Are Green Funds for Real?*

Coralie Jaunin[†] Luciano Somoza[‡] Tammaro Terracciano[§]

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Abstract

We empirically study green funds' investments following earning calls where firms discuss the climate transition. To do so, we use an unsupervised machine learning algorithm to extract a measure of climate transition talk during earning conference calls and look at how mutual funds respond to it. We find that after starting to discuss the climate transition, firms see their green fund ownership increase by twice as much as matched firms with similar characteristics but that did not discuss the topic. As expected, we do not find any differences in non-green ownership. Importantly, we also show that firms discussing the climate transition limit their carbon emissions compared to the market portfolio. Contrary to claims of generalized greenwashing, our results indicate the existence of a channel for firms to communicate their climate stance to green investors effectively.

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[†]PhD Candidate at the Swiss Finance Institute and Department of Finance, HEC Lausanne, University of Lausanne. E-mail: coralie.jaunin@unil.ch.

[‡]PhD Candidate at the Swiss Finance Institute and Department of Finance, HEC Lausanne, University of Lausanne. E-mail: luciano.somoza@unil.ch.

[§]PhD Candidate at the Swiss Finance Institute and Geneva Finance Research Institute, University of Geneva; visiting fellow at Harvard University. E-mail: tammaro.terracciano@unige.ch.

1 Introduction

With the worsening of the climate crisis, investors are under pressure to contribute to global efforts to reduce carbon emissions. Many have explicitly included environmental objectives in their mission, and initiatives like the Climate Action 100+ are gathering widespread support.[1] One aspect of the problem is that, while financial performance is easy to measure and quantify, environmental performance is elusive and the determinants of future environmental performance even more so.

Therefore, it is fundamental to understand whether green investors are actively trying to foster the climate transition or passively doing the bare minimum for marketing purposes. In other words, do green mutual funds actively screen firms for environmental efforts? Is there a way for them to identify firms that eventually have better environmental performances? This paper addresses these questions by investigating how mutual funds respond to firms that talk about the environment during their earning calls.[2] We show that green funds respond to firms discussing the climate transition by increasing their investments. This is rational, as one year after engaging in environmental talk, firms limit their carbon emissions better than the market at large. Our results suggest the existence of an effective communication channel between green investors and firms. Our evidence on the pro-active behavior of green funds supports the idea of a deep commitment to the environmental transition rather than marketing-related objectives.

Our empirical approach relies on machine learning and natural language processing to measure the extent of environmental talk in earnings conference calls. Specifically, we quantify the proportion of each call dedicated to talking about the environment using Latent Dirichlet Allocation (LDA), a probabilistic topic model. Topic models infer common topics,

[1] Climate Action 100+ is an investor-led initiative joined in 2017 to ensure the world's largest corporate greenhouse gas emitters take necessary action on climate change. As of 2022, it is backed by 700 institutional investors managing a total of $68 trillion in assets.

[2] We focus on earning calls as many studies demonstrate how earnings conference calls provide information to market participants. See among others Frankel, Johnson, and Skinner (1999), Bushee, Matsumoto, and Miller (2003), Mayew and Venkatachalam (2012), Price, Doran, Peterson, and Bliss (2012), Blau, DeLisle, and Price (2015), Dzieliński, Eugster, Sjöström, and Wagner (2022)

i.e., clusters of words used in the same context, from a large number of textual documents. Intuitively, they are dimensionality-reduction techniques akin to principal component analysis, which summarize the complex informational content of raw text into a few topical dimensions. Topics model offer two main advantages over dictionaries and word frequency methods. First, LDA is unsupervised and does not require an arbitrary dictionary or list of keywords, thereby limiting researcher-induced biases. Second, topic models do not seek to capture a single specific dimension of the text. Rather, it divides a text along multiple dimensions, thus limiting the risk of false positives. As an example, in our trained LDA model, the word "sustainable" is a bigger contributor to the topic "growth", than "climate transition". We build a textual corpus from 143,096 transcripts of calls occurring between January 2006 and December 2021 and covering 4,446 US firms and train our LDA model to summarize this high-dimensional data into 75 topical dimensions. We then define a *climate transition talk* measure based on the topic capturing words related to the climate transition.[3]

We start our analysis by focusing on the evolution of sustainable finance between 2006 and 2021. We document that overall the climate transition is rarely discussed in earnings conference calls and only 14% of calls talk about the climate transition (consistently with Eckerle, Whelan, and Tomlinson, 2020). Between 2006 and 2021, the share of assets under management (AUM) held by green funds more than doubled, but climate transition talk did not follow suit. We find that the year 2019 proves a turning point for sustainable investing. The share of green funds over total AUM starts to grow exponentially, and firms spend more time discussing the climate transition.

We continue the analysis by incorporating data on fund holdings. Using funds' self-reported investment objectives, we manually label as *green* every fund that explicitly mentions environmental concerns. It is worth noting that this restrictive classification leaves us with around 2% of total AUM held by green funds.[4] To test whether green funds exhibit

[3]e.g. solar, wind, renewable, carbon, environmental, emission, green, climate

[4]The actual figure is likely to be much larger, as many funds include environmental impact among their investment criteria without explicitly mentioning it in their mission statement.

preferences for environmental talk, we regress aggregate green fund ownership on climate transition talk and a set of financial and environmental controls, including environmental scores. We find a strongly significant and positive relationship between climate transition talk and green ownership. The average firm discussing the climate transition spends 3.92% of its call on the topic. This magnitude of climate transition talk translates into a 17% higher level of green ownership (i.e., 0.7 standard deviation).

We show that a firm's first climate transition talk leads to an increase in green funds ownership in the following quarter. Four quarters on, green ownership in firms that talked about the climate transition has on average grown by 16% more than it did for matched firms with similar characteristics but that did not discuss the topic. As expected, we do not observe any differences in non-green ownership between the two groups. These results support green funds' claim that they pay attention to firms' environmental communications, and that they actively seek to invest responsibly.

Finally, we explore whether climate transition talk is a useful measure of future environmental performances. We focus on the one-year percentage change in carbon emission between the market portfolio and the firms that talked about climate transition in the past year. While both groups increase their emissions, the increment of the latter is almost half, namely 3.4% versus the 6.7% of the market. Moreover, firms that do not talk about climate transition increment their carbon emissions by 7.4%. Interestingly, we observe that firms that talk about climate transition have a way bigger carbon intensity (i.e., carbon scaled by total revenue). This means that green funds give trust to firms that seem relatively worse, but that perform better in the future. Therefore, by listening to climate transition talk, green funds overcome the potential stigma associated with such firms and contribute to a faster climate transition.

To conclude, our results suggest that green funds and firms expressing clear environmental objectives do not systematically engage in greenwashing. They also hint at the existence of a channel for firms to efficiently communicate their climate stance and future commitments to green investors. This channel has important implications for the relationship between green investors and environmentally inclined firms and capital allocation. Going forward, in a world with a large sustainable finance sector, firms might be tempted to abuse this communication channel to attract investors and reduce their cost of capital (Pastor, Stambaugh, and Taylor, 2021). Hence, to avoid abuses, governments should develop clear and standardized reporting guidelines for environmental disclosure, and ensure that climate-related reporting is held to the same standard as financial reporting. In this sense, our findings directly speak in favor of initiatives, such as the United Nations Task Force on Climate-Related Financial Disclosures, seeking to develop consistent environmental reporting frameworks.

Related Literature This paper contributes to the literature that studies investors' preferences regarding corporate social responsibility. Hong and Kacperczyk (2009) show that "sin" stocks are less held by institutions subject to social norm pressure. More recently, Bolton and Kacperczyk (2021) find that institutional investors hold smaller fractions of firms with high Scope 1 carbon emissions. Hartzmark and Sussman (2019) show that mutual fund flows react positively to high sustainability ratings. A growing theoretical literature studies the asset allocation choices of green investors. For example, Pástor, Stambaugh, and Taylor (2021) and Pedersen, Fitzgibbons, and Pomorski (2021) show that in equilibrium green investors tilt their portfolios toward stocks with high ESG characteristics. Flammer, Toffel, and Viswanathan (2021) show that green ownership positively relates to the decision to disclose climate risk. Closely related to our work, Ilhan, Krueger, Sautner, and Starks (2021) use a change in UK law to show that green ownership increases in firms forced to disclose carbon emissions. We complement the literature by documenting that green mutual fund ownership is positively related to climate transition talks in earnings conference calls. Furthermore, we highlight how mutual funds' interest in climate transition talk is separated from their preferences for third-party environmental ratings.

We also contribute to the growing literature studying environment-related talks in corporate disclosure. Hail, Kim, and Zhang (2021) show evidences of *greenwashing* in earnings conference calls. On the contrary, Chava, Du, and Malakar (2021) and Dzieliński et al. (2022) find that firms "walk the talk" and that more environmental talk is associated with greater environmental performance, such as reductions in carbon emissions and more green patents. We contribute to the literature by showing that green mutual funds are not deaf to environmental talk and shed light on investors' reactions to climate transition talk.

Finally, our work also contributes to the fast-growing literature that applies textual analysis in finance.[5] Recently, various papers have developed methods to measure climate talk. Engle, Giglio, Kelly, Lee, and Stroebel (2020) and Dzieliński et al. (2022) use climate change white papers to build a "climate change vocabulary". Sautner, van Lent, Vilkov, and Zhang (2021) start from a hand-picked set of bigrams and apply a keyword discovery algorithm to capture four different aspects of climate risk. Kölbel, Leippold, Rillaerts, and Wang (2020) use BERT, an advanced natural language processing algorithm developed by Google LLC, to quantify climate risk disclosures in 10-K reports.[6] We apply LDA, a unsupervised probabilistic topic model, which has the great advantage of not needing any dictionary or discretionary human judgement.[7] Although we do not make a methodological contribution, to the best of our knowledge, our paper is the first that applies LDA to earnings calls transcripts.

2 Climate Transition Talk in Earnings Conference Calls

Quarterly earnings conference calls offer investors and firms a regular platform to communicate and discuss past performances and future objectives. While most of these discussions concern the firm's financial performance, managers and analysts often talk about various other topics, such as efforts toward the climate transition. Using Refinitiv Eikon, we build a

[5]See e.g. Loughran and McDonald (2011); Price et al. (2012); Wiesen and Wysocki (2015); Loughran and McDonald (2016); Koijen, Philipson, and Uhlig (2016)

[6]See also Varini, Boyd-Graber, Ciaramita, and Leippold (2020); Diggelmann, Boyd-Graber, Bulian, Ciaramita, and Leippold (2020)

[7]Bybee, Kelly, Manela, and Xiu (2020) is an interesting application of LDA in finance in which they extract the "structure of economic news" from newspaper articles.

text corpus from the transcripts of 143,096 earnings conference calls held by 4,446 US firms between January 2006 and December 2021. In order to dissociate the topics being discussed, we train a Latent Dirichlet Allocation (LDA) model (Blei, Ng, and Jordan, 2003). LDA is a probabilistic topic model that analyzes the semantic content of a corpus and infers the data's hidden thematic structure. Specifically, LDA is a dimensionality-reduction technique akin to principal component analysis, which summarizes the complex informational content of raw text into a few topical dimensions. Frequently co-occurring terms are grouped into topics, thus reducing a text to a distribution over a small number of topics rather than an extensive vocabulary.

In the context of this paper, our LDA model first learns a set of 75 topics from the corpus of transcripts, before quantifying the proportion of each call dedicated to each topic. The corpus is thus summarized in a document-topic matrix of dimensions 143,096 by 75. We manually label each of the 75 topics based on the co-occurring terms they contain. Most topics corresponds to various aspect of company results, industries, and business models. However, we identify one topic characterized by a cluster of terms related to the climate transition, which we label as such. By capturing terms such as "carbon", "emission", "renewable", and "solar", this topic is especially well suited to measure the amount of climate transition talk in the corpus of earnings conference calls. Appendix C presents in detail our estimation of the LDA model. We also refer the reader to the literature on probabilistic topic modeling for a more detailed description.[8]

[Figure 1 about here.]

