Energy Policy 138 (2020) 111252

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Do carbon abatement opportunities become less profitable over time? A global firm-level perspective using CDP data

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ARTICLE INFO

Keywords:
CDP
Climate change
Energy efficiency
And carbon abatement

ABSTRACT

Firms around the world need to find ways to continuously reduce their carbon footprint, preferably in ways that are profitable or cost-effective. The opportunities available to them will change over time, as they implement the most profitable ones first and as technology changes. When designing and adjusting their carbon policies, policy-makers need to understand the abatement opportunities firms are facing. We explore this using data collected by CDP (formerly the Carbon Disclosure Project) on 20,920 carbon abatement projects implemented by more than 1400 firms worldwide over 7 years. Using fixed effects regression with energy price controls by country, our results show that the average payback period of implemented carbon emissions reduction projects remained relatively constant from 2010-2016, although there is tentative evidence that the projects are becoming smaller over time. We provide a novel firm-level perspective on carbon emissions reduction activities using data on projects implemented and reported by large, global firms, and discuss how the insights from such firm-level analysis can help inform the design and revision of carbon emissions policies over time.

1. Introduction

Evidence continues to mount about the importance of reducing global greenhouse gas (GHG) emissions. A range of different policy approaches aims at reducing GHG emissions from industry, often involving setting a price on emissions, whether in the form of a "carbon tax" or a cap-and-trade system. In theory, firms will continue to invest in reducing emissions as long as they find it profitable. Some opportunities to reduce emissions are already profitable on their own; for many others, the price associated with emissions should increase to encourage firms to exploit opportunities they would otherwise not pursue.

In the past, there was extensive debate about whether the most suitable policy to reduce GHG emissions would focus on price or on quantity controls. Weitzman (1974) already pointed out that which approach is preferred depends on the marginal costs and benefits associated with reducing emissions. More recently, Stavins (2019) argues that it is not so much the choice of policy type that matters, as the specific design of whichever policy is chosen. In a comprehensive comparison of carbon taxes and cap-and-trade mechanisms, Stavins (2019) concludes that in terms of key objectives such as incentives for emissions reductions, aggregate abatement costs, and effects on competitiveness, a carbon tax and a cap-and-trade mechanism can be perfectly equivalent. This means that setting the correct price for carbon emissions, whether directly in the form of a carbon tax or indirectly in the form of the design of a cap-and-trade mechanism, is the key challenge for policy-makers. In theory, policy-makers need to determine the social cost of carbon emissions, and then design the carbon tax or cap-and-trade mechanism in such a way that the carbon price faced by firms reflects that social cost of carbon emissions.

In practice, however, this is complicated by a number of factors. First, firms generally do not follow the theoretical prescription of equating marginal costs and benefits, but instead use simpler investment criteria, such as the payback period (defined as the total investment cost divided by the annual monetary savings). Firms often require a payback of less than two years, as documented by among others Cooremans (2011), Harris et al. (2000), Jackson (2010), and Fleiter et al. (2012b). Second, the profitability of carbon abatement projects is not static over time. As firms implement opportunities, presumably starting with the most economically attractive ones, the costs of the remaining opportunities are likely to be higher. Simultaneously, as new technologies emerge (partly spurred endogenously by the price on carbon), costs may decline. Third, as Stavins (2019) points out, there is a wide range of other factors that policy-makers need to consider, including aggregate abatement costs, effects on competitiveness, costs to regulated firms, distributional impacts, transaction costs, performance in the presence of uncertainty, interaction with complementary policies, and more.

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https://doi.org/10.1016/j.enpol.2020.111252
Received 8 October 2018; Received in revised form 3 January 2020; Accepted 4 January 2020
Available online 17 January 2020
0301-4215/

This means that policy-makers are not only faced with the challenge of determining an optimal carbon price, but with determining a globally efficient time path for carbon prices (Aldy et al., 2010). To assess whether policy-makers are achieving their objectives, it is therefore imperative to observe how firms respond, as Brännlund et al. (2014) and Bumpus (2015) also argue. By using firm-level data on what opportunities firms choose to implement, policy-makers can get additional insight on whether they are achieving their carbon reduction goals, and whether their policies are having unintended consequences for aggregate costs, competitiveness, or other dimensions that Stavins (2019) considers. The fact that costs are likely to change over time, for the reasons noted above, means that policy-makers also need to track how firms' behavior changes over time.

Payback period is not the optimal criterion for making capital allocation decisions. However, examining firm-level behavior through the perspective of payback periods is worthwhile, for several reasons. First, it is widely used by firms (see references above). Second, policy-makers do not observe the net marginal carbon abatement costs faced by firms. Third, firms will primarily choose to implement opportunities that are "profitable" (including a possible carbon price), and for profitable opportunities, the traditional marginal abatement cost (MAC) curve is problematic for reasons outlined by Taylor (2012) and Ward (2014). For these reasons, we study the evolution of payback periods and what this may mean for policy. Let us examine several possible patterns for the evolution of payback periods and project size over time and discuss potential policy implications of each.

If payback periods of implemented projects become shorter over time, what does that mean for policy-makers? Several phenomena could be occurring. If this is accompanied by a reduction in the overall size of emissions reductions, it is possible that firms are applying even stricter payback period thresholds, for instance in response to a perceived increase in risk associated with carbon abatement. Fankhauser and Hepburn (2010) review several ways in which intertemporal dynamics in carbon markets could lead to increased variance in carbon price, and hence an increase in risk. This perception also could occur if firms do not believe regulators' stated intentions regarding future carbon prices or allowances.

