Forthcoming in *Manufacturing & Service Operations Management*
manuscript MSOM-21-179.R2

A classification of carbon abatement opportunities of global firms

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Problem definition: Carbon abatement opportunities are diverse, making it difficult to classify them. Do latent classes of carbon abatement opportunities exist and is there a type that is financially and environmentally superior?

Methodology/results: In this study, we classify 16,525 implemented carbon abatement projects using text analysis. We benchmark our clustering method to the latent Dirichlet allocation model and verify our classifications using a crowd-sourcing platform. We then compare the payback period, financial hurdle (measured in upfront cost), savings, and carbon emissions reduction by type. Our results show that latent classes exist, and they statistically differ in the metrics we examine. Our regression results show that the type of project explains more of the variation in the financial and environmental outcomes than the firm-level financial controls we included. We find that liquidity (measured using cash-to-asset and current ratios) is associated with the number of reported projects, but the magnitude and direction varies by type. Our extension shows that marginal abatement costs statistically differ by type with a few exceptions. Lastly, we show that our classification is robust to sector-level variation.

Managerial implications: Although the results show that no single type of opportunity dominates in all four metrics, our classification provides a ranking of the types firms should pursue depending on their goals. Our results suggest that firms likely place different weights across these four metrics. This means that policies targeted at making investment costs more attractive (e.g., subsidies or better financing) may not have the same impact on firms that put more weight on savings compared to those more sensitive to costs. A classification of opportunities can contribute towards understanding whether a unifying theory or pattern across carbon abatement activities may exist or not.

Key words: carbon emissions reduction; energy efficiency; climate change; text analysis; sustainability

1. Introduction

The global Greenhouse Gas (or "carbon emissions") abatement potential from the adoption of more energy-efficient technologies and process improvements is estimated at 38 gigatons, roughly a third of which come with substantial cost-savings (Nauclér and Enkvist 2009; Enkvist et al. 2010). Some of the largest global firms have started to respond to climate change by investing in opportunities that lower their carbon footprint. Many firms are now investing in corporate green bonds (Flammer 2021), and these funds are used to finance the types of projects we examine. Still, very little empirical work has been done to examine the types of opportunities firms pursue to reduce their carbon footprint (Gillingham and Stock 2018). In this paper, we explore whether latent classes of carbon abatement opportunities exist. If so, is there a type that financially and environmentally dominates the rest?

Identifying the different types of carbon abatement opportunities is important for at least four reasons. First, a clear classification of these opportunities will allow us to examine opportunity-specific characteristics, such as cost, payback period, and annual savings, and whether those vary by type. This will help identify types of opportunities that are financially and environmentally superior. If a dominant type of opportunity exists, then firms should pursue that type first.

Second, although it is well-established that firms are more likely to pursue opportunities with shorter payback periods, lower cost, higher savings, and higher carbon emissions reduction (Anderson and Newell 2004), our findings can suggest whether firms place equal weights across these metrics. If there is substantial variation in these metrics across types, then that would suggest that these dimensions are not flat, i.e., firms do not necessarily weigh these metrics (or attributes) equally.

Third, our results have implications for designing policy. For example, policies designed to make savings more attractive (e.g., a carbon tax) may not necessarily encourage all firms equally because some firms may place more weight on upfront costs rather than savings. Fourth, we will explore whether measures of liquidity (i.e., cash-to-asset and the current ratios) explain adoption patterns, and we will compare the results between aggregating across different types and doing it separately.

Our paper departs from earlier works in carbon emissions management in several ways. Instead of examining a single opportunity in isolation (e.g., more energy efficient light bulbs or solar panels), we explore the set of implemented carbon abatement projects. Most papers in carbon emissions management focus on measurement (Blanco et al. 2016; Jira and Toffel 2013), allocation (Caro et al. 2013; Sunar and Plambeck 2016; Sunar 2016; Gopalakrishnan et al. 2021), or regulation (Kroes et al. 2012; Drake 2018; Subramanian et al. 2007). Very little work has been done to explore the profitability of the types of opportunities to reduce carbon emissions. Creating a classification of potential opportunities can contribute towards understanding whether or not a unifying theory or pattern exists across carbon abatement activities.

We examine carbon abatement projects that firms disclose to CDP, a non-profit organization that has been successful in engaging corporations to disclose their climate change strategies. The CDP works with more than 500 global institutional investors with combined assets of $96 trillion (CDP 2018). The CDP invites publicly traded companies with the largest market capitalization (e.g., firms listed on the FT500, S&P 500, FTSE 100, etc.) to take their climate change surveys, which includes questions on investments pursued by firms to reduce their carbon footprint. Many global firms, such as Apple, Boeing, Bayer, and Cisco, annually take the CDP survey.

There is a copious amount of text within the carbon abatement projects disclosed to CDP, but this resource is underutilized. Analyzing and comparing a large amount of text is arduous, so we address this challenge by using text-analysis methods designed to examine a collection of documents that share the same diction and jargon. We benchmark our results with the latent Dirichlet allocation (LDA), one of the most widely-used text classification methods. We show that our method gives unique outcomes within the top-20 words that loaded for each type, making our method easier to interpret compared to the LDA. We also verify our method using a crowd-sourcing platform. We construct a statistical measure comparable to Cohen's kappa to measure multi-rater reliability with an algorithm. The test statistic has an agreement value of 0.73, which is considered substantial based on Cohen's standards.

We discovered six latent types of opportunities based on our analysis of 16,525 projects disclosed by 1,305 firms to CDP from 2011−2016[1]. Using fixed-effects regression models and tests of equality of coefficients, we did not find a single type of opportunity that is superior in all financial and environmental metrics. Although the interpretation of our latent classifications is subjective (as with any latent classification method), we provide our best description of each type by examining the projects that cluster together.

We find that the average payback periods, investment costs, savings, and carbon emissions reductions are statistically different across types (with a few exceptions), and our classification can prescribe a ranking of opportunities based on the priorities of a company. We find that projects we labeled *renewable energy* have the longest average payback period at 3.74 years and the highest median investment cost at $845,000. The median investment cost for *renewable energy* projects is almost eight times greater than the overall median of $108,000 across all projects. The two types we labeled *transportation* and *materials* have the shortest average payback periods at 1.98 and 2.07 years. Although these types are financially attractive, they do not have the lowest upfront cost. Projects we labeled as *buildings* have the lowest median investment cost at $56,000, but they have the lowest annual carbon emissions reduction at a median of 140 metric tons. We conduct robustness tests by sector and show that our overall rankings hold in most sectors, suggesting that the classification is potentially generalizable across sectors.

There are eight sections in this paper. We discuss the background and theory in Section 2. We describe the data and summary statistics in Section 3, followed by the methods in Section 4. We

[1] We decided to focus from 2011−2016 because Blanco et al. (2020) find that the profitability of opportunities reported during this window remained relatively stable.

benchmark and verify our method in Section 5, followed by the results and discussion in Section 6. We conduct an extension and robustness checks in Section 7. The final remarks are in Section 8.

2. Background, Related Literature and Theory

We begin with related literature on the metrics we examine in this study. Then we introduce a simple decision framework that illustrates how firms can choose between opportunities based on the metrics we have chosen. The model, although simple, has the flexibility to allow firms to place different weights on the different metrics (or attributes). This captures how firms can rank the opportunities even if they have different goals (e.g., higher savings versus large carbon emissions reductions). We also include a section with a short discussion on liquidity and how that may influence the number of investments firms implement. We end this section with a few related papers on text analysis in sustainable operations management.

2.1. Financial and Environmental Metrics of Carbon Abatement Opportunities

The large upfront cost, small savings, or uncertain carbon abatement outcomes can limit the adoption of these carbon abatement opportunities (Aflaki et al. 2013; Jaffe and Stavins 1994). Using a government-sponsored energy audit, Anderson and Newell (2004) find that projects with longer payback periods, higher upfront costs, lower annual savings, and lower energy conservation are less likely to get adopted. However, they do not mention which types of energy efficiency projects dominate in these criteria. It is well-established that these metrics matter to the firm, so instead of examining these characteristics and how they influence adoption, we identify whether a specific type of opportunity dominates in these financial and environmental metrics. The projects we examine have already been implemented, therefore firms are able to provide actual cost and more accurate figures compared to projected values. This provides insights on the actual carbon reduction experience of firms.

There are other studies that explore the economic and non-economic factors that influence the adoption of energy efficiency opportunities. For example, Fleiter et al. (2012) show that projects with shorter payback periods are more likely to get adopted. Using data from the Industrial Assessment Centers (IAC), Muthulingam et al. (2013) find that non-economic factors such as placing opportunities higher on a list is associated with higher rates of adoption. Blass et al. (2014) and Dowell and Muthulingam (2017) also use the IAC dataset to examine manager-related and project-level factors (respectively) that may impede adoption. Blass et al. (2014) find that when operations managers are involved adoption rates increase by 13.4%. Dowell and Muthulingam (2017) find that more disruptive opportunities are less likely to get adopted. The IAC data focus on opportunities that are recommended by a government-led program while the projects we examine are not.