The advantages of using a probabilistic topic model instead of a dictionary approach are multiple. First, the low dimensionality of topic representation enables an easy classification of the texts and offers straightforward interpretability. Second, probabilistic topic models better mimic human discourse as they do not uniquely allocate terms to topics, but give each term a relative importance within each topic. In other words, a term can belong to

[8]See e.g. Blei et al. (2003), Huang (2005), Hoffman, Bach, and Blei (2010), Blei (2012), Blei (2013)

multiple topics but contribute to each of them differently. Figure 1 illustrates the relative contribution of a sample of climate transition related terms to our LDA topics. The term "climate" is allocated 30% of the time to the climate transition topic and 11% of the time to a topic discussing the weather. Interestingly, the terms "environment", "sustainability", and "sustainable" are only rarely attributed to the climate transition topic, conveying their versatile use in the English language. This observation speaks in favor of using LDA instead of a dictionary based approach which would allocate all dictionary terms to the unique topic considered. Finally, topic models are unsupervised machine learning algorithms. As such, they are agnostic, and the nature of the topics is not predefined but inferred directly from the data. Figure 1 shows that our model attributes most often the terms "carbon", "renewable", and "solar" to the climate transition topic. While these terms are unequivocally reminiscent of the climate transition, we, as researchers, had no hand in picking them. The climate transition topic endogenously arises from the corpus and is not a prerequisite of the model.

2.1 A Measure of Climate Transition Talks

In this paper, we measure climate transition talk using the dimension of the document-topic matrix corresponding to the climate transition topic. Therefore, our climate transition talk measure, CTT, explicitly captures for each transcript the percentage of text allocated to the climate transition topic by our LDA model. Table A.3 in the appendix illustrates how CTT relates to actual textual snippets from the earnings calls of various firms in diverse industries. We also consider alternative climate transition talk measures. CTT^{Pres} measures the percentage of climate transition talk in the presentation section of the call. CTT^{QA} measures the percentage in the Q&A section. $\boldsymbol{I}^{CT}$ is equal to 1 if CTT is larger than 0 , and 0 otherwise. All variables are defined in Table 1.

[Table 1 about here.]

Table 2 reports the cross sectional distribution of the climate transition measures across industries. Overall, the climate transition is seldom discussed during earnings conference calls, as only 14% of transcripts have a positive climate transition talk measure. We find that the average call only dedicates 0.84% of its time discussing the climate transition; with the topic being more talked about during the presentation than the Q&A. Conditionally on discussing the topic, a call spends 5.95% of its length on it. We find significant differences in climate transition talk across industries, with Capital Goods talking about the climate transition the most, and Pharma., Biotechnology & Life Sciences mentioning it the least often. In fact, the industries discussing the climate transition most frequently correspond to the most carbon-intensive ones.[9]

[Table 2 about here.]

Importantly, Table 2 exposes the utility industry as a clear outlier. It is the only industry in which nearly all the transcripts mention the climate transition, and in which the average firm dedicates more than 10% of a calls to the climate transition topic. This noteworthy difference is due to the classification among utilities of electricity and renewable energy producers, whose jargon significantly overlaps with the terms belonging to our climate transition topic. In effect, the LDA model is tailored to the entire corpus and does not differentiate between industries, which means that it is not able to dissociate the usual talk in the utility industry from special attention to the climate transition. In practice, this implies that our measure of climate talk is likely overstated for the utility industry. As a consequence, we prudently drop this industry from our empirical analysis.[10]

3 Data

This study combines mutual fund holdings with firm level data. We gather mutual funds holdings and characteristics from Refinitiv Lipper, and complement them with firm characteristics from CRSP-Compustat, carbon emissions data from Trucost, environmental scores from Refinitiv ESG, and our climate transition talk measures.

[9]Our top industries in climate transition talk match those with the highest carbon emissions as measured by MSCI in May 2021 (https://www.msci.com/documents/1296102/26195050/MSCI-Net-Zero-Tracker.pdf).

[10]The results presented in this paper are robust to the inclusion of this industry, albeit more noisy.

3.1 Mutual Funds Data

We use Refinitiv Lipper to obtain the list of all funds that were active at any point between 2006 and 2021, as well as their investment objectives, characteristics and stock holdings. We restrict our study to mutual funds and exchange traded funds (ETFs) invested in equities or with mixed assets. Additionally, we only retain funds with geographical focus defined as either "Global", "United States of America", or "North America". We further exclude small funds that on average manage less than $1 million or report less than 10 stock holdings. We also drop funds that were active for less than 8 quarters during our time period. Our final sample is comprised of 8,964 funds. Finally, we use short descriptions of funds' investment objectives to identify 955 *green* mutual funds, that explicitly communicate sustainable intent in their mandate.[11]

[Figure 2 about here.]

We further confirm the greenness of green funds by comparing the industry portfolio weights of the aggregate green funds to those of the aggregate non-green funds. Figure 2 shows the five industries for which weight discrepancies are the largest. Compared to their conventional counterparts, green funds are under-invested in the Aerospace & Defense, Tobacco, and Gaming industries. This fact is consistent with socially responsible investors screening out sin stocks from their portfolio (Hong and Kacperczyk, 2009). We also observe that they swap less sustainable stocks for more sustainable ones with similar risk exposures. Within the GIC 4 industry group Pharmaceuticals, Biotechnology & Life Sciences, green funds favor the Life Sciences Tools & Services industry at the expense of the Biotechnology and Pharmaceuticals industries.[12] Additionally, green funds favor manufacturing firms in the

[11] We use a two-step process. First, we identify all descriptions mentioning any of the following words: "environment", "sustainability", "sustainable", "green", "carbon", "decarbonisation", "emissions", "responsibility". We then manually revising each of these descriptions to understand the context and validate the *green* status of the fund. A sample of green fund objectives can be found in Table A.2 in the appendix.

[12] Unreported numbers confirms that the favored industry exhibit much higher environmental score than the less-like counterparts. This holds for both Refinitiv and MSCI environmental scores.

Semiconductor & Semiconductor Equipment, Electrical Equipment, and Machinery industries. These observations are in line those of the IMF's Global Financial Stability Report. This report documents that green funds are more heavily invested in industries showing strong transition opportunity, especially the manufacturing sector.[13]

3.2 Firm Characteristics

Firm characteristics and stock prices are from the CRSP-Compustat merged database. We complement these data with earnings data from I/B/E/S, corporate social responsibility variables from Refinitiv ESG, and carbon emissions data from Trucost.[14] In line with the existing literature, we exclude financial firms and those with negative book equity, drop observations for which the number of shares outstanding are missing, and whose stock price is either missing or below 1. Additionally, we require each firm to have at least one available earnings conference call transcript. Finally, as explained in Section 2.1, we remove the utility industry from our sample. The resulting sample contains 4,218 firms.

The percentage of ownership in firm i held by fund j at time t is computed as:

$$h_{ijt} = \frac{H_{ijt} P_{it}}{MC_{it}},$$

where H_{ijt} is the number of shares of firm i held by fund j at time t, and P_{it} and MC_{it} are respectively the price and the market cap of firm i at time t. Aggregate fund ownership in firm i at time t is defined as $FO_{it} = \sum_j h_{ijt}$. We consider three measures of aggregate fund ownership. FO^{Total}, FO^{NG}, and FO^{G} respectively measure the fund ownership of all funds, non-green funds, and green funds.

Let CE_{it} be the volume of scope 1 and 2 carbon emitted by firm i in year t, and CI_{it} be firm i's carbon intensity level, a relative measure of emissions adjusted by revenue. We define two measures of yearly changes in firm-level carbon emissions. The annual percentage

[13] See https://www.imf.org/en/Publications/GFSR/Issues/2021/10/12/global-financial-stability-report-october-2021

[14] At the time of writing, the Trucost data was only available to us until 2019.

change in carbon emissions between years t and $t-1$ is given by:

$$\Delta CE_{it} = \frac{CE_{it} - CE_{i,t-1}}{CE_{i,t-1}},$$

and the annual absolute change in carbon intensity by:

$$\Delta CI_{it} = \Delta CI_{it} - \Delta CI_{i,t-1}.$$

Table 3 presents the summary statistics for our sample of firms. We observe that aggregate green ownership is much smaller that the one of their non-green counterparts. While non-green funds hold on average 24.57% of the shares in our sample of firms, green funds only hold 0.26%. We also see than more than a quarter of firms are not held by any green funds. The distributions of both absolute and relative carbon emissions are very skewed, with a few very large emitters dragging average emissions far above the median. We note that, during our sample period, most firms have increased their absolute carbon emissions by more than 3.48% each year. However, a majority of them become more efficient and simultaneously improve their carbon intensity.

[Table 3 about here.]

Finally, we define portfolio-level measures of carbon emissions. The carbon footprint, CF^P_{jt}, measures the amount of carbon emissions credited to an investor per million of dollar invested in the portfolio. The portfolio carbon intensity, CI^P_{jt}, which measures the volume of carbon emitted to produce one million dollar of revenue.

$$CF^P_{jt} = 1,000,000 * \sum_j h_{ijt} CE_{it}$$

$$CI^P_{jt} = \frac{CF^P_{jt}}{1,000,000 * \sum_j h_{ijt} Revenue_{it}}$$

We measure portfolios' annual carbon performances as,

$$\Delta CF^P_{jt} = 1,000,000 * \sum_j h_{ij,t-1} \left(CE_{it} - CE_{i,t-1}\right).$$

and:

$$\Delta CI^P_{jt} = \frac{\sum_j h_{ij,t-1} CE_{it}}{\sum_j h_{ij,t-1} Revenue_{it}} - CI^P_{j,t-1}$$

Table 4 exhibits the main summary statistics for our sample of funds. On average, green funds manage less than half the assets than their conventional counterparts do, and are less diversified. During our sample period, green funds experienced higher inflows, and obtained comparable returns to non-green funds. Finally, green funds exhibit better environmental performances. These observations are in line with findings of the Global Sustainable Investment Alliance documenting a growing sustainable investment sector and the prevalence of negative and exclusionary screening strategies among green funds.[15]

[Table 4 about here.]

4 Empirical Analysis

4.1 Green Finance through Time

We start our analysis by commenting interesting time trends in our data. A milestone often referred to when talking about environmental sustainability is the Paris Agreement objective of net-zero carbon emissions by the middle of the 21st century. With this goal in mind, we analyse the evolution over time of carbon emissions in our sample. Panels A and B in Figure 3 display our findings. Total carbon emissions have risen between 2006 and 2021. The sharp increase from 2016 to 2019 is due to the addition of many small firms in the Trucost dataset. Looking at a reduced sample of firms present both prior to 2016, a small, but steady, increase in carbon emissions is confirmed. Additionally, we observe a steady

[15] See http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf

decline in levels of emissions intensity during our sample period. These results are to be contrasted with observations from Table 3. While Figure 3 reveals that the market does not improve its carbon emissions over time, Table 3 shows that more than 25% of observations report decreasing carbon emissions. Given the mounting pressure on financial institutions to participate in global efforts toward the net-zero goal, Panel A and B of Figure 3 beg the question of how can green funds identify the firms who will reduce their emissions and build decarbonization portfolios.

[Figure 3 about here.]

In this paper, we study whether climate transition talk is used by green funds as an investment criterion. Panel C in Figure 3 shows the cross-sectional mean of climate transition talk between 2006 and 2021, as well as the number of firms talking about the climate transition each year. We find a generally low level of climate transition talk throughout our entire sample period. Discussions about the climate transition only constitute between 0.28% and 0.72% of the average earnings call. Few firms discuss the topic in a given year, with no noticeable increase over time except in the very last year of our sample. These findings are consistent with Eckerle et al. (2020) and Setterberg and Sjöström (2021) who find no evidence of widespread environmental talk in earnings conference calls. Our topic model is less generous than word frequencies (Hail et al., 2021) or similarity measures (Dzieliński et al., 2022) when ascribing environmental talk to earnings calls. However, while magnitudes are different, the time series pattern of our measure of climate transition talk closely match the one reported by Dzieliński et al. (2022). Like us, they find higher level of climate talk around 2010, followed by a decline, and a sharp rise starting in 2019.

Finally, Panel D in Figure 3 illustrates the proliferation of green mutual funds between 2006 and 2021. While sustainable investing has existed since the beginning of our sample, we observe a notable change in the growth of green AUM starting in 2019. The expansion of green AUM has overall matched the global rise in capital under professional management between 2007 and 2018, but largely outpaces it afterward. Between December 2018 and

December 2021, green AUM rose from 2.11% of total AUM to 4.33%. We also observe a constant augmentation of the number of green funds throughout our sample period. These observations are in line with our expectations given the well-documented growth in sustainable finance in the last decade.[16]

Interestingly, the time series pattern of climate transition talk observed in Panel C closely match the evolution of the ratio of green AUM to total AUM displayed in Panel C. Taken together Panels C and D provide anecdotal evidence of a link between firms' decision to communicate on the climate transition and the size of green mutual funds in the economy.