Alternatively, if the overall magnitude of the projects firms implement is constant over time or even increasing, then a shortening payback period could reflect that the price of carbon is higher than needed to spur investment in carbon abatement, and that firms simply do not have the internal capacity to implement all projects that meet their payback period threshold. They would still prioritize the most profitable ones, but the shorter observed payback period would not mean that they are not willing to invest in projects with longer paybacks. If that is the case, policy-makers should focus on finding ways to increase the rate at which firms can implement projects. This could mean decreasing transaction costs, setting up support mechanisms, or providing training and education. Programs focusing on information dissemination such as the Industrial Assessment Centers program in the US (Anderson and Newell, 2004) or the Commonwealth Government's Enterprise Energy Audit Program in Australia (Harris et al., 2000) are examples of such approaches.

If payback periods become longer over time, what does that mean for policy-makers? As before, lengthening payback periods can signify several underlying phenomena. Firms would be accepting looser payback period thresholds, which could be an indication that they perceive the risk associated with carbon abatement to be lower than before. This could be a sign that firms expect future carbon prices to increase, or that regulators have gained more credibility when announcing increasing carbon prices (Helm et al., 2003). If the overall magnitude of emissions reductions is constant or even increasing, then the lengthening of payback periods would signal generally greater willingness by firms to make such investments. Policy-makers could infer that their approach is working reasonably well overall; an area of focus for policy-makers would then be to verify whether unintended consequences are occurring, for instance competitive imbalance or distributional inequity.

Table 1
Policy responses depending on the evolution of payback periods and the size of carbon emissions reduction.

Observation	Shortening payback period	Lengthening payback period
Increasing or constant carbon emissions reduction size	Policies should aim at increasing rate of adoption; information dissemination are good examples	Policies in place are successful; focus on competitive imbalance or distributional inequity
Decreasing carbon emissions reduction size	Focus on decreasing perceived risks of carbon emissions reduction policies	Increase carbon tax or tighten emissions allowance

Conversely, if lengthening payback periods are accompanied by a reduction in the emissions reductions achieved, this would likely reflect that the remaining abatement opportunities are becoming less profitable over time. In other words, the low-hanging fruit would be diminishing. Firms would then apparently still be willing to make some investments in carbon abatement, even with less attractive payback periods than before, but the shrinking size of emissions reductions would indicate that firms do so reluctantly and are not willing to make large investments. In this situation, policy-makers would need to consider whether to increase the price of carbon, by increasing the carbon tax and/or reducing the number of allowances, in order to make the remaining abatement opportunities more profitable for firms.

We summarize the policy responses based on different outcomes of the evolution of payback periods and the size of carbon abatement opportunities in Table 1.

How do we identify which of these scenarios is actually occurring? In this paper, we examine the payback period of 20,920 carbon reduction projects implemented and reported by over 1400 firms worldwide over a 7-year period. Using a fixed-effects panel regression analysis, we find that the average payback period exhibits no significant deterioration over our horizon, suggesting that firms are not running out of profitable opportunities in the short term and not making substantial adjustments in their capital allocation criteria for carbon abatement projects. We find that the average payback period of carbon abatement activities implemented from 2010–2016 is 2.20 years. If payback periods are short (i.e., an average of two years), that indicates that many profitable opportunities are not being exploited (Jackson, 2010). Jackson (2010) claims that firms typically have a strict payback period requirement for carbon abatement projects because they perceive them to be more risky. For policy-makers, this highlights that they need to reduce the risk and uncertainty associated with carbon abatement opportunities, in order to encourage firms to adopt looser payback period thresholds. In an attempt to provide further nuance, we also examine how the number of projects and size of emissions reduction per project evolve, but we find mixed evidence on this front.

The contribution of this paper is to provide an initial firm-level perspective on firms' decisions related to investing in carbon abatement over time. As firm-level carbon disclosure continues to become more widespread and more comprehensive, whether to CDP or through other mechanisms, it will be increasingly important for policy-makers to take such firm-level data into account when considering which carbon policies are appropriate for given sectors or geographic regions.

In what follows, we first discuss the CDP data and energy data that we used. We then describe the regression methods and results, and the various tests we performed to assess the robustness of our findings. We highlight some limitations of our work. We then conclude with the policy implications of our findings.

2. Data

We first describe our main source of data, from CDP, and then the data we used to correct for the cost of energy.

2.1. Data from CDP

CDP was founded as the Carbon Disclosure Project in 2000, aimed at encouraging firms to disclose more information about their climate-change-related risks and opportunities. CDP conducted its first survey in 2002, and by 2015 more than 5500 firms worldwide responded to their survey requests (CDP, 2018). This includes many of the world's largest firms, such as Walmart, Boeing, Cisco, Pfizer, Hewlett-Packard, J. Sainsbury, SABMiller, Unilever, Nissan, Sony, Hyundai, Samsung, and many others. A sample of 1089 global companies that CDP identified as having the highest impact (by market capitalization and GHG emissions) disclosed total (Scope 1 and 2) emissions of 6361 million metric tons of CO2-equivalent in 2016. For comparison, the total US energy-related CO2e emissions in 2016 were 5172 million metric tons (EIA, 2019).

Although the CDP data are far from perfect, Kolk et al. (2008) already observed that they are becoming increasingly reliable. Turner and Kent (2017) report that investors consider CDP data when making investment choices, further illustrating their relevance. The data are also frequently used in scholarly studies. Okereke (2007) uses the CDP responses to examine the motivation, drivers, and barriers to carbon management. Using the CDP data with the KLD Research & Analytics SOCRATES database, Reid and Toffel (2009) provide regression-based evidence of the drivers of why firms disclose their climate change strategies. Blanco et al. (2016) find that the total carbon emissions disclosed to CDP expanded over time. Matsumura et al. (2013) use CDP carbon emissions data to test how the market responds to climate change disclosures. Gasbarro et al. (2017) use CDP data to identify physical, regulatory and market-based risks associated with climate change. Using CDP responses on firm incentives related to climate change, Dahlmann et al. (2017) find that offering incentives to a large, broad set of recipients can be effective in reducing carbon emissions. Gallego-Álvarez et al. (2014) find evidence that financial performance has a stronger relationship with environmental performance, measured using CDP data, in times of an economic crisis. These studies suggest that CDP data are considered useful for scholarly research.