Some scholars claim that the rate of adoption of profitable carbon abatement opportunities remains slow (Gerarden et al. 2015), but there are studies that observe the opposite (Kok et al. 2011). Gillingham et al. (2009) provide a comprehensive review of some of the market and behavioral barriers associated with the slow adoption of energy efficiency, and they mention several areas in energy efficiency where empirical evidence is limited. Our contribution is to examine opportunity-specific characteristics rather than firm or program-specific idiosyncrasies.

2.2. Comparing Opportunities Based on Several Metrics

We present a simple decision model for how firms can compare two types of opportunities based on the different metrics we described in 2.1. Let Z_k be a vector of n metrics (or attributes) of an opportunity, $Z_k = (z_{k1}, z_{k2}, \ldots, z_{kn})$. Suppose that each component is greater than zero and that higher values are more attractive. (For attributes where lower values are more attractive, we can use its inverse.) Let w_j denote (non-zero positive) weights on how important attribute j is to the firm, and that the sum of the weights add to one, $\sum_{j=1}^{n} w_j = 1$. Two opportunities are compared by computing the following product:

$$P(Z_k/Z_l) = \prod_{j=1}^{n} (z_{kj}/z_{lj})^{w_j}. \tag{1}$$

If the value of $P(Z_k/Z_l)$ is greater than 1, then opportunity Z_k is preferred over Z_l. We prove in the Online Companion that if a certain type of opportunity dominates all other types, that is $z_{kj} > z_{lj}$ for each $j = 1, \ldots, n$ and $k \neq l$, then $P(Z_k/Z_l) > 1$ for any weighting scheme such that $\sum_{j=1}^{n} w_j = 1$.

This framework can be used to rank opportunities based on priorities of the firm encoded in w_j.

2.3. Firm Liquidity and Types of Opportunities

There is a rich literature in the link between liquidity and investments (Fazzari et al. 1987; Kaplan and Zingales 1997), but very little empirical work has been done to examine measures of liquidity on the types of opportunities firms pursue to reduce their carbon footprint. One reason for this is that data on carbon abatement investments for large firms have only been collected in the past decade. We further contribute to this literature by not only exploring the link between two measures of liquidity, the cash-to-asset and the current ratios, but we examine whether these patterns are consistent or different by type of investment.

Examining the link between firm liquidity and carbon abatement investments by type is important for at least three reasons. First, investment decisions by firms are sensitive to liquidity. Although this sensitivity depends on whether firms are financially constrained or not (Cleary 1999), it is beyond the scope of this paper to quantify these constraints, which is not a trivial endeavor (Kaplan and Zingales 1997). Instead we want to explore the link between liquidity and the type of carbon abatement investments firms pursue. Second, capital constraints have been identified as one of the potential barriers in the adoption of energy-saving opportunities (Nauclér and Enkvist 2009, p. 17). Very few papers have examined this connection at the scale (number of global firms) and breadth (by type of opportunity) we do so here. Third, although it is not going to be surprising to see a link between liquidity and the number of opportunities firms pursue, it remains unclear whether the association between measures of liquidity vary by type. By exploring these patterns we can infer which firms (i.e., high or low liquidity firms) match with certain types of opportunities. By doing so, we are able to better design policies that account not only for the type of opportunity but are also flexible to different types of firms.

2.4. Text Analysis and Sustainable Operations Management

Text mining is uncommon in sustainable operations management, but its application in this area is becoming more relevant. Text mining is more common in services (e.g., Mankad et al. 2016; Chen and Mankad 2022) and marketing (e.g., Büschken and Allenby 2016; Kim and Allenby 2022) or at the interface of both (Keskin et al. 2022), but its application in sustainable operations is growing. For instance, Blanco (2021) used text analysis to identify the various climate change management practices that contributed to shifts in climate change disclosures. There are also applications of natural language processing in sustainable supply chain research (Huang et al. 2020a) and the adoption of solar panels (Huang et al. 2020b). Our paper contributes to this growing body of literature by showing how text analysis can be used to classify carbon abatement opportunities that firms can implement.

3. Data

The CDP currently holds one of the most comprehensive collections of climate change-related surveys from the largest companies around the world (CDP 2020). Each year CDP invites firms with the largest market capitalization from 90 countries, and over 2,000 firms annually submit their climate change surveys.

We use firm responses to question CC3.3b in 2016 and the corresponding questions in previous years. (See the Online Companion for a screenshot of the survey questions.) The CDP survey changes each year, which can make it difficult to merge several years of responses, but the CDP provided us a way to identify related questions from year to year. Firms describe their carbon emissions reduction activity and report the cost, annual monetary savings and annual carbon emissions reduction in question CC3.3b (2016).

Prior to 2015, CDP did not collect whether the source of emissions reduction is from Scope 1, 2 or 3[2], but the reported projects in 2015 and 2016 mostly cover Scopes 1 and 2. In 2016, roughly 39%

[2] Scope 1 referts to direct emissions. Scope 2 refers to emissions from the purchase of electricity or heat. Scope 3 refers to emissions within the supply chain not included in Scopes 1 and 2.

of the reported projects cover Scope 1 and 63% of the projects cover Scope 2; these two numbers exceed 100% because some projects cover both Scopes 1 and 2. Only 14% of the reported projects in 2016 cover any Scope 3 emissions. The distribution of Scopes 1 and 2 in 2015 are similar at 42% and 63% respectively. Only 15% of reported projects in 2015 include any Scope 3 emissions. Carbon footprinting from Scopes 1 and 2 sources is more mature compared to Scope 3 (Blanco et al. 2016; Blanco 2021), so we believe that these estimates are reasonably accurate.

In the next subsections, we provide excerpts of the reported carbon abatement projects, then we describe the variation in the reporting.

3.1. Examples of Carbon Abatement Projects Reported to CDP

We selected six excerpts from the survey responses to provide examples of the different carbon abatement projects firms report. The description, cost, annual monetary savings, payback period, and annual carbon emissions reduction are summarized in Table 1. The first two examples are from Goodyear and SunPower Corp. in 2012 and 2016 respectively. Goodyear, a large US-based tire company, implemented a building-related energy efficiency project in their facility. The total cost of the project was around $59,400, and the annual savings was $21,120. The payback period is 2.81 years. Goodyear avoided 106 metric tons of carbon emissions from this initiative. SunPower Corp., a US-based solar energy company, reported adding new solar projects to their sites. The total cost of the project was roughly $645,000 with an annual savings of $75,000[3]. The payback period for the solar project is long at 8.61 years. The annual emissions reduction from the project is 296 metric tons.

The next two examples are from Bemis and Air Products & Chemicals. Bemis, a US-based global manufacturer of flexible packaging products, reported replacing their boiler at one of their facilities. The total cost of the project was $248,000 with an annual savings of $138,000. The payback period for this investment is 1.8 years with an annual emissions reduction of 1,718 metric tons. Air Products & Chemicals is an American corporation that sells gases and chemicals for industrial use. In 2015, they reported carbon emissions reduction opportunities related to transportation and delivery that reduced fuel consumption. The cost of the project was $400,000, and the annual savings is $670,000. The project has a very short payback period of less than one year, and a large carbon emissions reduction of 1,300 metric tons per year.

The last two examples are from Raytheon and Royal KPN. Raytheon, a US-based defense manufacturing company, implemented sustainability training programs and offered incentives to employees who performed energy-saving initiatives. The total cost for implementing these programs

[3] This firgure captures the avoided fuel costs in switching to renewable energy. A detailed description of how companies should calculate monetary savings are available in pages 55-60 of the 185-page CDP survey guidelines. The survey guidelines are available upon request.

Table 1 Examples of carbon abatement opportunities firms disclose.

Year	Company	Description	Total Cost	Annual Savings	Payback period (years)	CO2e reduction
2012	Goodyear	Insulated the building envelope of the process oil storage area to maintain a certain temperature.	$59,400	$21,120	2.81	106
2016	SunPower Corp.	We installed more new solar projects at a number of our sites in 2015.	$645,550	$75,000	8.61	296
2015	Bemis	Boiler replacement at US facility	$248,000	$138,000	1.80	1,718
2015	Air Products & Chemicals	Voluntary improvements to transportation vehicles and delivery route optimization, reducing fuel use.	$400,000	$670,000	0.60	1,300
2016	Raytheon Company	Implemented short training modules of various sustainability programs and offered rewards on energy-based actions for employees who complete a given task.	$20,000	$75,000	0.27	1,000
2013	Royal KPN	Eco-design for customers: provided energy-efficient modems and setup boxes to consumers.	$136,013	$ 408,040	0.33	10,000

Notes: The annual avoided Greenhouse Gas emissions are in metric tons of carbon emissions equivalent or CO2e. The values reported here are not adjusted to 2020 values, but the data on cost and savings in all analyses have been adjusted to 2020 values.

was $20,000 with an annual savings of $75,000 and an annual carbon abatement of 1,000 metric tons. The payback for this initiative is short at 0.27 years. Royal KPN, a Dutch telecommunications company, described their carbon reduction initiatives with creating energy-efficient products for their customer. They spent $136,013 for this initiative but saved $408,040 and avoided 10,000 metric tons of carbon emissions annually.