4.2 Climate Transition Talk and Aggregate Fund Ownership

We formally test the relationship between ownership by green mutual funds and climate transition talk by regressing aggregate fund ownership on climate transition talk and a set of controls.

$$FO_{it} = \beta_0 + \beta_1 CTT_{it} + \beta_2 \text{E-Score}_{it} + \beta_3 X_{it} + \gamma_{s_i t} + \varepsilon_{it}, \tag{1}$$

As we do no expect green funds and non-green funds to have similar environmental preferences, we consider three different dependent variables, green fund ownership, FO^G, total funds ownership, FO^{Total}, and non-green fund ownership, FO^{NG}. The dependent variable of interest in CTT, our measure of climate transition talk. We control for firms' environmental score, E-Score, to disentangle the effects of observable environmental metrics and firms' climate speech during earnings calls.[17] The matrix X_{it} is a set of financial control variables that includes Size, Market-to-Book, Profitability, Leverage, Tangibility, Investments and EPS Surprise,[18] and $\gamma_{s_i t}$ denotes industry-quarter fixed effects. Standard errors ε_{it} are

[16] As a comparison, the https://www.imf.org/en/Publications/GFSR/Issues/2021/10/12/global-financial-stability-report-october-2021 discloses 980 environment funds owning 7.6% of total AUM by the end of 2020. The IMF statistics are not restricted to equity funds.

[17] We present results using Refinitiv's environment score. Using MSCI ESG variables (Environment Pillar Score, Average Industry Score, Weighed Average Score, Climate Change Theme Score and Carbon Emission Score) or Trucost's carbon emissions measures instead does not impact the magnitude and significance of our results.

[18] All variables are defined in Table 1.

clustered at the firm level.

Equation (1) allows us to test two hypotheses. First, we hypothesize that climate transition talk is not simply a noisier measure of observable environmental metrics, and that funds extract from it an additional signal regarding firms' climate stance. Environmental scores mostly capture the status quo, i.e., where the firm stands in terms of sustainability. Conversely, we argue climate transition talk is a more forward-looking measure. Managers often use earnings calls to provide market participants with forward guidance and to announce new projects. In other words, climate transition talk is a noisy signal of a firm's future efforts to lower its environmental footprint. Second, we postulate that green funds react positively to climate transition talk, while non-green funds react negatively.

[Table 5 about here.]

Table 5 reports the regression estimates for various specification of equation (1). Columns (1) and (2) analyze the relationship between green fund ownership and our main measure of climate transition talk, CTT. We observe that both CTT and E-scores are positively and significantly correlated with green fund ownership. Importantly, the sign nor the magnitude of the coefficient of CTT is not impacted by the inclusion of environmental scores among the control vairables. The coefficient corresponding to the main independent variable of interest, CTT, is equal to 0.1127 and is statistically significant at the 1% level. As previously reported, conditional on talking about the climate transition, a firm spends an average of 3.92% of its call on the topic. Our regression coefficient implies that the average firm that discusses the climate transition has a 44 bp higher percentage of green ownership than a comparable firm remaining silent. This effect is substantial when contrasted with the sample mean green ownership of 0.26%.

Columns (3) and (4) respectively report the estimates when considering total and non-green fund ownership. In both cases, the coefficients on CTT are negative, confirming that the effect we observe for green funds is not a universal phenomenon. The coefficients on E-score are negative and significant, indicating that overall fund ownership tends to be lower for firms with high E-scores, further corroborating the idea that green funds pay extra attention to environmental aspects. Overall, non-green funds seem to avoid companies that discuss the climate transition or have high E-scores. While this effect is hard to interpret, it is possible that there is substitution between green and non-green funds, with the former buying green companies from the latter, as they have a non-financial preference for environmentally conscious firms.

Columns (5) and (6) confirms the results of column (2) using alternative measures of CTT.[19] In Column (5), we replace CTT by I^{CT}, a dummy variable equal to 1 if CTT takes a positive value and 0 otherwise. Column (6) splits our CTT measures between the share of talk occurring during the presentation, CTT^{Pres}, and during the Q&A, CTT^{QA}. The coefficient on climate transition talk remains positive and statistically significant in all specifications.

Columns (7) and (8) further dissects the relationship between climate transition talk and green fund ownership by dividing the observations into two sub-periods. We analyse the persistence of the positive relationship described in column (2) before and after 2019, the year when sustainable finance started to grow exponentially. The objective of this exercise is to verify that the effect we capture is not driven by a particular period. We find that the effect is positive and significant for green funds across both time periods. Moreover, the magnitude of the correlation between CTT and green ownership remains comparable between our baseline specifications in column (2) and the two time periods in columns (7) and (8). In addition, we note that environment scores have had a larger impact on green ownership during the last three years of our sample period.

Having confirmed a positive correlation between climate transition talk and green ownership, we now focus on the mechanism driving this relationship. To do so, we focus on the

[19] In addition, the results shown in Panel A are robust to: 1) dropping *E-scores* from the set of controls, thus greatly increasing the sample size, 2) including the set of CSR controls used in Dzieliński et al. (2022), 3) using Refinitiv's variable for CO_2 *Emissions* instead of *E-scores*

instances in which firms discuss climate transition for the *first* time and look at whether this prompts an increase in green ownership. This way, we exclude the presence of possible confounding factors, such as firms talking about the climate transition because of the over-representation of green shareholders (e.g., Flammer et al., 2021; Ilhan et al., 2021).

4.3 Are Funds Listening to Climate Transition Talk?

Does higher green ownership precede climate transition talk or does talking about the climate transition convince green funds to invest in a firm? Our objective is to isolate the selection effect on green ownership of talking about the climate transition from the influence effect. We propose to focus on the specific set of events when firms talk about the climate transition for the first time.

We estimate the effect of first talk event using the difference-in-difference procedure proposed by Imai, Kim, and Wang (2019) which relies on matching methods to consistently estimate average treatment effects in panel data.[20] We briefly summarize our steps in the next paragraph and refer the reader to the original paper for an extensive description of the method.

We first identify 401 events in which a firm talks about the climate transition for the first time. Explicitly, we define an event as a firm-quarter observation whose latest earnings call discussed the climate transition ($CTT_{i,t} > 0$) while never having mentioned the topic in the past two years ($CTT_{i,t-l} = 0 \; \forall \; l = 1, \ldots, 8$). We refer these events as "first talk events". The set of first talk events makes up the treatment group. For each treated observation, we construct a match set of controls. We require controls to match exactly on time period, industry, and climate transition talk history. Formally, for a treated observation (i, t), the matched set of control is defined as:

$$\mathcal{M}_{it} = \{i' : i' \neq i, s_i = s_{i'}, FO_{i',t-l} = 0 \; \forall \; l = 0, \ldots, 8\} \tag{2}$$

[20] Athey and Imbens (2022) shows that common estimation methods, such as difference-in-difference regressions, do not correctly estimate the average treatment effect for staggered treatments.

We measure the average treatment effect after F period using the difference-in-difference estimator $\hat{\delta}(F)$.

$$\hat{\delta}(F) = \frac{1}{\sum_{i=1}^{N}\sum_{t=0}^{T} D_{it}} \sum_{i=1}^{N}\sum_{t=0}^{T} D_{it} \left\{ (FO_{i,t+F} - FO_{i,t-1}) - \sum_{i'} w_{it}^{i'} \left(FO_{i',t+F} - FO_{i',t-1}\right) \right\}, \tag{3}$$

where $w_{it}^{i'}$ is the relative weight of matched observation i' in matched set $\mathcal{M}_{it}$. We consider two alternative weighting strategies based on propensity scores, single-nearest-neighbor and propensity score weighting. Propensity scores estimate the conditional probability of treatment for each observation given a set of covariates. We estimate propensity scores using a logistic regression model using the covariates described in Section 4.2. Single-nearest-neighbor limits the size of the matched set to the matched observation whose propensity score is closest to that of the treated. Propensity score weighting retains all observations in the matched set and weight them based on their distance to the propensity score of the treated observation.

[Figure 4 about here.]

Our framework, like other difference-in-difference setups, makes the parallel trend assumption. Figure 4 shows the evolution of fund ownership around first talk events. We observe that both green and non-green ownership exhibit parallel trends prior the treatment time $t = 0$. Interestingly, we note that while the treatment and control groups display similar average green ownership before treatment, the treatment observations have lower non-green ownership. These observations suggest that the first time firms talked about the climate transition, green funds were not over-represented among the firm's shareholders, compared to matched firms. This is at odds with the influence hypothesis saying that the ex-ante presence of green funds drives firms to talk more about the climate transition. Figure 4 also shows a widening difference in green fund ownership between treated and control groups following first climate transition talks. This change does not exist for non-green ownership.

[Figure 5 about here.]

We formally test the significance of the post-treatment differences observed in Figure 4 using the difference-in-difference estimator expressed in equation (3). Figure 5 displays the average effect of first talk in the four quarters following the climate transition talk. The top panels show the effects on green ownership, while the bottom ones describe the effects on non-green ownership. The panels on the left use the matched control group build using propensity score weighting. The right panels use single-nearest-neighbor matching. Figure 5 shows that, following a first talk event, green ownership increases significantly more in the treatment group than in the control groups.[21] Within a year of a first talk occurrence, the percentage of green ownership has grown 5.33 basis points more for treated firms than comparable ones. Contrasted with the fact that average green ownership the quarter before the climate transition talk is 0.36%, the magnitude of this effect is important.

To make sure that the differences we observe are explained by the fact that funds are green and not by unobserved variables, we conduct a set of falsification tests for non-green ownership in Panel B. Notably, all coefficients are insignificant up to one year after the event. This strongly suggests that our empirical strategy properly identifies the effect of talking about climate transition for the first time. In other words, even thought we do not have any exogenous shock to exploit, the insignificance of these tests validates our hypothesis that green funds do listen and increase their holdings in firms that start talking climate transition. It is also worth noting that our findings show that non-green funds do not penalize firms

[21] Our results are robust to 1) using 6, 10 or 12 quarters instead of 8 to define "first talk events", 2) focusing on later periods of our sample when Refinitiv offers better coverage thus increasing the size of the matched sample. Dropping E-score from the set of covariates used to measure propensity scores increases the number of events to 702, but leads to a matched sample of lesser quality. While positive effects on green ownership are still observed, they are not statistically significant. Considering only event occurring after the surge of responsible investing in 2018 leads to effects of larger magnitude, but the low number of remaining events does away with most of the statistical significance. The results from these robustness checks can be found in Figure B.1 in Appendix B.

talking about the climate transition. Arguably, this means that non-green funds do not consider talking about climate transition as an indication have lower financial performances. Indeed, if this was the case, they would divest from them. Alternatively, our results might indicate that non-green funds tend to invest more passively and do not actively listen to earning calls as green funds do.

Overall, these findings corroborate the idea that green funds are forward-looking and actively seek firms that show interests in tackling the climate transition. They are willing to pay the extra-cost of listening to firms' communication about the climate transition, showing real commitment to their green mandates.

4.4 Does listening help decarbonize a portfolio?

In this section, we explore whether a green investor can improve the carbon emissions of his portfolio by listening to climate transition talk. The simplest way for an investor to decarbonize his portfolio is to exclude the worst polluters from his holdings. As Table 3 shows, carbon emissions are very skewed. Therefore, excluding the rightmost firms on the distribution of carbon emissions has a very large impact on portfolio level emissions. Bolton and Kacperczyk (2021) find that institutional investors implement exclusionary screening based on carbon emissions intensity in a few salient industries, and Jondeau, Mojon, and Pereira da Silva (2021) show how excluding a small fraction of highly polluting firms can massively reduce the carbon footprint of a portfolio. We propose to enhance the exclusionary screening strategy by reallocating the proceeds only into firms that discussed the climate transition in the past year.

[Table 6 about here.]