The main fields in the data that we use are those related to payback period of implemented projects, the number of projects for which firms provide details, and the emissions reductions achieved with those projects. The CDP surveys include these items since 2010. Our sample covers all global firms that reported at least twice during the period 2010–2016. This includes 1417 firms in the 33 countries for which we have energy price data (see below), who jointly report details on 20,920 projects. This panel is not balanced over time, as not all firms report in each year. Therefore, we also conduct our analysis with a balanced subsample, consisting of the 102 firms that report complete data for at least one implemented project in every year between 2010–2016; this yields 3051 projects. The unbalanced panel has the benefit of being substantially larger, while the balanced panel allows us to rule out potential effects of year-to-year variations in the composition of the sample.

2.2. Data on energy cost

Energy prices may influence the adoption and profitability of carbon abatement opportunities, so it is important to control for them. Sato et al. (2019) is one of the most comprehensive and rigorous compilations of energy prices weighted by fuel source across 48 countries from 1995 to 2015. Although our study covers 2010–2016, this data is still applicable because the projects reported to CDP are from the previous year. For example, the 2016 CDP reports typically cover financial and environmental performance for 2015.

Sato et al. (2019) calculate energy prices based on weighted averages of fuel prices by fuel consumption. The energy prices include electricity, gas, coal and oil. They compute energy prices for various sectors, such as chemicals, food, paper, textile and transport equipment and take the average prices across these sectors to create a single energy price by country. They compute energy prices in real terms with the purpose of using them in cross-country comparisons and regression analysis. We take the natural log of the energy prices in our analysis as they recommend.

Table 2
Summary statistics of the unbalanced and balanced panel.

Year	Unbalanced sample			Balanced sample		
	Firms	Total projects	Mean payback period[a]	Firms	Total projects	Mean payback period[a]
2010	298	879	1.97	102	318	1.72
2011	457	1503	2.09	102	385	2.18
2012	733	2580	2.20	102	397	2.27
2013	941	3333	2.20	102	452	2.35
2014	1066	3917	2.25	102	472	2.23
2015	1150	4474	2.21	102	525	2.01
2016	1069	4234	2.24	102	502	2.11
Overall	**1417**[b]	**20,920**	**2.20**	**102**[b]	**3051**	**2.12**

[a]Payback period is measured in years as the ratio of total cost divided by the annual monetary savings.
[b]This number represents the total number of unique firms, not the total number of firm-year observations.

2.3. Descriptive statistics

Table 2 shows the descriptive statistics for the unbalanced and balanced panel. The average payback period varied from 1.97 years in 2010 to 2.24 years in 2016 in the unbalanced sample. Examining the smaller set of 102 firms that reported in every year, we see that the average payback period shows a similar pattern, ranging from 1.72 years in 2010 to 2.11 years in 2016 (though reaching higher values in between). Overall, this suggests that the average payback period for implemented projects is slightly above two years, and does not deteriorate substantially during our horizon. We will test this more formally using regression analysis in the next section.

These average payback periods hide a substantial variation. Fig. 1 shows the histogram of payback period for the entire unbalanced panel (left top chart), and then for each year separately. Fig. 2 shows the same for the balanced panel. The charts are consistent with the view that there are many (highly) profitable projects, but they also show that firms implement some projects with much longer payback periods. In the unbalanced panel in 2010, 63% of projects had a payback period of 2 years or less (the area under the two leftmost vertical bars); in 2016, that percentage was 57%. Each year also includes a few projects with payback periods of 8 years or more. Although there is some variation between years, the overall shape of the histogram looks fairly similar; there is no clear shift towards longer-payback projects over time. The balanced panel in Fig. 2 shows similar trends, though with higher variation due to the smaller sample size.

Table 3 shows energy prices in USD per tonne of oil equivalent for six illustrative countries as calculated by Sato et al. (2019). The average energy prices vary from country to country and from year to year. For example, the energy price in the USA is the lowest across the six countries shown and is highest in Brazil. We see that the average energy price is slightly increasing for Japan from $906 per tonne of oil equivalent in 2009 to $1196 in 2015. In contrast, the energy price in the United Kingdom has been relatively stable at $840 per tonne of oil equivalent in 2009 to $869 in 2015. We include energy prices in our analysis of the trends of average payback periods.