These examples show the diversity of opportunities firms can pursue. The total annual carbon emissions reduction in this study is roughly 38 million metric tons; this is equivalent to removing roughly 76 100-MW coal power plants around the world[4].

3.2. The Variation in Text and Reported Metrics

There is substantial variation in the text of reported carbon abatement projects. Table 2 summarizes the total number of firm responses in this study. The projects include free-form text with substantial variation in the length across projects and over time. The median word count decreased from 22 in 2011 to 17 in 2016, and the mean word count decreased from 39 in 2011 to 31 in 2016. The standard deviation of the word count decreased from 48 in 2011 to 40 in 2016. We will use text analysis to classify the projects.

The variation in reporting is rich enough for us to explore our research questions. CDP did not collect emissions reduction data by project in 2011, but they did request this information from

[4] Assuming a rate of 0.646 CO2 mt/MWh and a capacity factor of 90%.

2012−2016. The reporting rate for carbon emissions reduction is high at 92% in 2012 and 99% in years after 2013. This suggests that firms either became more transparent over time or that they got better in measuring and reporting these figures.

Table 2 Summary statistics of the carbon emissions reduction activities disclosed to CDP.

(1) Year	(2) Total firms	(3) Total projects	(4) % with CO2e data	(5) Median word count	(6) Mean word count	(7) SD of word count
2011	365	1,243	–	22	39	48
2012	579	2,123	92	26	47	55
2013	738	2,742	98	31	46	49
2014	824	3,151	99	25	40	46
2015	880	3,556	99	19	35	43
2016	917	3,710	99	17	31	40
Overall	**1,305**	**16,525**	**91%**	**22**	**39**	**47**

Notes: Any project without information on both savings and costs were not included in this study because we cannot compare their financial outcomes with other investments. CDP did not collect emissions data of individual projects in 2011. CO2e is shorthand for carbon emissions equivalent, which is a measure of the Greenhouse Gas contribution in units of carbon emissions. CO2e is reported in metric tons. We remove any project with payback periods greater than 20 years as these could potentially be outliers. The number 1,305 represents the number of unique firms in the data.

3.3. Challenges in Using the CDP Data

CDP reporting is voluntary, and firms may only report investments that are profitable or successful. Self-selection of attractive projects is very likely, but this may not necessarily limit us from exploring our research question. Suppose for a moment that only the best (top 3-5 most profitable) projects are reported. It remains possible to examine whether a superior type exists among the best-reported projects. This makes the research even more intriguing because the key metrics (cost, savings, emissions reduction, payback period) remain diverse across the best sample of projects. Our initial assessment of the data reveals substantial heterogeneity in the reported projects even if firms may only report their most successful and profitable opportunities.

4. Methods

In this section, we describe the methods to identify latent types of carbon abatement projects using text analysis. We encode the text in a document-word matrix using weights we designed for a collection of standardized reports[5]. We present how we use singular value decomposition (SVD) to reduce the dimension of the text[6], then we use the maximum orientation to classify the opportunities. At the end of this section, we describe the statistical tests to detect differences among the types.

[5] We interchangeably use the words “reports” and “documents” to refer to the same thing.

[6] Principal component analysis (PCA) is related to the SVD, but PCA is typically implemented on the covariance matrix of the data instead of the data itself.

4.1. Clustering Types of Carbon Abatement Projects

The SVD decomposes the document-word matrix into three matrices[7], where information on the latent clusters across the documents and the words are encoded. We use the maximum orientation of the singular vectors of the decomposed matrix to classify the projects. The use of singular value decomposition (SVD) in text analysis is not new (Deerwester et al. 1990), but our approach extends its application by using a different weighting scheme to cluster responses. (See the Online Companion for more details on how we construct the weights.) An advantage of our approach in this setting is that it accounts for the standardized nature of the reports.

The clustering approach begins with the SVD of the $m \times n$ document-word matrix M with rank k. The values of m and n represent the number of documents and (unique) words in the corpus. The SVD is a matrix decomposition of M such that

$$\boldsymbol{M} = \sum_{i=1}^{r} s_i \boldsymbol{u_i} \boldsymbol{v_i}' + \sum_{i=r+1}^{k} s_i \boldsymbol{u_i} \boldsymbol{v_i}', \tag{2}$$

where $s_i \geq 0$ are constants called the singular values, $\boldsymbol{u_i}$ are called the left singular (column) vectors, and $\boldsymbol{v_i}'$ are the right singular vectors. One interpretation of equation (2) is that it decomposes M into r key components and $k - r$ "error terms."

SVD is applied to reduce the rank of a matrix, thus reducing the dimension of M by approximating it with a few singular values and vectors while retaining the most essential information. The rank, r, is the number of latent classes we want to retain. In some cases, we want to use $r-1$ for the number of latent classes if we want to treat the largest singular value as an intercept. Not using the largest singular value, which is common in practice, is akin to a regression model with an intercept; the intercept captures the common (average) theme in the corpus.

The left ($\boldsymbol{u_i}$) and right ($\boldsymbol{v_i}'$) singular vectors carry information on the documents and words, respectively. Therefore, we can approximate M with the singular values and the collection of left and right singular vectors such that $\tilde{M} = \boldsymbol{U_r} \boldsymbol{S_r} \boldsymbol{V_r}'$. Each row of the matrix $\boldsymbol{U_r} = [\boldsymbol{u_1}, \boldsymbol{u_2}, \ldots, \boldsymbol{u_r}]$ corresponds to a document and the columns represent the latent classes. This means that each document, represented by the rows of $\boldsymbol{U}$, is a linear combination of the different latent classes. Similarly, each row vector of $\boldsymbol{V_r} = [\boldsymbol{v_1}, \boldsymbol{v_2}, \ldots, \boldsymbol{v_r}]$ is associated with a word and the columns represent the latent classes. This means that each word is also a linear combination of the latent classes. Next, we describe how to cluster each document to one of the $r-1$ latent classes.

We cluster each document based on their maximum orientation. To do so, we introduce a new function, denoted Φ, that takes vectors as inputs and outputs the index of the largest value of that vector. For example, the maximum value of the 2-dimensional vector $\boldsymbol{x} = \{0.6, 0.8\}$ is 0.8, so

[7] The vectors encoded in these matrices are called "singular vectors."

$\Phi(\boldsymbol{x}) = 2$, the index of the largest value in the vector. This means the vector $\boldsymbol{x}$ is oriented towards the y-coordinate of a plane. The vector $\boldsymbol{x} = \{0.8, -0.6\}$ is oriented towards the x-coordinate. We use the maximum orientation to classify each document to one of the $r-1$ latent classes as shown in equation (3).

$$\boldsymbol{U_r} = \begin{array}{c c} & \begin{array}{cccc} \textit{type } 1 & \textit{type } 2 & \dots & \textit{type } \mathrm{r} \end{array} \\ \begin{array}{c} \textit{doc } 1 \\ \textit{doc } 2 \\ \vdots \\ \textit{doc } m \end{array} & \begin{pmatrix} u_{11} & u_{12} & \dots & u_{1r} \\ u_{21} & u_{22} & & u_{2r} \\ \vdots & & \ddots & \vdots \\ u_{m1} & u_{m2} & \dots & u_{mr} \end{pmatrix} \end{array} \xrightarrow{\textit{by type}} \begin{array}{c} \Phi(\{u_{11}, u_{12}, \dots, u_{1r}\}) = \mu_1 \\ \Phi(\{u_{21}, u_{22}, \dots, u_{2r}\}) = \mu_2 \\ \vdots \\ \Phi(\{u_{m1}, u_{m2}, \dots, u_{mr}\}) = \mu_m \end{array} \tag{3}$$

Here $\mu_i \in \{1, 2, \dots, r\}$ is the latent type of each document. We apply the methods we presented to cluster 16,525 carbon emissions reduction projects disclosed to CDP.

We present a simple numerical example next. Suppose we have 1,500 reported projects. The average document frequency is $\overline{n} = 300$[8] and the standard deviation is $\sigma = 50$. In our example, we limit the types of carbon emissions reduction activities to three. Suppose that some of the common phrases in the collection include "wind energy," "recycling," and "less energy in transportation." In this example, we see that the words "wind," "recycling," and "transportation" differentiate the three carbon abatement activities, but the word "energy" does not.