We sort our observations along two dimensions. First, we split our sample between two climate transition talk categories, Talk and No-Talk. We classify as (No-)Talk a firm that has (never) spoken about the climate transition in the past year. Second, we split firms between those to be Excluded or Included in a decarbonization portfolio based on their carbon intensity. Within each period, Excluded (Included) firms are those making up the 25%(75%) of total market capitalization with the highest (lowest) carbon intensity. Table 6 displays time-series average of value-weighted current carbon intensity CI, one-year forward change in carbon intensity ΔCI, and one-year forward percentage change in carbon emissions ΔCE for the four categories, and their intersections. Panel A shows that divesting from the 25% of market capitalization with the worst emissions intensity lowers the average value-weighted carbon intensity of portfolio firms from 126.44 tons per million dollars of revenue to 32.19. Additionally, we observe that firms that talk about the climate transition have on average worst current carbon intensity. These observations are consistent those made when discussing Table 2, and observing that the most polluting industries discuss the climate transition the most.

However, Panels B and C demonstrate that firms that talk about the climate transition in the past year have better environmental performances in the following year. While the effect is statistically insignificant, firms that discuss the climate transition reduce their carbon emissions per million dollar of revenue by 0.23 tons, or 23%, more than the other firms. This better future carbon performance is even more visible and statistically significant when comparing percentage changes in carbon emissions. While the average firm that does not discuss the climate transition increases its emissions by 7.38%, the ones that discuss it only increase their emissions by 3.44%. Moreover, these effects are driven by the subset of Included firms that are considered in a decarbonization portfolio. Finally, Table 6 shows that removing the worst polluters comes at the cost of removing the firms that exhibit the best improvement in carbon intensity over the next period.

[Table 7 about here.]

We further exemplify our findings by comparing the environmental and financial performances of three portfolios. We compare the market portfolio to two decarbonization portfolios. The first decarbonization portfolio excludes the 25% of firms with the worst carbon intensity. The exclusion proceeds are proportionally reinvested in the remaining firms. The second one, called strategic decarbonization, similarly excludes the worst polluters, but only reinvest the proceeds among firms that have discussed the climate transition in the past year.

Table 7 exhibits our findings. First, all three portfolios obtain similar annual returns. Second, while the strategic decarbonization portfolio has slightly worst current environmental performances than the simple decarbonization one at the beginning of each period, it performs better during the holding period. These findings are further illustrated in Figure 6, which shows the cumulative performance of the three portfolios between 2010 and 2019. The strategic decarbonization portfolio is the one responsible for the least amount of carbon emissions. The simple decarbonization portfolio offers a slightly better cumulative return.

[Figure 6 about here.]

5 Discussion - A Crucial Communication Channel

In section 4, we show that green funds actively listen to earning calls, extract information regarding a firm's commitment to the climate transition, and react accordingly. The existence of such communication channel is non-trivial, as it implies sustained and costly monitoring efforts by green funds. These efforts go beyond the simple selection of the investment universe based on easily observable environmental criteria. Instead, it shows a strong commitment to the climate transition, with an active strategy and a forward-looking view of firms.

This communication channel is ever more critical given the steep increase in green funds in recent years.[22] Nevertheless, this surge can affect managers' incentives, as they internalize the shift in investors' preferences. By discussing the climate transition, managers can attract capital flows with potential personal benefits, thus incentivizing them to engage in greenwashing. This temptation threatens the ability of green funds to allocate capital, as

[22] See Figure 3.

greenwashing pollutes the quality of the communication and, consequently, disrupts green funds' efforts and threatens their credibility. While there are strict accounting and reporting standards for financial information, there is no legislation addressing how firms communicate their environmental commitments. Sustainability reports, emissions, and other environmental reporting are increasingly regulated but remain inherently backward-looking. Green funds need to rely on the credibility of managers, which is hard to evaluate and built over long time horizons. Policymakers should address this growing conflict and design solutions to limit greenwashing while creating favorable conditions for an effective disclosure of their environmental commitments.

With enough credibility, forward guidance in earning calls could be crucial in supporting the climate transition. Firms willing to invest in reducing their environmental footprint would be safe knowing that public markets support them. It is worth remarking that this communication channel is distinct from environmental rating, as they are mostly backward-looking. Relying on environmental rating would mean that a firm's efforts are only rewarded ex-post, making it harder to roll out ambitious environmental plans. In this sense, understanding how green funds gather information during earning calls might play a pivotal role in changing firms' incentives and ultimately powering the climate transition.

6 Conclusion

Financial institutions are expected to contribute to global efforts to reduce carbon emissions by financing firms that take steps toward the climate transition. However, determining whether a firm will reduce its carbon emissions is not trivial. In this paper, we document that green mutual funds rely on firms' environmental communications to inform their investment decisions, and that discussing the energy transition during earning calls is correlated with a better future environmental performance.

We use LDA, a probabilistic topic model, to measure talks about the climate transition in earnings conference calls for US firms between 2006 and 2021. We first observe that green funds favor firms that discuss the climate transition, and those with high environmental ratings. Using a difference-in-difference setting, we provide evidence of a selection channel under which green funds use climate transition talk as an investment criterion. Precisely, we show that when a firm discusses the climate transition topic for the first time, green funds react by increasing their holdings in the next year. We conclude by showing that firms that talk about climate transition limit their carbon emissions more than other firms.

The existence of a channel for firms to efficiently communicate their climate stance and future commitments to investors has important policy implications. In the future, with a large green finance sector, firms may be tempted to abuse of such a channel to attract green investors and lower their costs of capital, without truly planning to undertake any significant climate-related project. In the future, to avoid greenwashing, governments should ensure that corporate environmental disclosures are held to the same integrity standards as financial ones.

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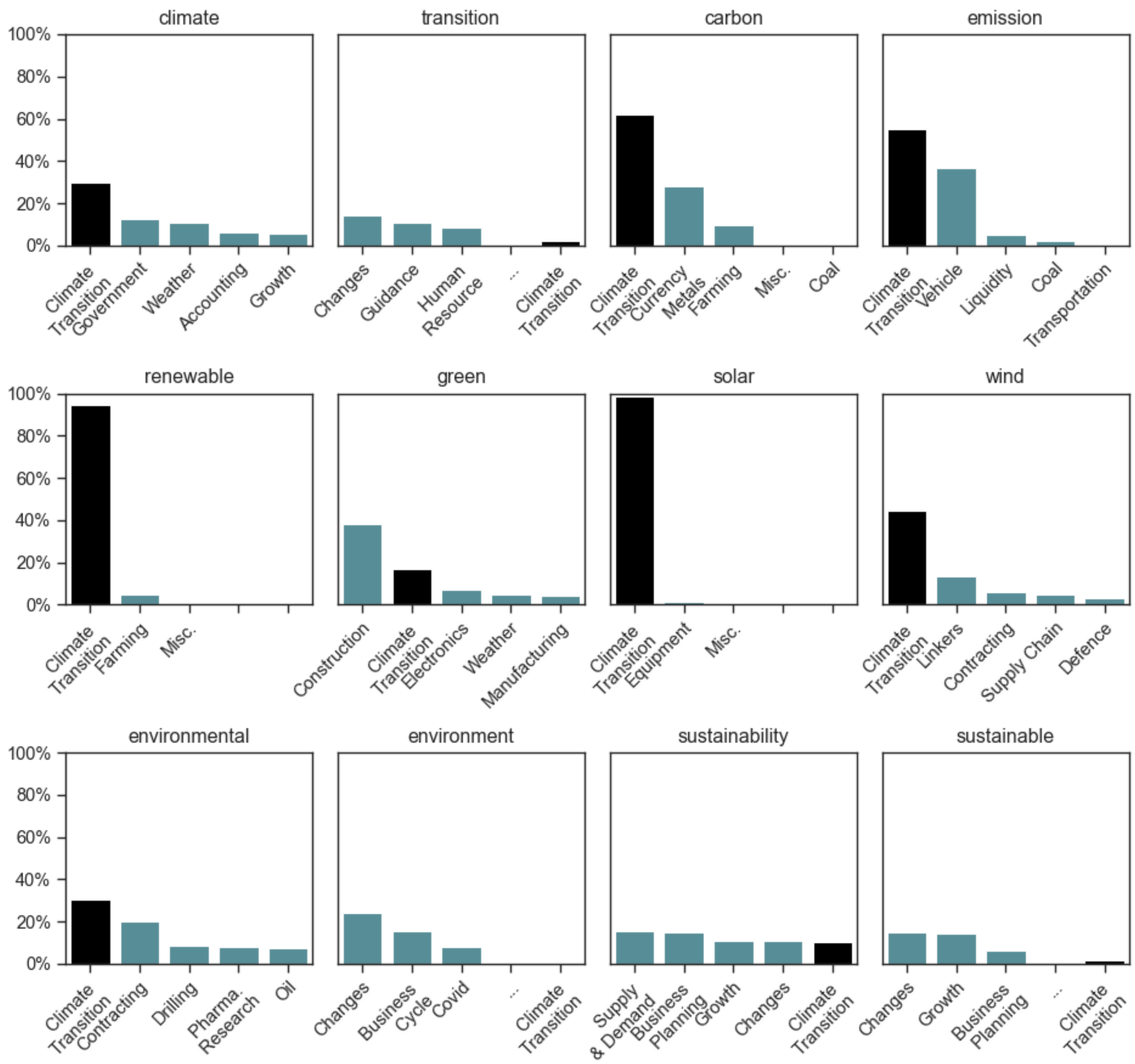
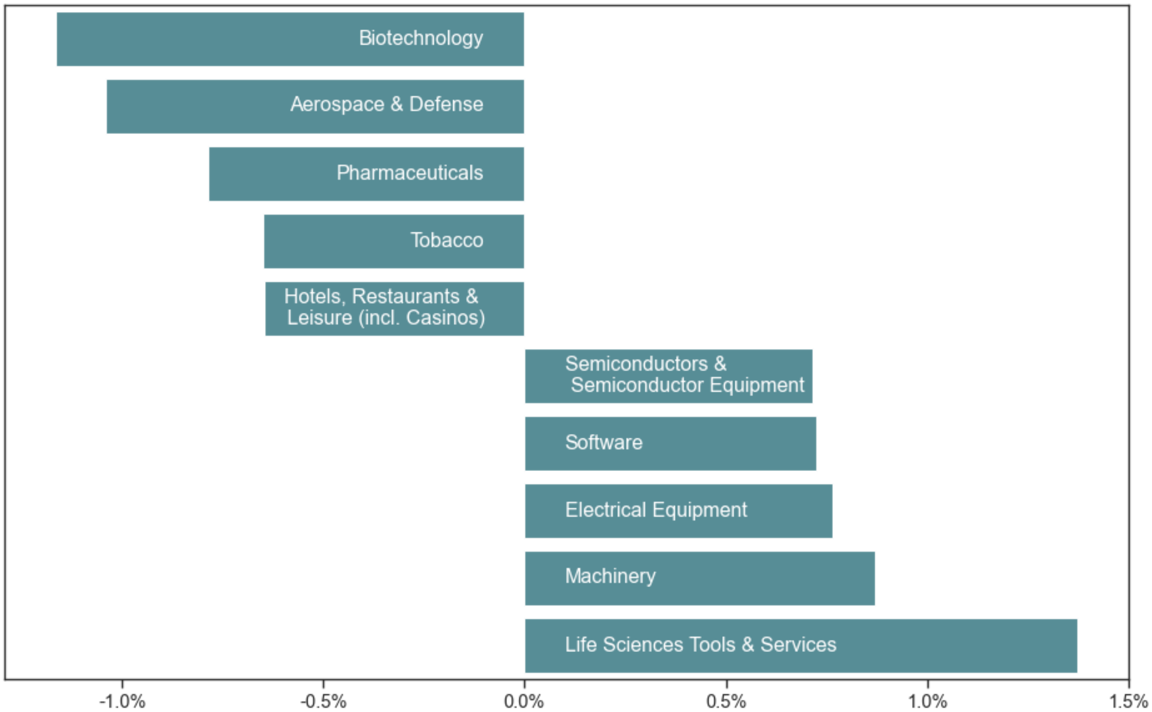
Figure 1: **Terms Allocation to Topics**



