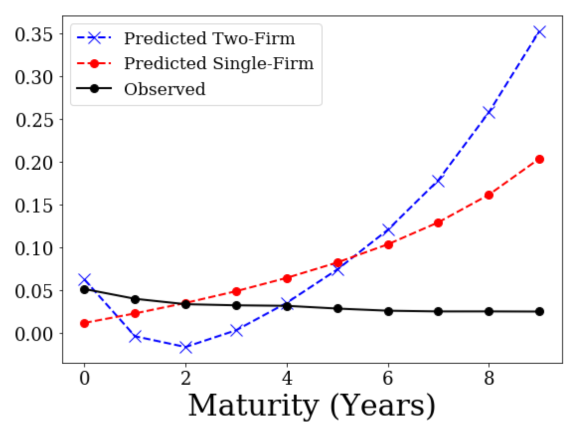
$$e_\tau = \frac{1}{N_\tau} \sum_{it} e_{it,\tau} \tag{43}$$

where N_τ is the total number of firms i and reporting years t with a strictly positive yearly reduction rate $e_{it,\tau}$ at maturity τ, and the maturity τ. To compare the observed term-structure of the abatement plan with the ones implied by the single-firm and leader-follower model (recalling that we impose a representative target year $T = 2020$), we then only consider maturities $\tau = 1, \ldots 9$ years.

Figure 5

Model-Implied and Observed Term-Structure of the Abatement Plan

The plot compares the observed term-structure of the abatement plan (black-thick line) and the model-implied term-structure of the abatement plan for the single-firm setting (red-dashed line) and leader-follower setting (blue-dashed line) respectively. The observed term-structure of the abatement plan is computed as in (43). Calibrated parameters for the single-firm and leader-follower models are reported in the first and second column of Table 2, Section 4 respectively. Input beliefs refer to the full-sample representative firm with and without plans in the dataset.



B.4 Alternative Setup

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

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

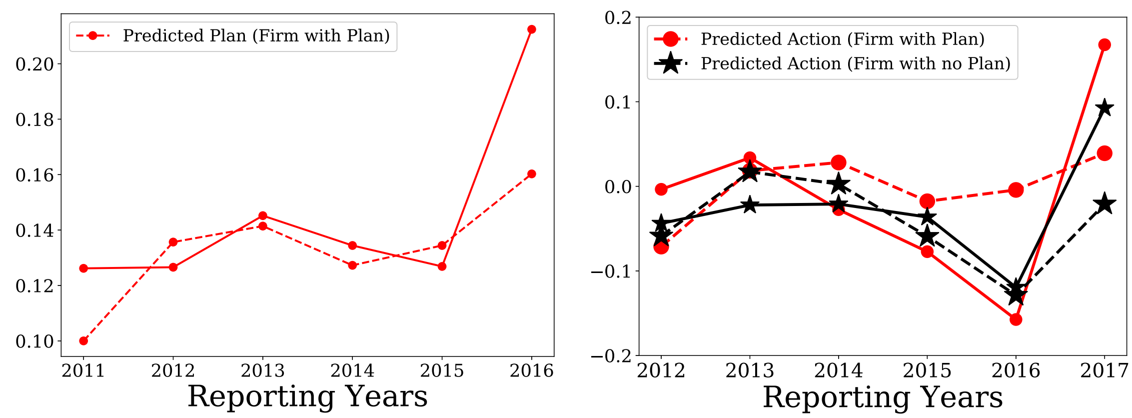
where we let the adjustment cost parameter ϕ_i vary across firms with and without plans to capture fundamental differences across firms with and without plans in the data.

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 6 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 6

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 $\omega = 0.75$, $\beta = 0.93$, $T = 2020$; calibrated parameters are $\hat{\phi}_l = 17.5$, $\hat{\phi}_f = 17.4$, $\hat{\eta} = 1.01$, $\hat{\gamma} = 8.59$, $\hat{g} = 0.50$. The parameter $\hat{\rho}$ is set to 0.



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