Table 3 shows the document frequency of the words "energy," "transportation," "recycling," and "wind." If the word "energy" appears in 446 documents, then its weight is $exp(-\frac{(446-300)^2}{50^2}) = 0.12$. The word "transportation" appears 371 times, which is closer to the average frequency of 300. The weight on the word "transportation" is 0.60. The word "recycling" appears less frequently than "transportation" but it is closer to the average at 248, thus, its weight is higher at 0.76 compared to the weight given to "transportation." The word "wind" received the highest weight of 0.88 because it is closest to the average document frequency.

Table 3 Numerical example of the proposed weighing scheme.

Word	Document frequency	Weights using eq. (A1)
Energy	446	0.12
Transportation	371	0.60
Recycling	248	0.76
Wind	336	0.88

Notes: equation (A1) is in the Online Companion.

The weights provide a way to measure words that are likely to carry most of the variation that will differentiate the different types of carbon abatement activities. We apply our clustering approach to the document-word matrix we created using the weights we proposed.

[8] This means that each word appears in roughly 300 documents on average.

The document-word matrix of the example data in Table 3 is

$$\boldsymbol{M} = \begin{array}{r} \\ \textit{project } 1 \\ \textit{project } 2 \\ \textit{project } 3 \end{array} \begin{array}{c} \begin{array}{cccc} \textit{wind} & \textit{energy} & \textit{recycling} & \textit{transp.} \end{array} \\ \begin{pmatrix} 0.88 & 0.12 & - & - \\ - & - & 0.76 & - \\ - & 0.12 & - & 0.60 \end{pmatrix} \end{array} \tag{4}$$

Its left and right singular vectors are

$$\boldsymbol{U_r} = \begin{array}{r} \\ \textit{project } 1 \\ \textit{project } 2 \\ \textit{project } 3 \end{array} \begin{array}{c} \begin{array}{ccc} \textit{type } 1 & \textit{type } 2 & \textit{type } 3 \end{array} \\ \begin{pmatrix} \boxed{0.99} & 0 & -0.03 \\ 0 & \boxed{1} & 0 \\ 0.03 & 0 & \boxed{0.99} \end{pmatrix} \end{array} \tag{5}$$

$$\boldsymbol{V_r} = \begin{array}{r} \\ \textit{wind} \\ \textit{energy} \\ \textit{recycling} \\ \textit{transp.} \end{array} \begin{array}{c} \begin{array}{ccc} \textit{type } 1 & \textit{type } 2 & \textit{type } 3 \end{array} \\ \begin{pmatrix} \boxed{0.99} & 0 & -0.05 \\ 0.14 & 0 & \boxed{0.19} \\ 0.00 & \boxed{1} & 0.00 \\ 0.02 & 0 & \boxed{0.98} \end{pmatrix} \end{array} \tag{6}$$

The row-wise maximum of each project and word is boxed. The approach maps each word and document to exactly one of the latent types.

4.2. Statistically Comparing the Differences in Financial and Environmental Metrics by Type

We use fixed-effects regression to examine the differences in financial and environmental metrics by type. We do not intend to test or suggest that the latent types have a causal effect on the key metrics we examine. The regression-based approach aims to efficiently test the differences in the key metrics by latent type while controlling for some firm-level characteristics that may influence the outcomes of carbon abatement opportunities. We can use the results of a single regression to conduct pairwise tests of equality of coefficients across all pairs of types.

We include seven firm-level controls. We control for cash-to-asset and current ratios as we discussed in Section 2.3. We include income-to-assets (or returns-to-assets) to control for how efficiently firms use their resources to generate income. We include EBIT[9]-to-sales ratio to control for how efficiently a company generates profits from its operations.

We also control for COGS[10]-to-sales ratios and the fraction of short-term to long-term debt. COGS-to-sales measures the percent of sales used to cover expenses, a measure of cost efficiency. The last firm-level control is the fraction of short-term to long-term debt. Short-term debts are typically obtained at lower (debt) costs but carrying higher short-term debt can be more vulnerable

[9] EBIT stands for earnings before income and taxes. This is sometimes referred to as operating earnings.

[10] COGS stands for cost of goods sold.

to liquidity shocks (i.e., not having enough liquidity) compared to firms that keep that ratio low. We control for this because it may influence the outcomes of carbon abatement activities. All regression models we test include firm and year fixed effects.

We believe that our approach is also robust to potential regression-based issues of endogeneity. First, the classification of the projects are external to the firm, that is, our algorithm identified these classifications and the firms are not aware of our classification approach. Second, firms do not necessarily know a priori whether their reported project is better or worse compared to what others will report. Third, the correlation table (in the Online Companion) of the different types and firm-level characteristics show that the correlations across these variables are very weak.

5. Benchmarking the Clustering Method

We benchmark our method to the latent Dirichlet allocation (LDA), then we validate our classifications using a crowd-sourcing platform, MTurk. We compare our method to the LDA because it is one of the most popular text classification methods (Blei et al. 2003).

5.1. Comparing the Classification with the Latent Dirichlet Allocation

We first present the collection of words by class (or cluster) using our method, then we contrast it with the outcome of the LDA. The top-20 words with the highest scores that loaded within each type is in Table 4. (We have not yet taken the maximum orientation of the words.) Cluster A includes the words "trucks," "driving," "road," and "transportation." The second cluster (B) includes the words "materials," "packaging," and "recycling." Cluster C consists of the words "employee," "awareness," "staff," and "campaigns." So far, the collection of words that loaded high for clusters A−C are distinct enough to describe each latent type.

The collection of words in the remaining clusters are also distinct. The words "motor," "compressors," and "pumps" describe cluster D and the words "fluorescent," "sensors," "LEED[11]," and "certification" differentiate cluster E. Cluster F consists of the words "MW[12]," "wind," "fossil," "fuel," and "generated." The collections of words seem sufficient to characterize each type, but a closer look at the description of each project within each latent class can provide more context.

Now we present the collection of words with the highest probability of occurring by cluster when we use the LDA. Although the (latent) clusters using the LDA may not appear in the same order as the clusters we discovered using our method, we can still compare their outcomes. Table 5 summarizes the collection of the top-20 words with the highest probability by cluster. The first striking outcome of the LDA is that the words that appear in the top 20 by cluster are not unique.

[11] LEED stands for Leadership in Energy and Environmental Design.

[12] MW stands for megawatt.

Table 4 The top 20 words that load on each latent type using the method in Section 4.1.

Cluster A	Cluster B	Cluster C	Cluster D	Cluster E	Cluster F
trucks	materials	employee	variable	fluorescent	MW
driving	material	campaign	drives	lamps	wind
road	paper	awareness	speed	friendly	fossil
vehicle	packaging	climate	frequency	LEED	fuels
truck	recycling	encourage	motors	certified	grid
hybrid	recycled	day	pumps	certification	biomass
transportation	product	meetings	fans	sensors	generated
transport	raw	staff	compressors	conferencing	capacity
engine	products	utility	thermal	motion	produced
diesel	printing	external	pump	France	generate
rail	plastic	promote	pressure	panels	alternative
logistics	processes	campaigns	hot	car	sources
delivery	gases	local	chillers	cars	coal
Km	resources	national	load	roof	produce
engines	chain	home	KW	headquarters	generating
drivers	electronic	raise	chiller	fixtures	equivalent
miles	greenhouse	monetary	compressor	head	metric
route	landfill	engagement	boilers	photovoltaic	clean
drive	environment	online	ventilation	video	avoided
routes	carried	payback	MWh	policy	fired

Notes: This table shows the top-20 words that loaded for each factor. We have not yet taken the maximum orientation of the words. We decided to cut it off at six types because the top-20 words that loaded the highest in the subsequent factor were no longer unique. Although we can uniquely cluster each word to a type, we have not yet done so to benchmark our results.

For instance, the word “energy” appears in the top-20 words across all clusters, and the word “emissions” appear in five out of the six clusters. In contrast, these two words do not appear in the top 20 of any cluster in Table 4. The words that appear in the top-20 list in Table 4 are unique within each cluster. Our method makes it easier to classify and interpret the types.

There are some latent clusters that seem to align between the two methods. Clusters 4 and 6 seem to align with clusters D and A respectively. For example, cluster 4 share common words that loaded high in cluster D, such as “compressor” and “pump.” Although the collection of words are different, the two clusters seem to refer to industrial-related processes. Cluster 6 and cluster A both include the word “transport.” Although the collections of words are different, clusters 6 and A seem to align with transportation-related projects.

In summary, the top-20 collection of words by type is more distinct by latent class when we use our method compared to the LDA. Although we believe that the LDA is likely to outperform our method in most other settings, our benchmark shows that the nature of the data matters and the classifications are sensitive to the method used to examine the text.

Table 5 The top 20 words that have the highest probability of occurring in each type based on the Latent Dirichlet Allocation.