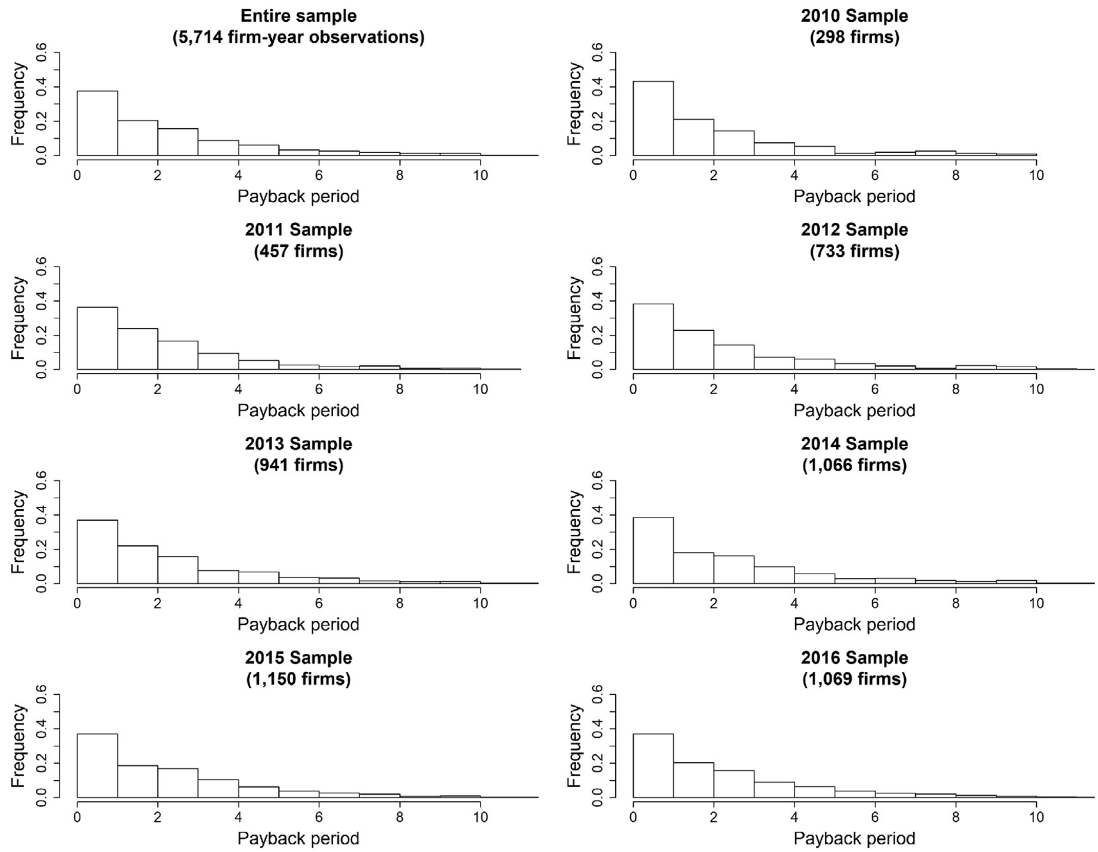

Fig. 1. The distribution of payback period for the entire sample (unbalanced panel) and for each year from 2010–2016.

Table 3
The average annual energy prices in USD per tonne of oil equivalent from 2009 to 2015 for 6 countries.

Year	Australia	Brazil	Denmark	Japan	United Kingdom	USA
2009	666.51	1131.15	904.01	906.62	840.69	421.31
2010	713.72	982.57	945.02	946.44	801.42	425.87
2011	788.46	937.96	966.65	1042.39	848.61	440.82
2012	866.64	1007.29	1040.89	1116.39	871.01	397.17
2013	904.82	972.78	1053.57	1220.85	899.07	410.71
2014	719.04	965.29	936.43	1296.15	891.42	417.41
2015	651.44	1286.14	871.26	1195.97	868.72	346.80

The data is described in Sato et al. (2019, pp. 16–17).

3. Methods

The descriptive statistics presented above already suggest that the average payback period of implemented carbon abatement projects does not change much over the time horizon in our sample. Given that firms' decisions related to investment in carbon abatement over time is an important input for policy-makers when designing and adjusting their carbon policies, it is worthwhile estimating the trend more carefully, recognizing that the period 2010–2016 is too short for definitive conclusions. We will draw a brief comparison to a different firm-level energy efficiency dataset with well over 30 years of data, but we also encourage regulators to redo our analysis below as more data over longer horizons become available.

Our objective is to determine whether the average payback period of carbon abatement projects changes over time. We test this by conducting a regression analysis, with the average payback period across all projects for each firm as the dependent variable and a time trend as the main independent variable. We need to control for firm-level factors and other effects, as the nature of abatement opportunities will vary widely from one firm to the next. We also need to account for the possible effect of changes in the cost of energy over time. To do so, we use a fixed effects panel regression analysis:

$$Payback\ period_{it} = \gamma_i + \beta_1 \times Year_t\ + \beta_2 \times \log(Energy\ price_{i(t-1)}) + \epsilon_{it}, \quad (1)$$

where index i refers to firms and t to year (between 2010–2016). $Payback\ period_{it}$ is the average payback period of all projects reported in year t by firm i; $Year_t$ increases from $Year_{2010} = 1$ to $Year_{2016} = 7$; and ϵ_{it} is a random error term. The firm fixed effects γ_i in Eq. (1) control for firm-specific variation. Greene (2012) and Cameron and Trivedi (2005) provide a thorough discussion of the fixed-effects panel model.

4. Results and discussion

We present our results on the trends of average payback period in this section, followed by several robustness tests.

4.1. Main results

Table 4 summarizes the regression results where the dependent variable is the average payback period. We begin with the results from the unbalanced sample. The average payback period is increasing by 0.03 years (or 2 weeks) per year at a significance level of $p = 0.17$. The economic impact of this increase is almost negligible compared to the average payback period across all implemented projects of 2.2 years. This increase is about 1.4% of the overall average payback period across all years. The 95% confidence interval is from −0.01 to 0.06 year. The sample size is large enough that it can detect changes of 0.001 year with at least 80% power at a 0.10 significance level. Overall, the point estimates and the range of the interval of the regression models suggest that payback periods remain relatively stable over time.