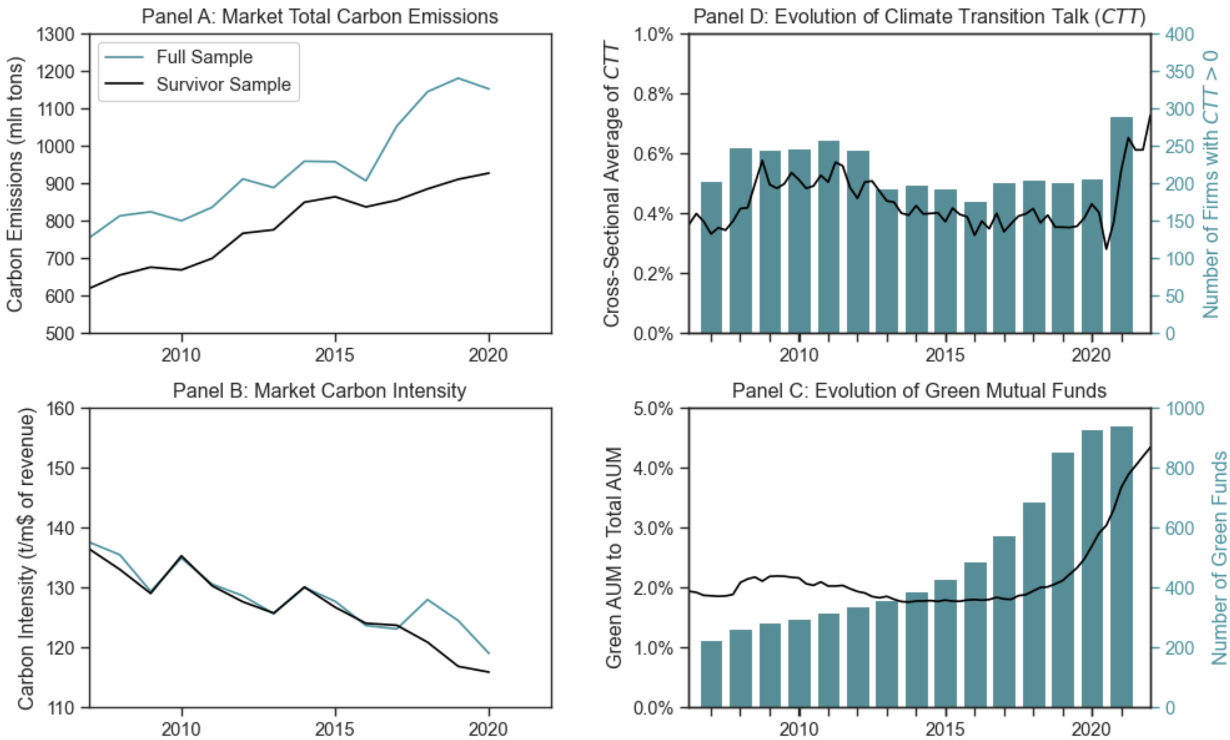
The figure shows the frequency with which our LDA model allocates a sample of terms to various topics. Each panel concerns a different term which is used as title. The x-axis indicates the topics most often associated with each terms. The y-axis denotes the percentage of time the term is attributed to the topics. Black bars indicate the climate transition topic, while blue bars are used for all other topics.

Figure 2: **Differences in Industry Portfolio Weights**



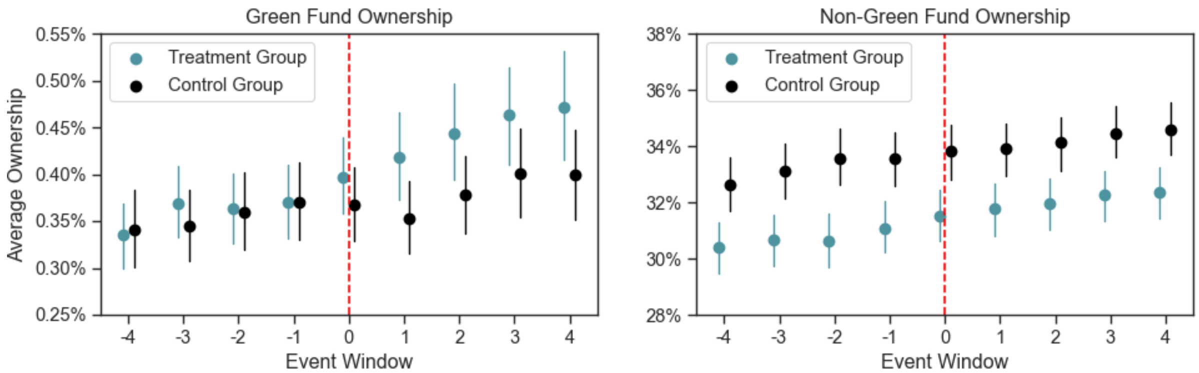
The figure shows the differences in GIC 6 industry portfolio weights between the aggregate green and non-green funds. We report the time series average of the difference between the two weights and only display the five industries with the most and the least discrepancies. A positive value on the x-axis means that green funds put more weight in the industry than brown funds.

Figure 3: **Green Finance in the Time Series**



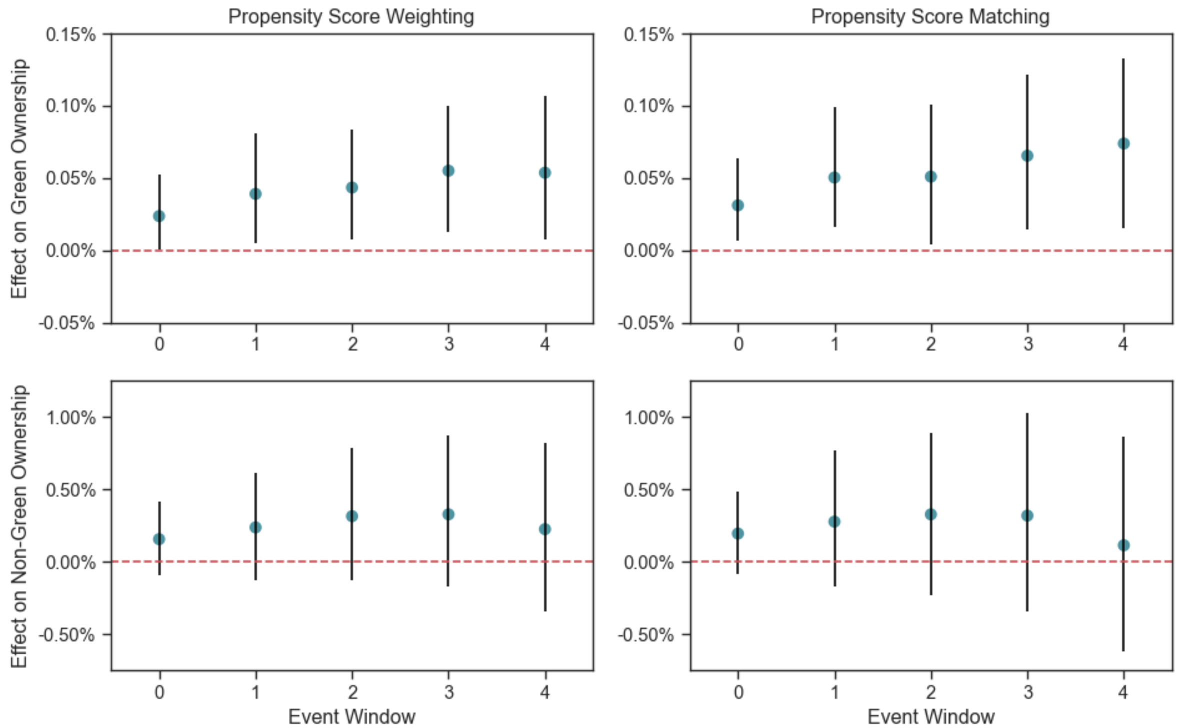
The figure illustrates the historical evolution of green finance from 2006 to 2021. Panel A exhibits the growth of yearly direct carbon emissions, CE, summed across firms. Direct emissions are the sum of scope 1 and scope 2 emissions. The blue line tracks the emissions of the full sample of firms, while the black one measures those of a survivor sample of firms present throughout our sample period. Panel B describes the evolution of the cross-sectional mean of carbon emissions intensities, CI. The blue line tracks the full sample of firms, while the black one measures the mean for a survivor sample of firms present throughout our sample period. Carbon emissions variables are winsorized at the 1st and 99th percentiles. Panel C tracks the evolution of green mutual funds. The blue bars denote the number of green funds in each year. The black line tracks the percentage of total AUM held by green funds. Total AUM is the sum of the AUM of all the funds in our sample. Panel D shows the historical evolution between 2006 and 2021 of the cross-sectional mean of climate transition talk in earnings conference calls. The blue bars count the quarterly average of the number of firms talking about the climate transition each year. The black line tracks the proportion of climate transition talk in the entire calls, CTT. The climate transition measures are winsorized at the 99th percentile.

Figure 4: **Fund Ownership around First Mentions of the Climate Transition**



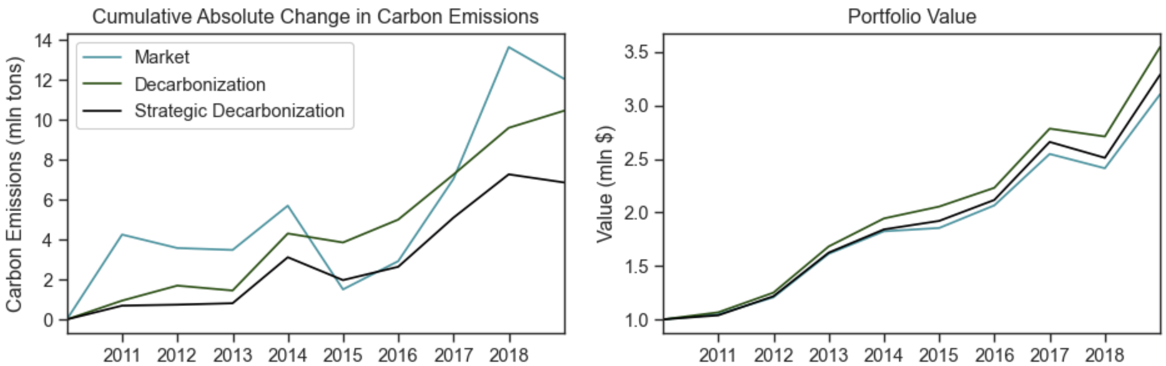
The figure shows the evolution of fund ownership around first mentions of the climate transition. An event is defined as an earning conference call which mentions the climate transition, but whose previous 8 calls haven't talked about it. The staggered events are aligned to occur at $t = 0$ in the event window. The treatment group, composed of 401 events, is matched to a control group of equal size. Matching is done within industry-quarter and is based on propensity scores. Propensity scores are computed at $t = -1$ from the covariates described in section 4.2. The panel on the left displays the cross-sectional average of green ownership FO^G, while the one on the right considers non-green ownership FO^{NG}. The black dots track the average ownership in the treatment group. The blue dots track the average ownership in the control group. The red dotted lines indicate the event time.

Figure 5: **Estimated Average Effect of First Mentions on Fund Ownership**



The figure shows the estimated average effects of mentioning the climate transition for the first time on fund ownership. The estimated effects are shown for the event time and the consecutive 4 quarters. The top panels display the effects on green ownership FO^G, while the bottom ones consider non-green ownership FO^{NG}. Results are shown for two matching techniques. Panels on the left use propensity score weighting to construct the matched control group. Panels on the right use single-nearest-neighbor propensity score matching. 95% confidence intervals are based on block-bootstrap using 1000 iterations (Otsu and Rai, 2017).

Figure 6: **Portfolio Performances**



The figure shows the cumulative environmental and financial performances of the market, decarbonization, and strategic decarbonization portfolio between 2010 and 2019. The market portfolio is a value-weighted market portfolio. The decarbonization portoflio is a value-weighted portfolio only including the 75% of total market capitalization with the best carbon intensities, and rebalancing the proceeds proportionally in remaining firms. The strategic decarbonization portfolio invests in the same firms than the decarbonization portfolio, but reinvests the proceeds from excluded firms only into those that discussed the climate transition in the previous year. The left panel measures the cumulative additional carbon emissions imputable to the portfolios. The right panel shows the evolution of the portfolios' values.