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
energy	**lighting**	scope	**air**	**gas**	energy
solar	energy	voluntary	**water**	savings	reduction
emissions	**LED**	energy	**heat**	emissions	fuel
scope	projects	**activity**	system	energy	emissions
data	**building**	**expected**	**cooling**	fuel	reduce
power	scope	**lifetime**	plant	**annual**	scope
electricity	efficiency	emissions	energy	**natural**	efficiency
reduce	**HVAC**	reduction	installation	project	consumption
system	voluntary	efficiency	**control**	scope	**employees**
savings	**efficient**	consumption	**compressor**	efficiency	**environmental**
consumption	**lights**	project	efficiency	electricity	voluntary
UK	systems	**production**	**pump**	**million**	**fleet**
installed	**upgrades**	**nature**	**compressed**	projects	**management**
installation	emissions	**type**	**conditioning**	program	**time**
project	**office**	**steam**	**pumps**	reduction	**green**
initiative	**light**	plant	**temperature**	**estimated**	**activities**
systems	**controls**	process	process	**reduced**	program
renewable	replacement	reduce	**heating**	**cost**	**saving**
sites	**lamps**	**manufacturing**	replacement	reduce	**vessels**
voluntary	**facilities**	initiative	**recovery**	**waste**	**transport**

Notes: The words in bold are words that are unique within the top 20 of each cluster.

5.2. Verifying our Clustering Method with Crowdsourcing

Our goal is to determine whether latent types of opportunities exist, and we did so using text analysis. We verify the outcome of our classification using Amazon Mechanical Turk (MTurk), a crowd-sourcing platform. Before we present the statistical measures of agreement, we provide examples of projects that grouped together and how we labeled each cluster.

Table 6 lists several examples of projects that clustered together. Many projects that describe how to reduce emissions associated with delivery and transportation clustered together. Projects such as shifting from rail to road or replacing gasoline trucks with ones that use natural gas clustered within the same group. We label this latent type as *transportation.*

We describe some examples classified in Clusters B through D. Cluster B are carbon abatement projects related to redesigning products to reduce the use of raw materials, changing packaging, recovering materials, and recycling. We labeled this as *materials.* We label the next cluster of opportunities as *behavioral changes* because the examples include training employees to conserve energy and creating campaigns to promote energy efficiency practices. Cluster D include many examples related to variable frequency drives (devices that regulate the energy use of electric motors), pumps and more energy efficient motors. We label these opportunities as *industrial processes.*

We label the last two clusters as *buildings* and *renewable energy* respectively. Cluster E includes many examples of energy efficient lighting and building certification standards. The last cluster are projects related to installing renewable energy capacity or purchasing electricity from alternative,

Table 6 Representative sample of projects that are categorized in each latent type.

Cluster	Example responses	Author-defined classification
A	Shift long-distance transportation from road to rail; use hub and spoke model for package delivery operations; switching fuel to natural gas or electric hybrid trucks; use of navigational tools to reduce idle time; optimize vehicle use; improve ocean-vessel operations	Transportation
B	Recover materials from manufacturing; recycle; reduce packaging; incorporate recycled content into packages and products; redesign products to reduce the use of raw materials; conduct life cycle analysis of raw materials	Materials
C	Train employees on energy conservation; raise awareness among employees on environmental initiatives; create campaigns to promote energy efficiency; encourage video meetings to reduce business travels	Behavioral changes
D	Replace constant speed motor and inlet shrouds in each compartmental air handling unit and pumps with new inverter duty motor controlled by new variable frequency drives; upgrade to more efficient motors	Industrial processes
E	Retrofit lights; replace existing lamps and fixtures with more energy efficient bulbs; implement LEED (Leadership in Energy and Environmental Design) certification standards or its local equivalent; install motion sensors	Buildings
F	Purchase electricity generated from alternative (renewable) energy sources; purchase wind power; substitute fossil fuel, coal with biomass; install more renewable energy capacity	Renewable energy

low-carbon energy sources. Other examples in this cluster include switching from fossil fuel to biomass energy.

We used MTurk to hire 60 participants to classify 12 investments (2 examples per type) from a balanced list of 24 investments. We purposefully did not target energy or sustainability experts to classify the investments to test how effective our classifications are even when presented to those with little to no background in climate change reporting.

We presented Table 6 to the participants at the start of the survey, then we asked them to classify each project based on excerpts of the description. We did not include the entire description because they can be very long; this would likely reduce the response rate and its quality.

There are several practical and managerial implications doing it this way. First, this verifies whether participants will classify the opportunities in a consistent manner with our method. Second, doing it this way also allows us to test the practical use of our descriptions of the latent types. We then conducted statistical tests to determine the level of agreement of our participants among each other and with our method.

We measured the level of agreement using a comparable metric to Cohen's kappa (Cohen 1960), which is used to measure inter-rater reliability. This test statistic is more robust than calculating the percentage agreement because we need to account for the possibility that the classification matches by chance. However, using Cohen's kappa without modification is not appropriate in this scenario because it was designed to measure the agreement between two raters, not multiple ones. We describe how we calculate the test statistic in the Online Companion.

The test statistic uses the overall agreement p_0 and the probability that the raters match the classification by pure chance p_e. The test statistic is $\kappa = (p_0 - p_e)/(1 - p_e)$. (The details on how we calculate p_0 and p_e are in the Online Companion.) The summary of the percent match across 60 raters and the classification method is in Table 7. The overall agreement is about $p_0 = 77\%$, the chance of agreement is $p_e = 15\%$, and κ is roughly 0.73. According to Cohen's agreement standards, a value of 0.73 suggests substantial agreement among the raters (Landis and Koch 1977, p. 165) and the classification algorithm[13].

Table 7 Percent match across 60 raters and the classification method.

Type	Percent match
Transportation	89.2%
Material	70.0%
Behavioral Changes	86.7%
Industrial Processes	52.5%
Buildings	85.8%
Renewable Energy	77.5%
Overall	76.9%

Five out of the six types of opportunities have agreement rates that are higher than 70%. The type of opportunity with the lowest agreement rate in Table 7 is *industrial processes* at 52%, and *transportation* has the highest overall agreement at 89%, followed by *behavioral changes* at 87%. The agreements rates are reasonably high given that the participants do not necessarily have any background in climate change reporting or in sustainability. This means that our descriptions of the classifications have the potential to be used even with those with little to no background in operations management or sustainability. The overall agreement rate of $\kappa = 0.73$ means there is substantial agreement across the rates and the classification method we implemented.

6. Results and Discussion

Our results in this section show that latent types of opportunities exist and to what extent they statistically differ in the metrics we examine. We present the summary statistics of payback period, savings, costs, and the size of emissions reduction by type. We then conduct statistical tests to confirm their differences. The section ends with results on the association of measures of liquidity and the number of projects firms report.

[13] Cohen suggests that κ values of 0.81 – 0.99 are considered near perfect agreement, 0.61 – 0.80 implies substantial agreement, and values between 0.41 – 0.60 means moderate agreement. Values between 0.21 – 0.40 represent fair agreement, and anything below 0.20 is considered weak.

6.1. Payback Period, Savings, Costs, and Size of Emissions Reduction by Type

Table 8 summarizes the financial metrics and carbon emissions reduction by type. The two types with the shortest average payback periods are *transportation* (N=1,859) and *materials* (N=1,862) at 1.98 and 2.07 years. This is followed by *behavioral changes* (N=1,317) and *industrial processes* (N=8,135) at an average of 2.16 and 2.87 years. The two types with the longest average payback periods are *buildings* (N=2,209) and *renewable energy* (N=1,143) at 3.18 and 3.74 years. Firms interested in investments with short payback periods should explore transportation and material-related opportunities.

There is a substantial variation in the median investment cost, annual savings, and carbon emissions reduction by type. (All cost and savings data have been adjusted to 2020 USD values.) We decided to focus on the median rather than the mean because there are a few projects with extremely large values. We find that *renewable energy* has the highest median investment cost at $845,000 and the highest median savings at $735,000 per year. This type also has the largest annual carbon emissions reduction at 6,042 metric tons. If upfront costs are barriers to adoption (Anderson and Newell 2004), then this means that the adoption of *renewable energy* faces high hurdles despite having the largest carbon abatement potential across all types. Projects we labeled *materials* have the second highest median emissions reduction potential at 980 metric tons per year. We find that *buildings* have the lowest median investment cost at $56,000, but this also has the lowest median carbon abatement potential at 140 metric tons of carbon emissions. Firms that are interested in large carbon abatement opportunities should focus on *renewable energy* and *behavioral change* opportunities. Overall, no type is dominant in all four metrics we examine.

Table 8 Mean payback period, median savings, costs and emissions reduction by cluster.

(1) Type of opportunity	(2) Total observations	(3) Mean payback period*	(4) Median investment (1,000 USD)	(5) Median savings (1,000 USD)	(6) Median CO2e avoided
Transportation	1,859	1.98	60	216	850
Materials	1,862	2.07	99	210	980
Behavioral changes	1,317	2.16	80	176	884
Industrial processes	8,135	2.87	122	86	402
Buildings	2,209	3.18	56	39	140
Renewable energy	1,143	3.74	845	735	6,042
Overall summary	**16,525**	**2.72**	**108**	**116**	**500**

Notes: *Payback period is in years. This is based on observable, disclosed data. The descriptions of each cluster are based on the results in Tables 4 and 6. Column (5) is annual savings. Column (6) is in metric tons. Costs and savings data are adjusted to 2020 values.