The results for model (1) in Table 4 show that a 10% increase in the average energy price is associated with a 0.043 years (or 2

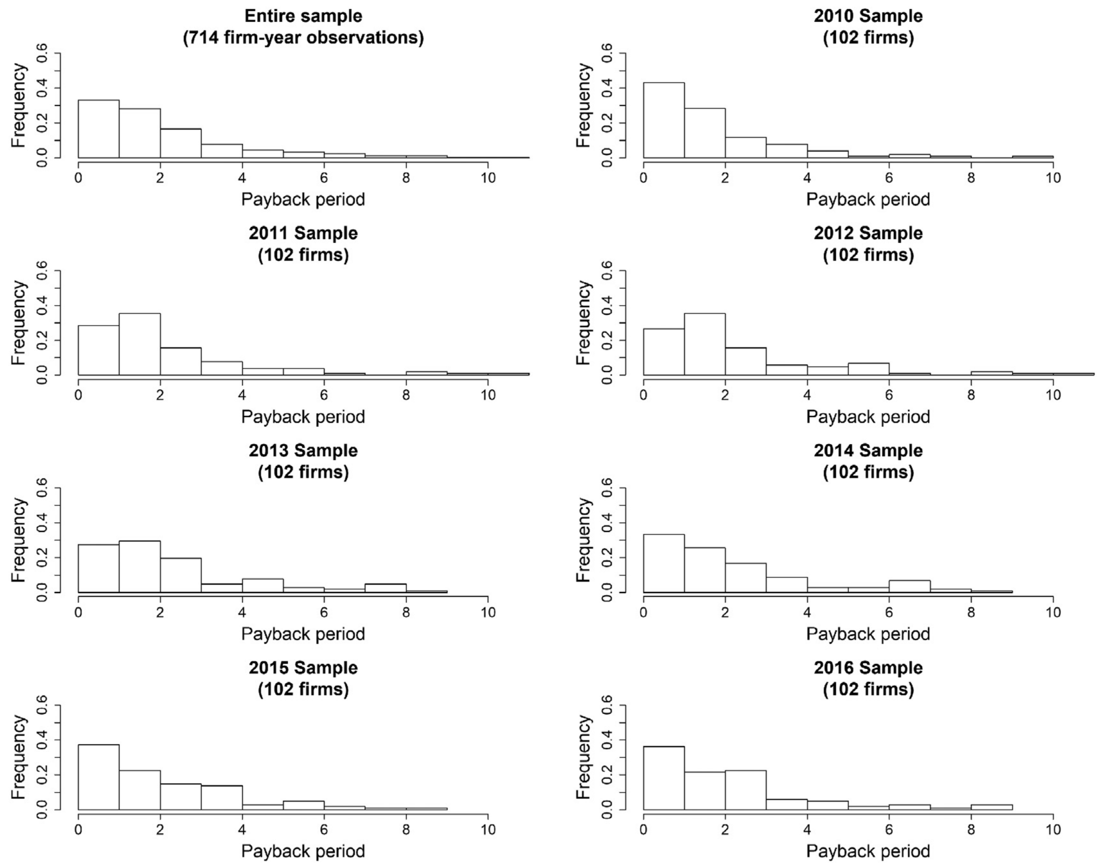

Fig. 2. The distribution of payback period for the entire sample (balanced panel) and for each year from 2010–2016.

weeks) shorter average payback period with a $p-$ value of 0.01. The average change in the dependent variable as the independent variable changes (holding all else constant) is given by $Payback(energy\ price_2) - Payback(energy\ price_1) = \beta_2 \times (\log(energy\ price_2) - \log(energy\ price_1)) = \beta_2 \times (\log(energy\ price_2/energyprice_1))$. A 10% increase in the energy prices is roughly equivalent to $log(1.1) \approx 0.10$ (for base e). Therefore, a 10% increase in the average prices is equal to $\beta_2 \times 0.10 = -0.43 \times 0.10 = -0.043$ years decrease in the average payback period. This result suggests that higher energy prices lead to slightly shorter payback period, but this effect largely disappears in the balanced sample.

The results for the balanced sample, model (2) in Table 4, are similar. The average payback period is increasing by 0.03 years (or 2 weeks) per year at a significance level of $p = 0.38$. In other words, we find no evidence to suggest that the payback period is increasing. The results for the balanced sample show that energy prices are not significantly associated with shorter payback periods ($p = 0.90$). Although this lack of a clear effect may seem surprising, it is consistent with other work. Some of the reasons for this weak association is that energy costs are a small share of the total cost of energy efficiency opportunities, that longer-term energy prices are unpredictable, and that there is often a delay in realized savings from implementing these projects (Abeelen et al., 2013, p. 415). Antonietti and Fontini (2019) find support that long term oil prices do affect energy intensity, but the effects are less clear in the shorter term and mixed across countries.

Table 4
Fixed-effects regression results of payback period for the unbalanced panel from 2010–2016.

Dependent variable: Payback period				
	(1) Unbalanced sample		(2) Balanced sample	
	Coefficient (S.E.)	95% confidence interval (*p*-value)	Coefficient (S.E.)	95% confidence interval (*p*-value)
Year	0.03 (0.02)	[−0.01,0.06] (0.17)	0.03 (0.03)	[−0.04,0.09] (0.38)
Log(Energy price)[a]	−0.43 (0.17)	[−0.77,−0.09] (0.01)	−0.06 (0.45)	[−0.95,0.84] (0.90)
Other controls				
Firm fixed effects	Included	–	Included	–
Total firm-year observations		5714		714
Total unique firms	1417		102	

S.E. stands for standard error.

[a]These are weighted average energy prices by fuel consumption across 12 sectors computed by Sato et al. (2019). "Included" means that those set of control variables are included in the regression model.

4.2. Robustness tests

We present three robustness tests in this subsection. First, we present an extension of the regression model of Eq. (1) that includes firm-level financial controls. Second, we perform a test where we interact the country-level energy prices by sector to allow more flexibility in the model. Third, we conduct additional tests with 31 years of data from the Industrial Assessment Center's dataset on energy efficiency projects.

4.2.1. Controlling for firm-level financial performance

So far, we have included firm fixed effects, but we have not controlled for firm-level financial performance. DeCanio and Watkins (1998) show that firm-level characteristics may matter in the adoption of energy efficiency, so the same may be true for carbon abatement activities. We perform the tests again but include the total assets, cost of

Table 5
Fixed-effects regression results of payback period with additional firm-level financial controls.