Table 1: **Variable Definitions**

Variable	**Source**	**Description**
Climate Transition Talk Variables		
CTT	Own	The proportion of the entire earnings conference call attributed to the climate transition topic by the trained LDA model.
$\boldsymbol{I}^{CT}$	Own	Takes the value 1 if the climate transition topic is discussed during the earnings conference call (i.e. $CCT > 0$), and 0 otherwise.
CTT^{Pres}	Own	The proportion of the presentation section of earnings conference call attributed to the climate transition topic by the trained LDA model.
CTT^{QA}	Own	The proportion the Q&A section of earnings conference call attributed to the climate transition topic by the trained LDA model.
Fund Ownership Variables		
FO^{Total}	Refinitiv	The percentage of shares outstanding held by all ETFs and mutual funds.
FO^{NG}	Refinitiv $\times$ Own	The percentage of shares outstanding held by non-green ETFs and mutual munds.
FO^{G}	Refinitiv $\times$ Own	The percentage of shares outstanding held by *green* ETFs and Mutual Funds.
Carbon Emissions Variables		
CE	Trucost	A firm's yearly absolute carbon emissions (scope 1 and 2) in tons.
CI	Trucost	A firm's carbon emissions intensity, a measure of relative carbon emissions (scope 1 and 2) defined as carbon scaled by yearly total revenue.
ΔCE	Trucost	A firm's yearly percentage change in absolute carbon emissions.
ΔCI	Trucost	A firm's yearly change in carbon emissions intensity.
CF^{P}	Trucost	Portfolio P's carbon footprint, measured as the sum through holdings of holding value divided by market capitalization times absolute carbon emissions.
CI^{P}	Trucost	Portfolio P's carbon intensity, measured as the portfolio's carbon footprint divided by the sum of holdings value divided by market capitalization times revenue.
Other Variables		
E-Score	Refinitiv	Refinitiv ESG's environment score.
Ln Size	Compustat-CRSP	The logarithm of total assets.
Ln Market-to-Book	Compustat-CRSP	The logarithm of the market value of equity divided by total assets.
Profitability	Compustat-CRSP	Income before extraordinary items, scaled by total assets.
Leverage	Compustat-CRSP	Book leverage.
Tangibility	Compustat-CRSP	Property, plants and equipment, scaled by total assets.
Investments	Compustat-CRSP	Capital expenditure, scaled by total assets.
EPS Surprise	I/B/E/S	The difference between realized earnings per share and the analyst consensus, scaled by price.
Ret^{P}	CRSP	Portfolio P's annual total return measured at year-end.

Table 2: **Climate Transition Talk Across Industries**

The table shows the prevalence of climate transition talk across GICS 4 industries. The first column presents the number of firms in each industry, while the second one describes the number of transcripts. The third column describes the percentage of transcripts that discuss the climate transition. The third column displays the cross-sectional mean of our main measure of climate talk, CTT, while the fourth column describes its cross-sectional mean conditional on mentioning the topic. The last two columns display the cross-sectional means of our measures of climate transition talk for the presentation and Q&A parts of the transcripts. The measures of climate transition talk have been winsorized at the 1st and 99th percentiles. CTT, $CTT_{>0}$, CTT^{Pres}, and CTT^{QA} are expressed in percentage points.

GICS 4	**Industry Name**	**# Firms**	$\frac{\sum \boldsymbol{I}_{it}^{CT}}{\#Obs}$	CTT	$CTT_{>0}$	CTT^{Pres}	CTT^{QA}
	All	4,446	0.14	0.84	5.95	1.02	0.63
	Without Utilities	4,347	0.12	0.46	3.92	0.58	0.36
1010	Energy	290	0.21	0.82	3.90	1.13	0.61
1510	Materials	202	0.22	0.64	2.86	0.87	0.53
2010	Capital Goods	411	0.34	1.71	4.98	2.04	1.33
2020	Commercial & Professional Services	168	0.18	0.70	3.84	0.82	0.56
2030	Transportation	76	0.11	0.24	2.06	0.38	0.19
2510	Automobiles & Components	45	0.23	0.72	3.06	0.86	0.59
2520	Consumer Durables & Apparel	169	0.03	0.04	1.67	0.08	0.05
2530	Consumer Services	183	0.03	0.05	1.72	0.07	0.05
2550	Retailing	229	0.02	0.03	1.64	0.06	0.03
3010	Food & Staples Retailing	38	0.08	0.26	3.30	0.40	0.24
3020	Food, Beverage & Tobacco	104	0.05	0.11	2.07	0.19	0.08
3030	Household & Personal Products	40	0.10	0.21	2.25	0.24	0.21
3510	Health Care Equipment & Services	456	0.03	0.09	3.01	0.11	0.09
3520	Pharma., Biotech. & Life Sciences	613	0.02	0.04	1.85	0.06	0.04
4510	Software & Services	548	0.04	0.19	4.61	0.24	0.15
4520	Technology Hardware & Equipment	327	0.12	0.48	3.88	0.60	0.38
4530	Semiconductors & Equipment	162	0.19	0.69	3.75	1.00	0.45
5010	Telecommunication Services	65	0.06	0.19	3.23	0.25	0.16
5020	Media & Entertainment	181	0.03	0.05	2.13	0.08	0.05
5510	Utilities	99	0.95	13.15	13.86	15.01	9.36
6010	Real Estate	40	0.11	0.52	4.63	0.64	0.40

Table 3: **Firm Characteristics Summary Statistics**

This table shows the main summary statistics for our sample of firms. The data is from the CRSP-Compustat, I/B/E/S, Refinitiv, and Trucost. Our sample includes all US-based firms that meet our data requirement between January 2006 and December 2021. We report the mean, standard deviation, and the three quartiles. All variables are defined in Table 1. Fund ownership variables have been winsorized at the 99th percentile. Carbon emissions variables and firm characteristics have been winsorized at the 1st and 99th percentiles.

	Count	**Mean**	**STD**	**25%**	**50%**	**75%**
Fund Ownership Variables						
FO^{Total}	145,653	24.57%	14.75%	12.16%	24.63%	35.54%
FO^{G}	145,653	0.26%	0.61%	0.00%	0.03%	0.25%
FO^{NG}	145,653	24.29%	14.60%	12.01%	24.35%	35.13%
Carbon Emissions Variables						
CE *(t)*	53,349	982,944	2,942,765	24,187	105,627	479,712
CI *(t/m$ of revenue)*	53,349	140.45	332.20	23.41	41.26	85.00
ΔCE *(%)*	44,818	10.44	42.53	-5.02	3.48	14.94
ΔCI *(t/m$ of revenue)*	44,818	-1.23	47.10	-2.78	-0.55	0.89
Control Variables						
E-Score	59,058	23.95	26.91	0.00	12.80	43.25
Ln Size	145,635	6.60	1.95	5.18	6.56	7.92
Ln Market-to-Book	138,138	0.99	0.88	0.40	0.91	1.49
Profitability	145,528	-0.01	0.07	-0.01	0.01	0.02
Leverage	140,304	0.35	0.35	0.04	0.29	0.52
Tangibility	145,408	0.22	0.22	0.06	0.14	0.31
Investments	145,405	0.01	0.01	0.00	0.01	0.01
EPS Surprise	126,702	-0.18	4.82	-0.14	0.07	0.36

Table 4: **Funds Summary Statistics**

This table shows the main summary statistics for our sample of funds. The data is from Refinitiv Lipper. Our sample includes all equity and mixed-assets funds invested in US-based firms between January 2006 and December 2021. We report the mean, standard deviation, and the three quartiles. All variables are defined in Table 1. Total net assets and numbers of holdings have been winsorized at the 99th percentile. All other variables have been winsorized at the 1st and 99th percentiles.

	Count	**Mean**	**STD**	**25%**	**50%**	**75%**
Green Funds	955					
Total Net Assets (m$)		440.09	920.67	48.03	142.93	411.08
Number of Holdings		81.97	143.50	18.00	31.00	68.00
Fund Flows		0.16	0.64	-0.03	0.01	0.10
Ret^P		0.13	0.31	-0.03	0.12	0.28
CF^P (t/m$ invested)		77.09	75.00	33.33	57.08	91.64
CI^P (t/m$ of revenue)		114.38	95.66	60.24	95.44	128.99
ΔCF^P (t/m$ invested)		0.57	7.45	-1.48	0.36	2.31
ΔCI^P (t/m$ of revenue)		0.81	9.56	-2.26	0.64	3.52
Non-Green Funds	8,009					
Total Net Assets (m$)		1,187.98	3,131.56	52.60	210.50	816.59
Number of Holdings		112.22	202.58	24.00	44.00	93.00
Fund Flows		0.10	0.53	-0.04	0.00	0.07
Ret^P		0.13	0.34	-0.05	0.11	0.29
CF^P (t/m$ invested)		80.92	80.45	29.56	60.03	99.80
CI^P (t/m$ of revenue)		110.39	99.25	51.43	93.50	129.21
ΔCF^P (t/m$ invested)		0.93	7.76	-1.29	0.45	2.68
ΔCI^P (t/m$ of revenue)		1.37	9.55	-1.91	0.77	4.06

Table 5: **Fund Ownership and Climate Transition Talk**

The table reports the results of regression (1). The dependent variable is the aggregate ownership of green funds, FO^{G}, in columns (1)-(2) and (5)-(8), of all funds, FO^{Total}, in column (3), and of non-green funds, FO^{NG}, in column (4). The independent variable of interest in columns (1)-(4) is our main measure of climate transition talk, CTT. In columns (5)-(6), the independent variables of interest are the alternative measure of climate talk, $\boldsymbol{I}^{CT}$, CTT^{Pres}, and CTT^{QA}. Column (7) considers the time period from 2006 to 2018. Column (8) considers the time period from 2019 to 2021. All specifications are panel regressions and include firm control variables and industry-quarter fixed effects. All variables are defined in Table 1. Standard errors are clustered at the firm level. t-statistics are in parentheses. ***, **, and * denote two-sided significance at the 1%, 5%, and 10% levels.

	(1) FO^{G}	(2) FO^{G}	(3) FO^{Total}	(4) FO^{NG}	(5) FO^{G}	(6) FO^{G}	(7) FO^{G}	(8) FO^{G}
CTT	0.1116***	0.1127***	-0.2274	-0.3819**			0.1117***	0.1087***
	(9.3927)	(6.4104)	(-1.4292)	(-2.3568)			(4.7726)	(6.1636)
$\boldsymbol{I}^{CT}$					0.2806***			
					(4.7716)			
CTT^{Pres}						0.0581***		
						(5.2349)		
CTT^{QA}						0.0602***		
						(4.0472)		
E-Score		0.0806***	-1.3966***	-1.4967***	0.0850***	0.0802***	0.0519***	0.1598***
		(4.9576)	(-5.0938)	(-5.5390)	(4.9558)	(4.9340)	(3.3585)	(6.0101)
Ln Size	0.1675***	0.1463***	3.2800***	3.1525***	0.1394***	0.1453***	0.0771***	0.1760***
	(19.810)	(7.5142)	(7.5907)	(7.4113)	(6.7824)	(7.4541)	(3.6736)	(6.6218)
Ln Market-to-Book	0.0571***	0.0736***	0.7072***	0.6305***	0.0734***	0.0734***	0.0161	0.1290***
	(8.1780)	(6.5547)	(2.8660)	(2.5830)	(6.3432)	(6.5392)	(1.4887)	(8.2283)
Profitability	-0.0021	0.0264**	1.8853***	1.8582***	0.0224*	0.0267**	0.0072	0.0370**
	(-0.3523)	(2.3318)	(6.7884)	(6.7743)	(1.8901)	(2.3551)	(0.6963)	(2.2122)
Leverage	-0.0318***	-0.0369**	-0.4934	-0.4701	-0.0356*	-0.0368**	-0.0048	-0.0762***
	(-2.8330)	(-2.0826)	(-1.3666)	(-1.3163)	(-1.9247)	(-2.0784)	(-0.2935)	(-2.7571)
Tangibility	-0.0295**	-0.0593***	-1.0802***	-1.0217***	-0.0549***	-0.0608***	-0.0762***	-0.0257
	(-2.4522)	(-3.4178)	(-3.1754)	(-3.0397)	(-3.0412)	(-3.5112)	(-4.8681)	(-0.9342)
Investments	0.0263***	0.0310***	0.1066	0.0717	0.0358***	0.0319***	0.0332***	0.0191
	(3.2792)	(2.7023)	(0.3404)	(0.2313)	(2.7997)	(2.7724)	(3.0588)	(0.9187)
EPS Surprise	-0.0030	0.0032	0.5454***	0.5418***	0.0025	0.0021	0.0130	-0.0008
	(-0.8057)	(0.4549)	(3.2583)	(3.2573)	(0.3778)	(0.3100)	(1.1447)	(-0.0829)
Time Period	2006-2021	2006-2021	2006-2021	2006-2021	2006-2021	2006-2021	2006-2018	2019-2021
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Observations	102,621	49,014	49,014	49,014	49,014	49,014	31,570	17,444
No. Firms	3,957	2,222	2,222	2,222	2,222	2,222	1,859	1,902
Adj. R-Squared	0.2053	0.1915	0.1768	0.1713	0.1638	0.1918	0.1243	0.2450

Table 6: **Carbon Intensities and Emissions by CTT and CI Categories**

This table shows the time-series averages of value-weighted carbon emissions variables across climate transition talk and carbon intensity categories Along the climate transition talk dimension, we group firms between those that talked about the climate transition in the previous year, and those that did not. Along the current carbon intensity dimension, we sort within each period firms by their current carbon intensity. Those belonging the 25%(75%) of total market capitalization with the highest(lowest) carbon intensity are labelled Excluded(Included). Panel A displays results for CI, the current carbon intensity, Panel B for the one-year forward change in carbon intensity ΔCI, and Panel C for the one-year forward percentage change in carbon emissions ΔCE. Standard errors are adjusted following Newey and West (1987) for one lag. t-statistics are in parentheses. ***, **, and * denote two-sided significance at the 1%, 5%, and 10% levels.