We can use the results in Table 8 and equation (1) in Section 2.2 to rank the different types of opportunities based on different weights w_j that represent the priority of the firm. For example, if the weights are equal to each other (i.e., $w_j = 0.25$ for each j), then the order of preferences are *transportation*, *renewable energy*, *materials*, *behavioral changes*, *industrial processes*, and *buildings*. If a weight of 0.70 is placed on carbon emissions reduction and the remaining attributes receive equal weights of 0.10, then the order of preferences are *renewable energy*, *materials*, *transportation*, *behavioral changes*, *industrial processes*, and *buildings*. In contrast, if a weight of 0.70 is placed on cost and the remaining attributes receive equal weights of 0.1, then the order of preferences are *transportation*, *behavioral changes*, *materials*, *buildings*, *industrial processes*, and *renewable energy*.

There are alternative metrics. For example, we could look at the total investment value or total annual carbon emissions reduction to have a better sense of the magnitude of implementation by type. We can also examine the cost or savings per unit emissions abated. These alternative metrics are available in the Online Companion. We do conduct an extension on a widely-used metric called marginal abatement costs, and we present our findings using that measure in Section 7.1.

6.2. Are the Financial and Environmental Outcomes Statistically Different by Type?

Our classification approach is successful in distinguishing types that have short and long payback periods. We use regression-based tests because this allows us to examine the different types and their association with the key metrics while controlling for firm-level characteristics that might influence the outcome variables.

Before we present the results, we briefly comment on the correlation of the dependent and independent variables. The correlation matrix (available in the Online Companion) shows that the highest correlation between any two dependent variables is 0.55. This is the correlation between (the natural log of) savings and carbon emissions reduction. Although the correlations between any two dependent variable is not zero, none of them are strongly correlated. The correlation across the different types of opportunities and the seven firm-level controls are weak. The strongest correlation across these variables is between *materials* and short-term to long-term debt at 0.08. In sum, the types of opportunities are weakly correlated with firm-level characteristics.

Table 9 summarizes the regression results. The regression models in Table 9 are the same except for the outcome variables. The dependent variable in model (1) is payback period. The outcome variables for models (2) and (3) are the natural logs of cost and savings respectively. (These figures have been adjusted to 2020 USD values.) The dependent variable in the last model is the natural log of annual carbon emissions reduction in metric tons.

The goal of this study is to test whether the types of opportunities we discovered vary across the financial and environmental metrics we selected. To do so, we included indicator variables for each type except one to avoid multicolinearity. The type labeled *transportation* is set as the reference group. We can use the results in Table 9 to conclude whether the remaining five types of opportunities differ by average payback period, cost, savings or annual carbon emissions reduction potential. In model (1), we find no evidence that *materials* or *behavioral change* are statistically significantly different in average payback period to *transportation*. Model (1) confirms that the average payback period of *transportation* is roughly 0.80 years shorter ($p < 0.01$) when compared to *industrial processes*. The average payback period of *transportation* is roughly 1 - 1.4 years shorter compared to *buildings* and *renewable energy*.

Table 9 Regression results of the association of the latent type and financial or environmental outcomes.

	Dependent variable:			
	Payback	Ln(Cost)	Ln(Savings)	Ln(CO2e)
	(1)	(2)	(3)	(4)
(β_2) Materials	0.176	0.585^{***}	0.025	0.075
	(0.132)	(0.220)	(0.091)	(0.089)
(β_3) Behavioral Changes	0.136	−0.003	-0.215^{**}	−0.023
	(0.163)	(0.262)	(0.105)	(0.103)
(β_4) Industrial Process	0.795^{***}	1.464^{***}	-0.208^{***}	−0.011
	(0.111)	(0.208)	(0.079)	(0.078)
(β_5) Buildings	1.002^{***}	1.059^{***}	-0.629^{***}	-0.482^{***}
	(0.156)	(0.240)	(0.097)	(0.095)
(β_6) Renewable Energy	1.389^{***}	1.402^{***}	0.179	0.443^{***}
	(0.207)	(0.262)	(0.112)	(0.114)
Cash-to-Asset Ratio	-0.967^{**}	0.283	−0.106	0.388
	(0.425)	(0.583)	(0.453)	(0.253)
Current Ratio	0.658	1.108	−0.006	−0.602
	(0.675)	(1.056)	(0.612)	(0.463)
PPEGT-to-Asset Ratio	−0.522	0.189	0.467	0.254
	(0.683)	(0.913)	(0.491)	(0.551)
Income-to-Asset Ratio	0.656	−0.464	−0.548	0.413
	(0.598)	(0.940)	(0.632)	(0.438)
EBIT-to-Sales Ratio	−0.068	−0.117	−0.165	0.028
	(0.140)	(0.145)	(0.113)	(0.090)
COGS-to-Sales Ratio	1.293	−1.316	-1.760^{*}	0.549
	(1.846)	(1.836)	(1.028)	(1.001)
Short-to-Long-Term Debt Ratio	0.200	0.131	−0.164	-0.334^{*}
	(0.270)	(0.393)	(0.231)	(0.191)
Firm fixed effects	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included
Observations	16,105	13,716	13,716	14,568
R^2	0.249	0.375	0.514	0.561
Adjusted R^2	0.183	0.324	0.474	0.519

Notes: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parentheses. We lose observations for cost and savings due to missing currency data. We can still calculate payback period, but we cannot convert observations without currency data. The correlation table of all dependent and independent variables are in the Online Companion. The correlation table suggests that the types of opportunities are not strongly correlated with firm-level characteristics. We also tested models with the cumulative number of projects reported, and the conclusions remain the same.

Model (2) confirms that types labeled *materials*, *industrial processes*, *buildings*, and *renewable energy* are all statistically different to *transportation* in average (natural log of) costs at the 0.01 significance level. Model (3) shows that *behavioral changes*, *industrial processes*, and *buildings* differ statistically in savings to *transportation*. Model (4) shows that only *buildings* and *renewable energy* are statistically significantly different in the (natural log of) annual carbon emissions reduction.

We are also interested in testing whether the five types of opportunities included in the regression differ to each other. To do so, we conduct pairwise equality of coefficients hypotheses testing (e.g., $\beta_2 = \beta_3$) for each of the remaining five types. Table (10) summarizes the 10 pairwise tests for each metric. Row (1) summarizes the equality of coefficients for *materials* (β_2) and *behavioral changes* (β_3). Columns (1)-(4) present the χ^2 values for the test of equality for when the outcome variable is payback period, cost, savings, and annual carbon emissions reduction, respectively. Column (1) shows that 7 out of the 10 pairs are statistically significantly different in average payback periods at the 0.01 level. Column (2) shows that 8 out of the 10 tests have $p-$values of 0.05 or lower. Columns (3) and (4) in Table 10 confirm that annual savings and carbon emissions reduction vary by type. Column (3) shows that 8 out of the 10 tests are statistically significantly different at the 0.01 level. Column (4) shows that 7 out of the 10 tests are statistically significantly different at the 0.01 level. Overall, Table 10 shows that there are substantial differences in average payback period, (natural log of) costs, savings, and emissions reduction by type.

Table 10 Tests of equality of coefficients for the types of opportunities for each model in Table 9.

		Payback	Ln(Cost)	Ln(Savings)	Ln(CO2e)
		(1)	(2)	(3)	(4)
1	β_2 - $\beta_3 = 0$	0.066	6.139**	7.004***	1.038
2	β_2 - $\beta_4 = 0$	35.573***	23.991***	12.034***	1.482
3	β_2 - $\beta_5 = 0$	34.499***	4.572**	61.223***	41.890***
4	β_2 - $\beta_6 = 0$	36.034***	11.503***	2.272	12.448***
5	β_3 - $\beta_4 = 0$	23.424***	51.097***	0.009	0.020
6	β_3 - $\beta_5 = 0$	28.238***	17.671***	17.356***	21.720***
7	β_3 - $\beta_6 = 0$	32.537***	27.432***	12.284***	18.315***
8	β_4 - $\beta_5 = 0$	2.886*	7.073***	37.772***	44.792***
9	β_4 - $\beta_6 = 0$	10.039***	0.087	16.242***	25.521***
10	β_5 - $\beta_6 = 0$	3.249*	1.953	55.109***	65.191***

Notes: *p<0.1; **p<0.05; ***p<0.01. (β_2) is for *materials*, (β_3) is for *behavioral changes*, and (β_4) is for *industrial processes*. (β_5) is for *buildings* and (β_6) is for *renewable energy*.