Dependent variable: Payback period				
	(1) Unbalanced		(2) Balanced	
	Coefficient (S.E.)	95% confidence interval (*p*-value)	Coefficient (S.E.)	95% confidence interval (*p*-value)
Year	0.01 (0.02)	[−0.04,0.06] (0.44)	−0.02 (0.05)	[−0.12,0.08] (0.66)
Log(Energy price)[a]	−0.58 (0.23)	[−1.03,−0.13] (0.01)	−0.19 (0.54)	[−1.26,0.88] (0.72)
Other controls				
Log(Assets)	Included	–	Included	–
Log(COGS)	Included	–	Included	–
Log(Liability)	Included	–	Included	–
Log(PPEG)	Included	–	Included	–
Log(Sales)	Included	–	Included	–
Firm fixed effects	Included	–	Included	–
Total firm-year observations		4169		596
Total unique firms		1098		89

S.E. stands for standard error.
[a]These are weighted average energy prices by fuel consumption across 12 sectors computed by Sato et al. (2019). "Included" means that those set of control variables are included in the regression model.

goods sold (COGS), liabilities and property, plant and equipment values (PPEG), and annual sales. We include these because they capture the size of the firms, their costs and how efficient they are in managing their physical assets. For example, for a fixed amount of assets, an increase in COGS may force firms to find more profitable ways to reduce their energy use and carbon emissions. The regression equation for this robustness test is as follows:

$$Payback\ period_{it} = \gamma_i + \beta_1 \times Year_t + \beta_2 \times \log(Energy\ price_{i(t-1)}) + \beta_3 \times \log(Assets_{it}) + \beta_4 \times \log(COGS_{it}) + \beta_5 \times \log(Liabilities_{it}) + \beta_6 \times \log(PPEG_{it}) + \beta_7 \times \log(Sales_{it}) + \epsilon_{it}. \quad (2)$$

The results from the unbalanced and balanced panel are again consistent with each other and with our earlier results. The results for the unbalanced panel in Table 5 model (1) confirm that the average payback period remains roughly constant over time with an average increase of 0.01 per year and with $p = 0.44$. The estimates for the balanced sample in model (2) lead to the same conclusion.

4.2.2. *Controlling for energy prices and their effect by industry*

We conduct tests with a similar but more flexible regression model by interacting energy prices with the controls for industry sector. The regression equation for this model is

$$Payback\ period_{it} = \gamma_i + \beta_1 \times Year_t + \beta_2 \times \log(Energy\ price_{i(t-1)}) + \beta_3 \times Sector_i \times \log(Energy\ price_{it}) + \epsilon_{it}. \quad (3)$$

The interaction of the firm's sector with the energy prices allows the model to vary the impact of average energy prices by sector, but at the expense of losing observations for which we cannot determine the right match. The results for the unbalanced and balanced samples in Table 6 again show that the average payback periods remain largely constant over time.

4.2.3. *Contrasting results from CDP with 31 years of the industrial assessments center dataset*

We repeat our tests on the trends of the payback period with 31 years of data using the US Department of Energy Industrial Assessments Center (IAC) database. This dataset provides information on energy

Table 6
Fixed-effects regression results of payback period with energy prices interacted with industry sector controls.

Dependent variable: Payback period				
	(1) Unbalanced		(2) Balanced	
	Coefficient (S.E.)	95% confidence interval (*p*-value)	Coefficient (S.E.)	95% confidence interval (*p*-value)
Year	0.02 (0.02)	[−0.02,0.07] (0.35)	0.00 (0.05)	[−0.09,0.09] (0.99)
Log(Energy price)[a]	0.08 (0.21)	[−0.34,0.50] (0.72)	0.49 (0.88)	[−1.26,2.24] (0.56)
Other controls				
Firm fixed effects	Included	–	Included	–
Interaction of industry and energy prices	Included	–	Included	–
Total firm-year observations		4166		596
Total unique firms		1097		89

S.E. stands for standard error.
[a]These are weighted average energy prices by fuel consumption across 12 sectors computed by Sato et al. (2019). "Included" means that those set of control variables are included in the regression model.

efficiency projects implemented by small- and medium-sized US enterprises from 1981–2018, but we limit our analysis to 1986–2017, which are the years with available energy data from the US Energy International Administration (EIA). One drawback of the IAC dataset is that it does not allow us to track the same firm over time, thus this test is only on the variation across opportunities rather than longitudinal changes within a firm. The trends in the IAC data nonetheless provide insights on the average payback period over three decades.

Table 7 shows the results using the IAC dataset, with the following regression equation:

$$Payback\ period_t = \alpha + \beta_1 \times Year_t + \beta_2 \times \log(Energy\ price_t) + \epsilon_t. \quad (4)$$

Model (1) in Table 7 includes years from 1986–2017. Here we see that the trend for the average payback period is largely flat, increasing by 0.001 year per year, or 0.35 days per year ($p = 0.001$). Even over a 30-year period this only corresponds to a 1-month lengthening of average payback period. (The higher significance level relative to our CDP-based analyses is a result of the much larger sample size.) For a direct comparison with our results based on CDP, model (2) shows the trend of the average payback period from 2010–2016. We see that the average payback period is improving by about 0.04 years per year (with $p = 0.01$). Overall, this suggests that the average payback period of carbon abatement opportunities, in the form of energy efficiency, remained largely consistent in the US.

The robustness tests we present here all point in the same direction: payback periods remain reasonably stable over time, within and between firms.