Panel A: Current Carbon Intensity, CI, (t/m$ of revenue)

	All	Included	Excluded	Included-Excluded
All	126.44***	32.19***	412.99***	380.79***
	(31.68)	(15.60)	(31.48)	(30.56)
No Talk	91.78***	31.07***	342.95***	311.88***
	(28.93)	(16.50)	(23.68)	(21.32)
Talk	275.33***	39.73***	539.67***	499.94***
	(19.04)	(12.04)	(32.57)	(31.85)
Talk-No Talk	183.55***	8.66***	196.72***	-
	(12.29)	(5.52)	(10.06)	-

Panel B: One-Year Change in Carbon Intensity, ΔCI, (t/m$ of revenue)

	All	Included	Excluded	Included-Excluded
All	-0.92	-0.61**	-2.04	-1.43
	(-0.34)	(-2.71)	(-0.19)	(-0.14)
No Talk	-0.98	-0.63***	-2.75	-2.12
	(-0.50)	(-3.11)	(-0.29)	(-0.22)
Talk	-1.20	-0.64	-2.15	-1.51
	(-0.18)	(-0.65)	(-0.16)	(-0.12)
Talk-No Talk	-0.23	-0.01	0.60	-
	(-0.04)	(-0.01)	(0.09)	-

Panel C: One-Year Percentage Change in Carbon Emissions, ΔCE

	All	Included	Excluded	Included-Excluded
All	6.69%***	8.04%***	2.56%***	-5.48%***
	(4.38)	(4.54)	(1.91)	(-3.37)
No Talk	7.38%***	8.67%***	1.73%	-6.94%**
	(3.95)	(4.24)	(0.85)	(-2.88)
Talk	3.44%***	3.29%***	3.20%**	-0.09%
	(3.51)	(3.11)	(2.64)	(-0.07)
Talk-No Talk	-3.95%***	-5.38%**	1.46%	-
	(-2.01)	(-2.21)	(0.65)	-

Table 7: **Portfolio Performances**

The table reports the financial and environmental performances of three portfolios. Reported number are time-series averages of yearly portfolio-level variables. The market portfolio is a value-weighted market portfolio. The decarbonization portoflio is a value-weighted portfolio only including the 75% of total market capitalization with the best carbon intensities, and rebalancing the proceeds proportionally in remaining firms. The strategic decarbonization portfolio invests in the same firms than the decarbonization portfolio, but reinvests the proceeds from excluded firms only into those that discussed the climate transition in the previous year. The last column tests the difference between the decarbonization and strategic decarbonization portfolios. All variables are defined in Table 1. Standard errors are adjusted following Newey and West (1987) for one lag. t-statistics are in parentheses. ***, **, and * denote two-sided significance at the 1%, 5%, and 10% levels.

	Market	Decarbonization	Strategic Decarbonization	Difference
		Financial Performance		
Ret^P	0.14***	0.16***	0.15***	0.01
	(4.06)	(4.66)	(4.29)	(1.77)
		Current Environmental Performance		
CF^P	81.03***	22.70***	24.57***	-1.87***
	(15.98)	(11.22)	(10.15)	(-3.70)
CI^P	124.54***	35.53***	36.46***	-0.94**
	(117.23)	(43.01)	(38.61)	(-2.74)
		One-Year Environmental Performance		
ΔCF^P	0.77	0.56***	0.38**	0.18**
	(1.35)	(4.89)	(2.42)	(2.55)
ΔCI^P	-2.65***	-0.21	-0.50***	0.29
	(-5.55)	(-1.44)	(-2.00)	(1.80)

Appendix A Complementary Tables

Table A.1: **Estimated Average Effect of First Mentions on Green Ownership**
This table reports the estimated average effects on green ownership of mentioning the climate transition for the first time. t-statistics based on block-bootstrap using 1000 iterations (Otsu and Rai, 2017) are in parentheses. ***, **, and * denote two-sided significance at the 1%, 5%, and 10% levels.

	$\hat{\delta}(0)$	$\hat{\delta}(1)$	$\hat{\delta}(2)$	$\hat{\delta}(3)$	$\hat{\delta}(4)$
Propensity Score Weighting					
Green Ownership	0.0237**	0.0390**	0.0433**	0.0548**	0.0533**
	(1.8733)	(2.1112)	(2.2156)	(2.3972)	(2.0758)
Non-Green Ownership	0.1487	0.2296	0.2986	0.3069	0.1974
	(1.1355)	(1.1828)	(1.2409)	(1.1087)	(0.6429)
Propensity Score Matching					
Green Ownership	0.0312***	0.0503***	0.0516**	0.0649***	0.0727**
	(2.1518)	(2.4474)	(2.2008)	(2.4121)	(2.4505)
Non-Green Ownership	0.1868	0.2564	0.2937	0.2750	0.07377
	(1.2446)	(1.1023)	(1.0233)	(0.8239)	(0.1970)

Table A.2: **Green Mutual Funds Objectives Samples**

This table exhibits the self-declared objectives (our emphases) of five of the funds we labelled as *green*.

Fund Name	**Universe**	**Geo. Focus**	**Objective**
iShare Global Clean Energy ETF	ETF	Global	The Fund seeks to track the investment results of the S&P Global Clean Energy Index, which is designed to track the performance of approximately 100 clean energy-related companies. Under normal market conditions, the Fund generally will invest at least 80% of its assets in the component securities of its Underlying Index.
WisdomTree Cloud Computing UCITS ETF	ETF	USA	Fund seeks to track the price and yield performance, before fees and expenses, of the BVP Nasdaq Emerging Cloud Index. The Index is designed to track the performance of emerging public companies primarily involved in providing cloud software and services to their customers (each an Emerging Cloud Company) as determined by Bessemer Venture Partners (BVP). The Index employs an equal weighting methodology such that the selected securities are equally weighted with in the Index. The Index exludes companies based on environmental, social and governance criteria.
BlackRock Sustainable Advantage Lrg Cp Core	Mutual Fund	USA	The Fund seeks to provide total return while seeking to maintain certain environmental, social and governance characteristics, climate risk exposure and climate opportunities relative to the Funds benchmark. The Fund invests at least 80% of its net assets in large cap equity securities and derivatives.
Fidelity Funds American Growth	Mutual Fund	USA	The fund aims to achieve long-term capital growth, principally through a focused portfolio invested in companies having their head office or exercising a predominant part of their activity in the US. A minimum of 50% of the funds net assets will be invested in securities deemed to maintain sustainable characteristics. Environmental characteristics include but are not limited to climate change mitigation and adaptation, water and waste management, biodiversity, while social characteristics include but are not limited to product safety, supply chain, health and safety and human rights.
Calvert Global Water Fund	Mutual Fund	Global	The Fund seeks growth of capital through investment in equity securities of companies active in the water-related resource sector. The Fund employs corporate responsibility standards and strategies.

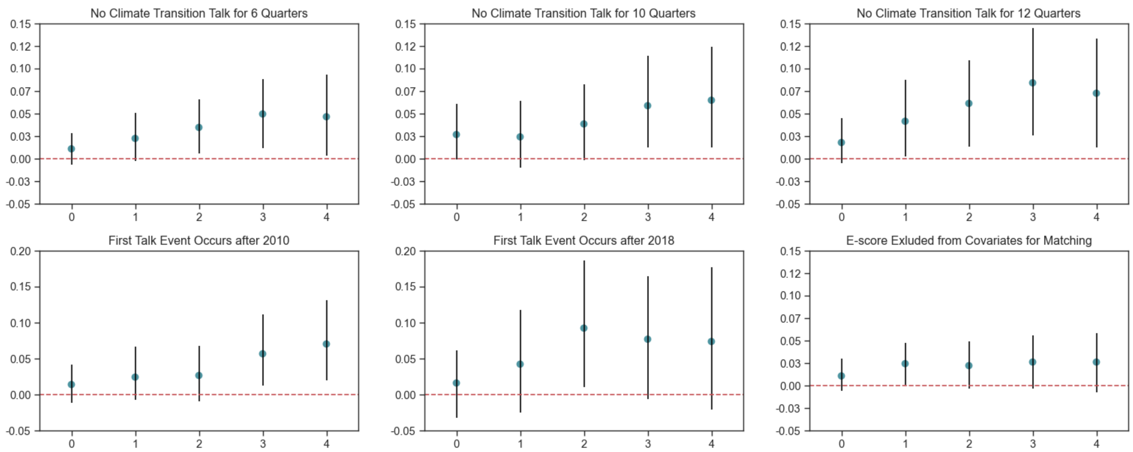
Table A.3: **Climate Transition Text Samples**

This table shows text samples of earnings conference call for which LDA has identified some climate transition talk.

Firm	**Industry Name**	**Quarter**	**CTT**	**Text Sample**
ADA ES	Materials	Q3 2009	18.55%	However, because of the health related issues there is a significant societal mandate to burn coal cleaner which creates increasing markets for our technologies. [...] The next topic relates to our business to provide our power generation customers with technologies to capture carbon dioxide from coal-based plants.
FuelCell Energy	Capital Goods	Q2 2018	28.47%	We're also working hard to implement our strategy for affordable distributed hydrogen and infrastructure to reduce emissions from the transportation sector, a significant source of CO2 and NOx globally. [...] Automakers, truck and bus manufacturers and industrial lift manufacturers have all indicated that fuel cells will have a role in cleaning up the transportation emissions issue we face globally
Tesla	Automobiles & Components	Q3 2019	10.46%	The energy teams have made great progress in both our solar and energy storage businesses. [...] Tesla's mission from the beginning has been to accelerate the advent of sustainable energy. That means sustainable energy generation and sustainable energy consumption in the form of vehicles, electric vehicles.
Darling Ingredient	Food, Beverage & Tobacco	Q3 2021	7.23%	Our M&A funnel of opportunities to grow our low CI feedstock footprint around the world and grow our green bioenergy production capabilities is rising.
Metabilix	Pharma., Biotech. & Life Science	Q3 2007	2.28%	Our evaluation and testing has revolved around five areas,the physical properties of Mirel, its biodegradability, low carbon footprint, high renewable carbon content and FDA food contact approval. [...] Mirel actually has a negative CO2 footprint. [...] Because Mirel is made from corn and utilizes renewable energy in its production, the environmental benefits are significant.
Apple	Technology Hardware & Equipment	Q2 2017	1.14%	I'm very proud to mention that we recently released our 10th annual Environmental Responsibility Report reflecting our amazing progress. In 2016, 96% of the electricity used at Apple's global facilities came from renewable sources of energy, reducing our carbon emissions by nearly 585,000 metric tons. We're now 100% renewable in 24 countries, including all of Apple's data centers. There's much more work to be done, but we're committed to leaving the world better than we found it.
Alphabet	Media & Entertainment	Q3 2019	1.63%	Finally, to round out a busy quarter, sustainability has always been a core value for us, and I'm proud that we have been carbon neutral since 2007. In September, we announced the biggest corporate purchase of renewable energy in history. We are increasing Google's existing renewable energy portfolio by more than 40%. These purchases are happening globally, spurring the construction of more than $2 billion in new energy infrastructure including millions of solar panels and hundreds of wind turbines across 3 continents.
Alexander & Baldwin	Real Estate	Q2 2014	3.22%	This investment reinforces Alexander & Baldwin's century-long commitment to generating clean, renewable energy for our island communities. We continue to actively seek out opportunities for additional renewable energy investments in Hawaii.