6.3. Does Firm Liquidity Explain Adoption Patterns?

Firm liquidity, measured with cash-to-asset and current ratios, is associated with the number of projects firms implement, but the direction varies by type. Table 11 summarizes the regression results. Model (1) is the regression outcome where the outcome variable is the total number of projects implemented. Firms implement nine projects on average. Higher measures of cash-to-asset ratios are, on average, negatively associated with the total number of projects reported ($p < 0.01$). We also see that current ratios are negatively associated with the number of projects reported ($p < 0.01$). Doing the analysis on the aggregate number of carbon abatement activities may suggest that more liquid firms are less likely to implement these projects, but the results are different if we examine this association by type.

Table 11 Firm liquidity and the number of carbon abatement projects firms implement and report.

	Dependent variable: Count of implemented projects						
	All types	Type A	Type B	Type C	Type D	Type E	Type F
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Cash-to-Asset Ratio	-4.697^{***}	-0.377^{***}	-0.429^{***}	-0.258^{***}	-3.963^{***}	0.079	0.251^{***}
	(0.650)	(0.090)	(0.090)	(0.058)	(0.561)	(0.187)	(0.063)
Current Ratio	-3.983^{***}	0.661^{***}	-0.497^{***}	-0.351^{**}	-3.775^{***}	-0.208	0.188^{**}
	(1.064)	(0.145)	(0.117)	(0.145)	(0.568)	(0.743)	(0.080)
PPEGT-to-Asset Ratio	-3.509^{***}	-0.136	-0.307^{**}	-0.379^{***}	-0.874^{*}	-2.108^{***}	0.295^{***}
	(0.868)	(0.148)	(0.143)	(0.118)	(0.488)	(0.422)	(0.087)
Income-to-Asset Ratio	-2.455^{*}	0.192	-0.302^{*}	-0.008	-1.971^{*}	0.010	-0.374^{***}
	(1.407)	(0.175)	(0.166)	(0.127)	(1.050)	(0.292)	(0.120)
EBIT-to-Sales Ratio	0.399^{**}	-0.158^{***}	-0.061^{***}	-0.021	0.433^{***}	0.099^{***}	0.106^{***}
	(0.198)	(0.052)	(0.021)	(0.023)	(0.167)	(0.030)	(0.022)
COGS-to-Sale Ratio	10.566^{***}	0.362	-0.459^{**}	0.578^{***}	8.336^{***}	1.554^{***}	0.196
	(1.999)	(0.333)	(0.216)	(0.187)	(1.700)	(0.405)	(0.225)
Short-to-Long-	2.197^{***}	-0.056	0.155^{**}	-0.007	1.214^{***}	0.841^{***}	0.050
Term Debt Ratio	(0.361)	(0.061)	(0.065)	(0.049)	(0.240)	(0.144)	(0.035)
Firm fixed effects	Included	Included	Included	Included	Included	Included	Included
Year fixed effects	Included	Included	Included	Included	Included	Included	Included
Observations	16,105	16,105	16,105	16,105	16,105	16,105	16,105
Adjusted R^2	0.812	0.635	0.661	0.753	0.771	0.807	0.585

Notes: *p<0.1; **p<0.05; ***p<0.01. Type A is labeled *transportation*. Type B is for *materials*, type C is for *behavioral changes*, and type D is for *industrial processes*. Type E is for *buildings* and type F is for *renewable energy*. The mean cash-to asset ratio is 0.12. The mean current ratio is 0.57.

Models (2)−(7) are the regression results by type. In model (2), the outcome variable is the number of projects reported labeled as *transportation*. The results of models (2)−(5) for the association of cash-to-asset ratio to the number of projects reported are consistent with that of model (1), but the results of models (6)−(7) are not. In model (6), we find that cash-to-asset ratios are not statistically significantly associated with the number of *building-related* projects. In model (7) we see that the cash-to-asset ratio (and current ratio) are positively associated with the number of *renewable energy* projects.

Although we detect statistical significance between liquidity and the number of projects, the economic magnitude of its association is moderate. The mean cash-to-asset ratio is 0.12 (the median is 0.09), and the magnitude of the coefficient in model (1) for this variable is −4.7. This means that going from 0 to 0.22 in cash-to-asset ratio is associated with one less implemented project. The association of the current ratio is slightly stronger. The mean current ratio is 0.57, and the coefficient in model (1) is roughly −4.0. This means that going from 0 to 0.25 in the current ratio is associated with one less implemented project. At the average current ratio of 0.57, the model predicts that firm to have two fewer projects.

There are a couple interpretations to the results. One interpretation is that firms that have high levels of liquidity are not necessarily more likely to fund these projects, with the exception of *renewable energy*. This suggests that improving liquidity does not immediately translate to more implemented projects. Another possible interpretation is that these firms may prefer to remain liquid than to pursue these opportunities. These findings are not consistent with the literature that suggest firms are likely to be cash-strapped or that the lack of available cash can be a barrier to adoption (Nauclér and Enkvist 2009). The result in model (7) shows that firms with higher cash-to-asset ratios are more likely to implement *renewable energy* projects. Even if the results are driven by self-selection it is insightful, that is, firms that have low liquidity select certain types of opportunities compared to high-liquidity firms. We are not aiming to prove causality, but we show that the link between liquidity and the number of implemented projects varies by type.

7. Extensions and Robustness Tests

We conduct an extension and robustness tests. We focus on payback period, costs, savings, and carbon emissions reduction because we can calculate these metrics with the available data without any further assumptions, but there is another widely-used metric used to compare and rank carbon abatement opportunities: the marginal carbon abatement costs. We will compare marginal abatement costs by type next. We end this section with a series of tests on whether the findings are robust to industry effects.

7.1. The Marginal Abatement Cost

The marginal abatement cost is a popular metric used to rank the cost-effectiveness of opportunities (Enkvist et al. 2007). We decided not to include it in the main analysis or perform regression models but as an extension because constructing this metric with our data requires a few assumptions. Using it in regression models is not straightforward as suggested in Taylor (2012), Ward (2014), and Blanco et al. (2020). Instead, we examine whether the median marginal abatement values differ by type using the Wilcoxon rank-sum tests.

Meier (1984) is one of the first scholars to study this metric, and several others have used the same formula to construct marginal abatement cost curves (Lovins and Lovins 1991; Mills et al. 1991). Meier (1984) calculated marginal abatement cost as the net present value (cost minus lifetime savings) of the project divided by the lifetime carbon emissions reduction[14]. To calculate marginal abatement costs we need a discount rate and the estimated lifetime of the project. The range of

[14] Although this may appear to look like the average abatement, it is called the marginal abatement cost because carbon abatement cost curves are constructed by ordering the opportunities based on this value.

estimates for discount rates of carbon abatement opportunities is wide from 5% to 15% (Lovins and Lovins 1991; Mills et al. 1991; Koomey and Sanstad 1994). For this study, we assume a discount rate of 10% to calculate the net present value and use data from the CDP on the average lifetime of the project.

Table 12 summarizes the mean and median marginal abatement costs by type. The more negative the marginal abatement cost the more attractive it is because it means that the company can save that amount per unit of carbon emissions avoided. Here we see that the type with the most cost-effective carbon abatement value is *transportation* at mean and median values of −\$97.29 and −\$80.41 respectively. Median values are robust to potential outliers compared to the mean, so it is more likely to be representative of the typical marginal abatement cost rather than the mean. Using the median values, the next two most attractive opportunities are *buildings* and *behavioral changes* at −\$71.75 and −\$62.30. The three types with the least attractive marginal abatement costs are *industrial processes* at −\$59.17, *materials* at −\$55.66, and *renewable energy* at −\$49.76.

Table 12 Mean and median marginal abatement cost (\$/metric ton) by type.

Type	Count	Mean	Median
Transportation	1,433	-97.29	-80.41
Materials	1,448	-81.58	-55.66
Behavioral change	956	-79.84	-62.30
Industrial process	6,178	-76.02	-59.17
Buildings	1,680	-84.41	-71.75
Renewable energy	936	-64.85	-49.76

Data are reported in 2020 values.

We compare our estimates of marginal abatement costs with a recent study by Gillingham and Stock (2018). In that paper (p. 59), the authors compile estimates of 23 carbon emissions reduction activities. Although they focus on energy efficiency policies, there is some overlap in the examples of opportunities between their study and ours. They also motivate their paper using the McKinsey abatement cost curve (c.f. Gillingham and Stock (2018) p. 56 and Enkvist et al. (2007) p. 4). A striking difference between their results and ours is that only 1 out of the 23 energy efficiency interventions in Gillingham and Stock (2018) is found to have a negative marginal abatement cost. In contrast, our results are more consistent with the findings of that of Enkvist et al. (2007) and subsequent McKinsey & Company reports (Nauclér and Enkvist 2009) that suggest many profitable opportunities have negative marginal abatement costs. One possible explanation for this difference in observation is that most studies in economics focus on policies that are designed to encourage the adoption of energy efficiency opportunities that are not voluntarily pursued because they are not likely profitable on their own. However, if we examine projects that are voluntarily adopted, then we begin to see a selection of projects that are profitable and cost-effective on their own.