4.3. *Number of projects and emissions reductions achieved*

We have seen that profitability of carbon abatement projects, measured using payback period, remained relatively stable during 2010–2016. In order to draw policy implications from this (or any other observed trend in payback periods over time), we also need to consider the number of projects implemented and the emissions reductions achieved.

Although it is possible to estimate marginal abatement costs of the projects implemented by the firms in our CDP sample, we conducted our analysis so far in terms of payback period rather than marginal abatement costs, for several reasons. The payback period data are

Table 7
The trend of the average payback period of energy efficiency opportunities reported to the Industrial Assessments Center in the US from 1986–2017 and 2010–2016.

Dependent variable: Payback period		
	1986–2017 (1)	2010-2016 (2)
Year	0.001	−0.044***
	(0.001)	(0.010)
Log(Energy price)	0.114***	−0.063
	(0.017)	(0.058)
Constant	1.008***	2.059***
	(0.043)	(0.280)
Observations	113,218	23,813
R^2	0.002	0.001

Notes: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

more reliable as they require less assumptions than MACs. Due to these assumptions (about project life and discount rate), our estimates of the marginal abatement costs experienced by a firm could differ substantially from any estimates the firm used internally, rendering any analysis based on such estimates potentially misleading. Payback periods are also more suited to dealing with profitable projects than MACs are. Moreover, payback period is closer to how most firms actually make decisions than marginal abatement costs are, as documented by Harris et al. (2000), Fleiter et al. (2012b), and Jackson (2010), among others.

However, payback period does not account for the magnitude of emissions reductions achieved. For that reason, we also looked at the number and size of projects with emissions reduction data. For each project that a firm discloses, the CDP survey asks firms to estimate the annual emissions reduction achieved. Table 8 shows the count of the number of projects disclosed with emissions data and the average emissions reductions achieved per project, for the unbalanced and the balanced panel. The average emissions reduction for the unbalanced panel increased from 112,000 metric tons of CO2e in 2010 to 529,000 in 2012, but declined to 186,000 in 2016. The pattern is similar but more pronounced for the balanced sample. We have less confidence in this data than in our earlier estimates of payback period: estimates of emissions reductions may be less accurate, firms may be subject to pressures to under- or over-estimate the reductions, and firms may not report these details on all projects they implement.

Nevertheless, subject to these caveats, we see that firms provide detail on more projects over time, but that the average emissions reductions attributed to each of those projects decreases over time. Due to the ambiguities mentioned above, we are reluctant to try to quantify the net effect; however, this perspective does provide a counterpoint to the earlier focus on payback period, as we explain further below.

4.4. Limitations

Our work shows that reports by firms on profitability of carbon emissions reductions projects they have actually implemented, and the evolution of that profitability over time, can help provide policy-makers with additional perspectives to take into account when designing and adjusting carbon policy. Clearly, though, our findings are preliminary; we hope that they will stimulate further research to overcome some of the inevitable limitations of our work.

Our main analysis focused on the period 2010–2016, which is clearly too short to be able to draw conclusions about long-term trends. The policy literature we reviewed suggested that profitability of emissions reductions projects would decline in the short term, but improve in the long term due to structural and technological changes. We find no statistically significant evidence of a short-term decline, but our horizon is too short to be able to draw conclusions about the long-term trends. CDP adds one year of data every year, but one might also look for other historical comparisons (such as with the data from IAC program) to gain further insight into the longer-term evolution of firm-level abatement costs.

Further, our analysis focused primarily on profitability, as measured by payback period. While we did briefly comment on the number and size of projects that firms report, more comprehensive analysis is needed of those factors and those examined in Fleiter et al. (2012b) before being able to draw firmer conclusions about the evolution of profitability of emissions reductions projects.

Moreover, our analysis focused on projects that were actually implemented by firms. While this is a strength of our work, adding a new perspective relative to existing studies that tend to focus on estimating the opportunities available to industry, it also means that we do not observe how the full set of opportunities evolves over time. If firms were to experience tighter capital availability, they might choose to implement fewer projects, which would presumably be the most profitable ones; that could be misinterpreted as an indication that carbon abatement is becoming more profitable. To inform policy, one needs the estimates of available opportunities as developed using top-down and bottom-up methods described earlier, in addition to the firm-level perspective that we provide here.

Given the preliminary nature of our analysis, we analyzed a global sample rather than focusing on specific countries or sectors. Yu et al. (2016) study environmental efficiency among US firms in 2012–13, using data from CDP and other sources on carbon emissions, investments, and monetary savings. They find substantial variation across sectors, and conclude that carbon policy recommendations should vary by sector.

Finally, the CDP data we use are self-reported by firms. There are reasons to believe the data are increasingly accurate (Kolk et al., 2008), and there is continued expansion of disclosure regulation around the world related to climate change. However, if CDP data is increasingly relied upon by regulators to set policy, that would introduce mixed incentives for firms to select different emissions reductions projects, or to potentially report inaccurate or incomplete information.

5. Conclusions and policy implications

In the introduction, we noted that, in theory, firms will implement carbon abatement projects as long as the marginal benefit of doing so exceeds the marginal cost. In practice, however, the marginal costs and marginal benefits are ambiguous, and unobserved, certainly to policy-makers. Firms are more likely to make decisions using the simple payback period (Harris et al., 2000; Jackson, 2010; Fleiter et al., 2012b). Policy-makers can learn something from observing the payback periods of projects that firms choose to implement that would not be apparent from existing marginal abatement cost curves.

In order to assess whether firms are responding to policy measures in the manner intended, it is important to observe what firms actually do, as Bumpus (2015) and Brännlund et al. (2014) also argue. If firms' responses are different than expected, that could be an indication that the price of carbon is too high or too low, which could point to the need to adjust the tax or number of allowances. Alternatively, if firms' response varies substantially across sectors, that could indicate that the carbon policy is having unintended competitive or distributional effects (Stavins, 2019). In the introduction, we outlined what policy-makers could learn from observing lengthening or shortening of payback periods, as summarized in Table 1.