Appendix B Complementary Figures

Figure B.1: **Green Ownership around First Mentions of the Climate Transition**



The figure shows the evolution of green ownership around first mentions of the climate transition.

Appendix C LDA and Earnings Conference Calls

C.1 Latent Dirichlet Allocation

LDA is a natural language processing tool designed to uncover the hidden thematic structure behind a corpus of documents. In its "bag-of-words" representation, a corpus is characterized by a document-term matrix w of dimension $V \times D$, where D and V are respectively the number of documents and the number of terms in the corpus. V is usually very large, making the document-term matrix difficult to interpret. LDA seeks to reduce the dimensionality of the corpus representation by limiting it to a chosen number of topics $K < V$. It does so by assuming documents are created by a probabilistic process.

LDA sees each documents as a mixture over the K latent topics common to the entire corpus. A document d is represented by a probability distribution θ_d over topics, where a high probability means that more textual content is attributed to this particular topic. Similarly, topic k is characterized by a probability distribution β_k over terms. A term with a large probability conveys a high topical content. Technically, LDA assumes that each word n in document d is drafted using the following process:

(i) Choose a topic $z_{d,n} \sim \text{Multinomial}(\theta_d)$

(ii) Choose a word $w_{d,n} \sim \text{Multinomial}(\beta_{z_{d,n}})$

where $z_{d,n} \in 1, ..., K$, and $w_{d,n}$ is a term from the corpus vocabulary.

While we observe both the documents and the vocabulary set, the per-document topic distributions $\boldsymbol{\theta} = [\theta_1, ...\theta_D]$ and the per-corpus topic distributions $\boldsymbol{\beta} = [\beta_1, ...\beta_K]$ are unobserved. LDA learns these hidden variables directly from the data. Concretely, inference is performed by balancing two objectives (Blei, 2013). First, the terms within each document must be allocated to as few topics as possible. Second, each topic must assign high probabilities to as few terms as possible. These two objectives clash since facilitating the first renders the second comparatively harder to achieve. Resolving this trade-off yields the optimal topics by identifying groups of co-occurring terms.

C.2 Corpus of Earnings Conference Call Transcripts

We build a text corpus from the transcripts of earnings conference calls provided by Refinitiv Eikon. We include the transcripts of all earnings conference calls held by US firms between January 2006 and December 2021. Typically, an earnings conference call starts with a presentation by the firm's management and finishes with a Q&A session in which analysts ask for additional details and interact with managers. We drop short transcripts whose presentation initially contains less than 100 words, and only keep the transcripts of firms finding a match in Compustat. Our final sample is composed of 143,098 transcripts concerning 4,446 firms.

Table C.4: **Earnings Conference Call Transcripts Summary Statistics**
This table shows the main summary statistics for our sample of earnings conference call. The data is from Refinitiv Eikon. Our sample includes the quarterly earnings conference calls transcripts of US-based firms occurring from January 2006 to December 2021. We report the mean, standard deviation, and the three quartiles.

	Count	**Mean**	**STD**	**25%**	**50%**	**75%**
Earnings Conference Calls	143,096					
Firms	4,446					
Number of Sentences (Pres)		136.99	55.40	100.00	131.00	166.00
Number of Terms (Pres)		1,884.47	662.96	1,397.00	1,871.00	2,349.00
Number of Questions		27.01	17.38	14.00	24.00	37.00

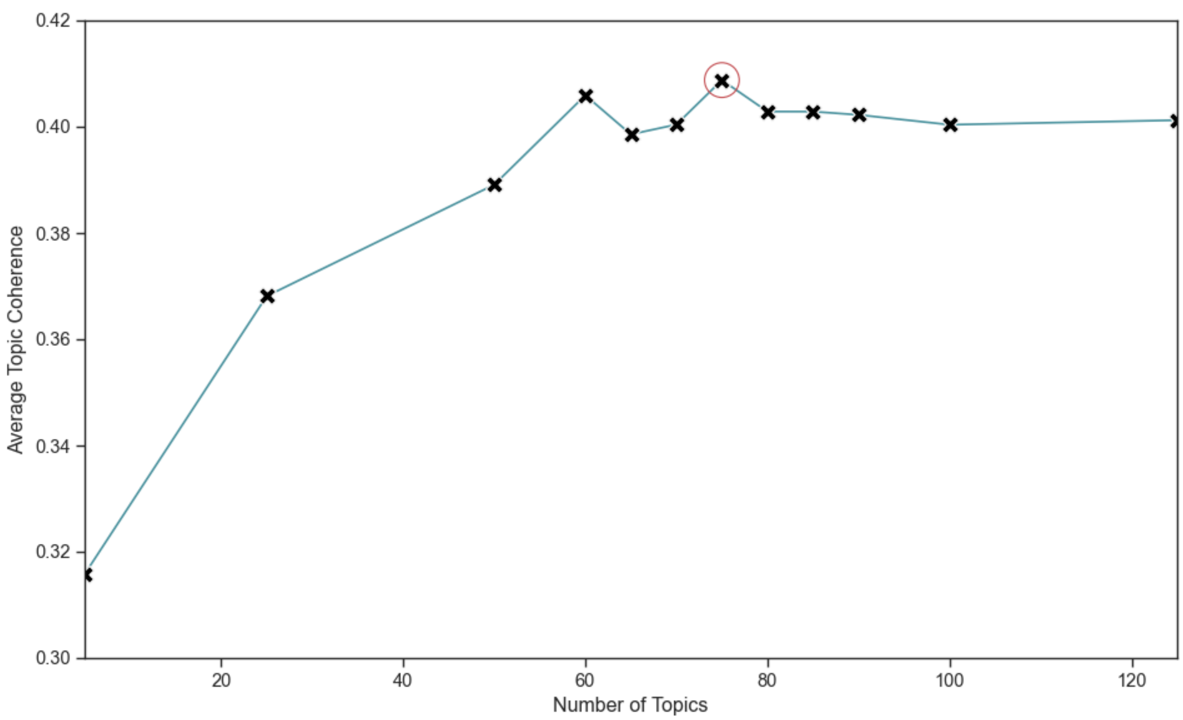
The vocabulary built from all words appearing in at least one transcript is vast. However, many of these words are uninformative when analyzing the topical content of a discussion (e.g., filler words). We apply standard cleaning procedures in natural language processing, thus restricting our vocabulary to 3,679 meaningful terms.[23] We complement our vocabulary of 3,549 words with 171 frequent bigrams or two-word idioms, and consequently change our nomenclature from words to terms. The content of the earnings conference call corpus is now summarized in a document-term matrix of dimensions 143,098 by 3,720.

[23]Mainly, we remove stop words and short words of three characters or less. We drop terms occurring in more than 80% of calls or less than 1% of them.

C.3 Topics in Earnings Conference Calls

Successfully employing the LDA algorithm requires selecting the appropriate number of topics as the algorithm does not autonomously determine it. Increasing the number of topics improves clarity up to a certain threshold. A model with too few topics generates imprecise topics spanning multiple subjects, while bulky models are overly complex and hinder interpretation. In this paper, we estimate multiple LDA models using various numbers of topics ranging from 5 to 125. To guide our choice, we rely on topic coherence, a measure of topic interpretability (Röder, Both, and Hinneburg, 2015). Figure C.2 shows that average topic coherence stops notably improving beyond 60 topics. We manually inspect the topics of models in this neighborhood and establish that 75 topics give the most readable results.

Figure C.2: **Optimal Number of Topics**



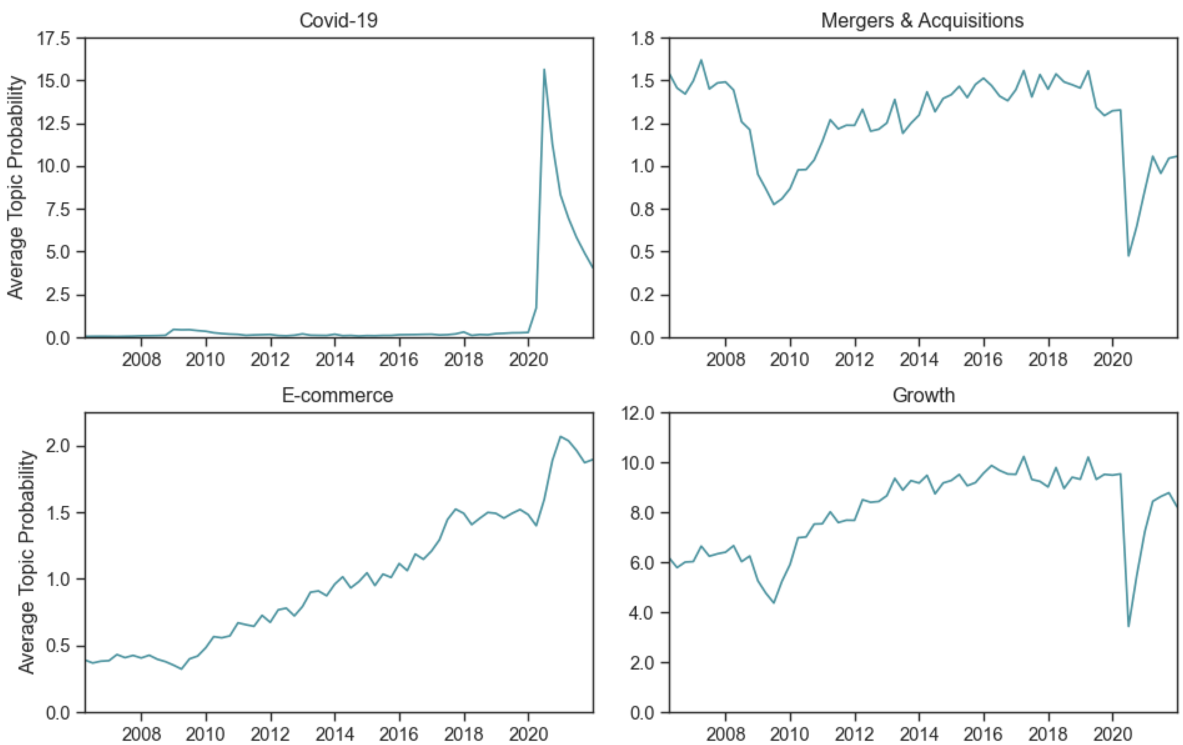
The figure illustrates the process used to select the optimal number of topics for LDA. We trained multiple LDA models using different numbers of topics, and sought to maximize average topic coherence. Topic coherence is a measure of topic interpretability. Each black cross marks the average coherence across topics for one of the trained model. The red circle highlights the model used in this paper.

We manually label the 75 topics. Since the model's input is earnings conference calls, we unsurprisingly identify many topics related to company results and earnings guidance. Beyond those, there are several clusters of more specific words related to various sectors, technologies, and business models. We identify a topic whose terminology include many terms linked to the climate transition such as "solar", "wind", "renewable", and "carbon", and label it "Climate Transition". It is worth noting that, by selecting the 75-topic model, we chose the model with both the highest average coherence within topics, and the highest coherence score for the climate transition topic. In other words, among the model we trained, the 75-topic model offers the most interpretable set of topics, as well as the most interpretable climate transition topic.

To bolster confidence in our LDA model, we provide four illustrative examples of how identified topics fit expected patterns. Figure C.3 reports the extent to which the topics "Covid-19", "Mergers & Acquisitions", "E-commerce" and "Growth" were discussed during earnings conference calls. These four patterns depict the evolution of these two topics over time, and thoroughly match what expectations would dictate. The "Covid-19" topic is flat for most of our sample, and spikes up only after the first Covid-19 outbreak in Wuhan at the end of 2019. The topics "Mergers & Acquisitions" and "Growth" exhibit sharp declines after the bankruptcy of Lehman Brothers in September 2008 and the Covid-19 outbreak. Finally, the topic "E-commerce" shows a steady growth throughout our sample period.

Overall, Figure C.3 shows that our application of LDA does not only deliver consistent clusters of words, but also an effective and informative description of the concerns that managers raise during earnings conference calls. We argue that these dynamics provide a solid qualitative validation of our model, and strongly suggests that we are not capturing noise in the transcripts.

Figure C.3: **Illustrative Topics in Earnings Conference Calls**



The figure illustrates the ability of LDA to accurately capture time series variations in the topical content of earnings conference calls. We use four topics from our LDA model, "Covid-19", "Mergers & Acquisitions", "E-commerce" and "Growth". The blue lines trace for each of the four topic the cross-sectional average topic distribution for all sample firms within each calendar quarter.