Unfortunately, we cannot directly compare our figures with estimates from the McKinsey & Company cost curve because they do not disclose details of individual opportunities. They do disclose key assumptions and details on how they arrived at each estimate, but the comprehensive values of the individual opportunities are not available. We could only infer the value of several opportunities from the graph. The estimate for commercial insulation on the McKinsey cost curve is at −\$78 (after converting from Euros). This opportunity would likely be classified as *buildings*, which has a median value of −\$72. Hybrid cars are estimated at around −\$40, and this would likely be classified as *transportation*, which has a median value of −\$80. Waste recycling is estimated to be around −\$17; this opportunity would likely be classified as *materials*, which has a median value of −\$56. Although the values may be closer for some but not for others, we can confirm that many of these opportunities have negative marginal abatement cost values.

We tested if the median differences in marginal abatement costs statistically differ by type. To do so, we conducted Wilcoxon rank-sum tests of marginal abatement costs for two types at a time. Table **??** in the Online Companion shows that all but four pairs (out of 15) are statistically significantly different in the median marginal abatement costs. This information can be used to prioritize which types of opportunities to focus on first if the main metric for making a decision is based on marginal abatement costs.

7.2. Are the Findings Robust by Sector?

We find that the results are robust for every sector. We provide summary statistics of the average payback period, median investment cost, and median carbon emissions reduction of each type by sector. Firms self-identify their sector in the CDP surveys using the Global Industry Classification Standard (GICS). Only 10 GICS sectors were used during the study period[15].

7.2.1. Average Payback Periods by Type and Sector We want to validate whether the average payback periods by type are consistent across different industries. The results in Table 13 show *transportation*, *materials*, and *behavioral changes* are three types that have the shortest payback period for all sectors except for Information Technology and Utilities. There are variations within the top three types of opportunities by sector, but our overall recommendation that *transportation* has the shortest payback period is consistent across six out of the ten industries. *Renewable energy* has the longest payback period in eight out of the ten sectors. In sum, the shortest and longest payback period remain relatively consistent by sector.

[15] In 2016, the Real Estate sector was moved out the Financials sector and became its own sector.

Table 13 Average payback period by type and sector.

Type	Consumer Discre-tionary	Consumer Staples	Energy	Financials	Health Care
Transportation	2.17	1.75	2.08	2.98	1.27
Materials	1.64	2.09	2.68	2.21	2.81
Behavioral changes	1.23	2.17	2.61	1.84	2.67
Industrial process	2.91	3.13	2.99	3.86	3.41
Buildings	2.89	3.47	3.74	3.78	3.44
Renewable energy	3.04	3.51	4.78	3.26	3.92
	Industrial	Info. Technology	Materials	Telecom. Services	Utilities
Transportation	1.97	2.06	1.42	2.44	3.38
Materials	2.14	1.67	1.96	2.73	3.17
Behavioral changes	2.18	2.18	1.57	3.08	4.03
Industrial process	3.05	2.18	2.03	3.45	3.49
Buildings	3.36	2.58	3.03	2.95	2.87
Renewable energy	3.48	1.87	3.06	4.19	6.16

7.2.2. Median Investment Costs by Type and Sector We check whether our findings on median investment costs by type are consistent across sectors. Table **??** in the Online Companion summarize the median investment costs by type in each sector. We find that types we labeled *transportation* have the lowest cost in six out of the ten sectors and *buildings* has the lowest cost in three sectors. This is consistent with our earlier findings that *buildings* and *transportation* are the two types with the lowest cost. *Renewable energy* has the highest cost in eight out of the ten sectors; it is only the second highest cost in the telecommunication services and financial sector. The types with the lowest and highest median cost remain relatively consistent across sectors.

7.2.3. Median Carbon Emissions Reduction by Type and Sector We examine the variation of the median carbon emissions reduction by type in each sector. In the main findings, we concluded that the types we labeled as *buildings* have the lowest carbon abatement potential. Table **??** in the Online Companion confirms that this type has the lowest median carbon emissions reduction in eight out of the ten sectors. The results remain roughly consistent across sectors with the exception of Telecommunication services and Utilities. Opportunities labeled *renewable energy* have the highest carbon abatement potential; this finding is consistent across all except for one sector. Overall, the findings suggest that classifications can be generalizable across sectors.

8. Limitations and Final Remarks

We discovered six latent types of carbon abatement opportunities based on 16,525 projects reported by 1,305 firms from 2011-2016. We examined four financial and environmental metrics often used to compare and prioritize carbon abatement projects. We found statistically significant differences in the average payback period, (natural log of) investment costs, annual savings, and emissions reduction potential by type. We found that no single type is superior in every financial and environmental metric we examined. These finding have several implications.

We contribute to the broader discussion on energy efficiency by examining which types of opportunities have large upfront costs, long payback periods, or small carbon emissions reduction potential. The projects we examine have been implemented, therefore firms are able to provide actual cost and savings figures as opposed to projected values. The rankings by each type across the four metrics we examine are summarized in Table 14. This provides insights on the actual carbon reduction experience of firms and how the different types of opportunities differ.

Table 14 Summary of rankings by metric.

Payback period (shortest to longest)	Costs (lowest to highest)	Carbon emissions reduction (highest to lowest)	Savings (highest to lowest)
Transportation	Buildings	Renewable energy	Renewable energy
Materials	Transportation	Materials	Transportation
Behavioral changes	Behavioral changes	Behavioral changes	Materials
Industrial processes	Materials	Transportation	Behavioral changes
Buildings	Industrial processes	Industrial processes	Industrial processes
Renewable energy	Renewable energy	Buildings	Buildings

The results can be used to assist firms in determining which types of opportunities to pursue first depending on their goals. For example, the mean emissions reduction from *transportation* and *behavioral changes* are, on average, similar but the mean costs are (statistically) different; therefore, firms should pursue *transportation*-related types of opportunities first based on these two metrics. We find that *materials* and *buildings*, on average, have the same investment cost but *materials* have shorter payback periods on average. Our results can be used to identify which types of opportunities should be pursued first depending on the attributes that matter most to the firm.

The diversity in the implemented projects suggests that no single metric drives carbon abatement investment decisions. Some firms pursue opportunities with low upfront costs even though they also have the lowest annual savings. In contrast, we also see a lot of projects with very high upfront costs (i.e., *renewable energy* and *industrial processes*), yet many firms continue to implement them. This is easy to understand for *renewable energy*, as these projects generally provide the highest overall savings and carbon emissions. However, *industrial processes* projects provide much weaker results, meaning companies may be better served allocating their investments to other types. The type of opportunity with the shortest payback period, *transportation*, is not necessarily the type that is most widely reported. This implies that firms may not necessarily weigh these attributes (costs, savings, payback period, etc.) equally. The commonly used metrics for making adoption decisions are not necessarily flat across firms.

Most studies in carbon abatement do not consider whether firm-level characteristics and their link with adoption decisions may vary depending on the type of the opportunity. The results show that a higher cash-to-asset ratio is negatively associated with the number of *transportation*, *materials*, *behavioral changes*, and *industrial processes* projects. This means that firms with higher liquidity are not necessarily more willing to implement these types of carbon abatement projects. However, we do find that cash-to-asset ratios are positively associated with *renewable energy*. We find no evidence that liquidity is linked to the number of projects we labeled *buildings*. Our findings show that liquidity is linked to adoption decisions albeit the direction and magnitude varies by type.

Our findings have policy insights. We identified that certain types of firms (low vs high liquidity firms) are more likely to pursue certain types of opportunities (as suggested in Table 11). Policies designed to make savings more attractive (e.g., a carbon tax) may not necessarily encourage all firms in the same way; some firms place more preference on lower upfront costs rather than higher savings. Similarly, policies targeted at making investment costs more attractive (e.g., subsidies or better financing) may not have the same impact on firms that put more weight on savings compared to those more sensitive to costs.

There are limitations to our paper. It is natural to ask whether we can calculate the weights for individual firms to understand the distribution of these weights. Although we presented numerical illustrations on what the order of preferences are for a given set of weights, unfortunately, we cannot recover firm-level weights with the current data. This is because we do not observe the values of the opportunities that firms do not pursue. Instead, we leverage the strength of the data where firms are likely to report their most profitable or attractive opportunities. Using this rich data, we were able to observe that there is wide variation in the payback period, costs, savings, and carbon emissions reduction even among the most profitable carbon abatement projects.

Prior research have mostly focused on firm-level characteristics to explain adoption or only examine one type of opportunity. Instead of exploring why opportunities do and do not get adopted, we examine the set of carbon abatement projects firms implement over a six-year window. Future research can examine other opportunity-specific characteristics of carbon abatement activities such as flexibility, duration, indirect benefits, and uncertainty in outcomes.

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