From our analysis of the CDP data, we find that payback periods are relatively stable over time. Although the estimates of the time trend are marginally negative, they are not significantly different from zero. We do find that emissions reductions achieved are shrinking over time. Based on the arguments outlined earlier, this would suggest that firms have not changed their thresholds for investing in carbon abatement, but that a higher price of carbon may be needed to spur them to return to investing in larger projects.

Table 8
Summary statistics of total firms that report emissions reduction data of projects, the total projects with available emissions reduction data, and the mean carbon emissions reduction of those projects.

Year	Unbalanced panel			Balanced panel		
	Total firms	Total projects	Mean CO2e reduction per project[a]	Total firms	Total projects	Mean CO2e reduction per project[a]
2010	278	830	111.97	99	303	167.27
2011	–	–	–	–	–	–
2012	694	2355	529.36	96	375	482.38
2013	928	3281	164.70	102	448	201.39
2014	1057	3867	291.09	101	467	52.31
2015	1141	4431	164.47	102	521	53.80
2016	1062	4191	185.63	102	501	67.83

Notes:
[a]This is measured in thousand metric tons. The number of firms is a subset of the original sample. The number of firms in the balanced sample is less than 102 in some years because some firms that reported cost and monetary savings data in early years did not include emissions reduction information. CDP did not ask firms to disclose emissions reduction information in 2011.

In our analysis, the average payback period of implemented projects is close to two years, which would indeed suggest that many profitable opportunities are not being implemented. Moya et al. (2011) provide an in-depth analysis of the link between payback period and profitability for the European cement sector; they show that opportunities that are profitable using the more appropriate net present value (NPV) criterion have a payback period of 6 or even 9 years, which means they are typically not implemented as common thresholds for payback period are generally shorter than 3 years (Cooremans, 2011). Jackson (2010) proposes that using risk-based decision tools, analogous to the Value-at-Risk criterion used in the financial sector, would reduce this bias against carbon abatement projects. For policy-makers, this highlights that they need to reduce the risk and uncertainty associated with carbon abatement opportunities, in order to encourage firms to adopt looser payback period thresholds.

From looking at the CDP data more closely than we can report here, it appears that the projects that firms actually implement are more diverse than what is often studied in the literature. Although many of the opportunities described in Pacala and Socolow (2004) such as low-emissions vehicles, more energy efficient buildings, improved plant efficiency, wind power, photovoltaic electricity, and biofuels|appear as well in the CDP data, firms also pursue operational, behavioral, and product-level innovations that are company-specific and therefore less likely to be mentioned in such studies (although there are a few exceptions such as the studies by Fleiter et al. (2012a) and Worrell et al. (2009)). Examples include projects related to transportation logistics, product materials, design, and packaging. There is a rich literature in Operations Management on continuous improvement, and these management practices are applicable to carbon abatement as well as illustrated by Finnerty et al. (2018). Policy-makers should seek to ensure that the appropriate conditions exist to foster such continuous improvement within firms, such as ensuring a stable and predictable business environment.

A related observation is that there is significant variation between firms in our data. As Figs. 1 and 2 show, some saw substantial improvements in average payback of their carbon abatement projects over time, while others experienced deteriorations. Some of this will no doubt be due to random variation, perhaps exacerbated by the discrete nature of many projects, but a deeper analysis of this variation could have additional policy relevance. Often, the effects of policies are not perfectly predictable, so when regulators introduce carbon taxes, cap-and-trade measures, renewable portfolio standards, energy-efficiency subsidies, or other instruments, they may have unexpected effects that could also differ by sector. If a particular industrial sector appears to show a noticeable decline in profitability of carbon abatement over our 7-year horizon, regulators should explore whether that is an unintended consequence of past policies or of complementary policies (Stavins, 2019) and, if necessary, remedy that.

On the other hand, even within a sector that continues to show constant or even improving profitability of carbon abatement projects, regulators should examine those trends more deeply as more data become available. It would be valuable to understand the mechanisms by which low-hanging fruit continues to emerge in those cases. That can be for "good" reasons, such as continuous emergence of new technologies, or firms uncovering new opportunities as they map more of their own and their supply chain's operations. It could also be for "bad" reasons, if firms introduce carbon emissions reductions projects now but do not continue to maintain those projects going forward. Processes in firms tend to deteriorate over time if not closely monitored and proactively managed. If regulators observe that is the main reason why firms continue to find profitable opportunities, they should explore policies that focus on maintaining existing improvements rather than continually looking for and implementing new ones. Implementing policies that require firms to document and report their carbon abatement efforts may help increase the longevity of those projects more than would be achieved from a focus on carbon price alone.

Our study departs from most earlier work in this field due to its focus on the experience of specific firms over time. Clearly, several of the implications outlined above require more detailed data over longer horizons, but we believe that the breadth and depth of the CDP data is such that it will provide a valuable additional tool for regulators.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Christian C. Blanco: Conceptualization, Writing - original draft, Writing - review & editing, Data curation, Formal analysis. **Felipe Caro:** Conceptualization, Writing - original draft, Writing - review & editing, Data curation, Formal analysis. **Charles J. Corbett:** Conceptualization, Writing - original draft, Writing - review & editing, Data curation, Formal analysis.

Acknowledgments

We are grateful to CDP for providing access to their dataset. We thank Patrick Crawford, Maia Kutner, Emma Whelan, and Jenny Frings for helpful discussions and assistance with the data. The early stages of this research was partially funded by the National Science Foundation Graduate Research Fellowship (Grant #2011131079). We are grateful to the reviewers for their constructive feedback on earlier versions of this paper.

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