Carbon-Transition Risk and Net-Zero Portfolios *

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Abstract

Net-zero portfolios (NZP), which aim to reduce carbon footprint exposure to zero by a target date, are becoming a popular vehicle to align investors' incentives with climate scenarios. We characterize the decision and timing to divest companies from NZP using a novel forward-looking measure, distance-to-exit (DTE), which calculates the distance, in years, until a company gets excluded from NZP. Companies with greater DTE values have higher valuation ratios and lower expected returns, consistent with the idea that DTE captures carbon-transition risk. The effect is stronger when climate pressure intensifies, and it is robust to various specification choices.

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1 Introduction

The growing concerns about climate change motivate the need for a transition away from fossil fuels to renewable energy. The resulting uncertainty about the process generates risk for companies and investors in the economy. Such transition risk embodies a wide range of shocks, including changes in climate policy, reputational impacts, shifts in market preferences and norms, and technological innovation. The measurement and scale of transition risk are some of the key questions tackled by the literature on climate finance. Two approaches have gained the most popularity in the literature. The first one (e.g., Bolton and Kacperczyk, 2022b) utilizes firm-level greenhouse gas data to quantify exposures to transition risk based on the idea that the social planner aims to achieve net-zero emissions in the future. In this approach, transition risk exposures are proportional to the size of expected decarbonization efforts, measured by either levels or changes in carbon emissions. The second approach (e.g., Kölbel et al., 2022; Sautner et al., 2023) uses textual analysis to measure exposure to transition risk based on regulatory disclosures or corporate communication of decarbonization plans. The benefit of the first approach is its direct quantitative link to a specific objective function, net-zero emissions, whereas the advantage of the second approach is its forward-looking nature. However, to date, there is no approach that would integrate the two economic ideas into a single transition risk metric. In this paper, we propose a novel framework for measuring transition risk that combines the scientific social objective to decarbonize the economy with the forward-looking elements of risk and examine whether such measures are priced in the cross-section of global stocks.

The starting point for building our measures of transition risk is the concept of net-zero portfolios (e.g., Bolton et al., 2022). Net-zero portfolios (NZP) aim to reduce carbon footprint over time, typically until 2050, by mimicking scientific paths of decarbonization for the global economy. The economic idea behind them is to reward companies that undertake emissions reduction, by including such companies in NZP, and to penalize companies that are behind the decarbonization curve, by excluding them from NZP. Their popularity among institutional investors has been rapidly growing, with more than \$130 trillion of assets under management currently covered by various initiatives.[1] The NZP initiative has also shaped discussions surrounding sustainable finance, as is the case for the EU Low-Carbon Benchmark Regulation, which establishes uniform rules for low-carbon investment benchmark indexes and sets their required decarbonization trajectories.[2]

Important in the NZP framework are scientific decarbonization paths that imply the dynamic carbon budget (in terms of their portfolio holdings' carbon footprint) that investors can allocate to their portfolio holdings every year. Given this budget, investors follow specific hierarchies of firms in terms of their efforts to decarbonize, and decide which stocks to select for their portfolios. Companies that do not fit within the budget of the portfolio are removed from NZP. As the budget gets progressively tighter, companies are more likely to exit NZP unless they change their own emissions or other attributes that make investors decide about which assets to hold. Companies for which the exclusion threat is greater face more pressure. We measure such exposures using the distance in years until the expected exclusion from the NZP takes place, and define them as distance-to-exit (DTE). We argue that DTE are forward-looking measures of carbon-transition risk implied by investor preferences, and thus investors should require compensation for bearing such risk. Moreover, given the economic importance of the net-zero movement, such pricing effects could be sizable.

There are at least three channels through which the pricing effect can operate. First, divestment by a significant fraction of investors can reduce risk sharing, and thus affect equilibrium returns (e.g., Merton, 1987). Second, given that asset prices discount future portfolio decisions, any expectation of future divestment could also affect prices. Finally, through net-zero portfolios, investors can communicate expectations of future divestment to corporates, and thus allow corporates to adjust their emissions to avoid potential penalties. With the expectation of a meaningful adjustment of emissions, investors would reprice their holdings. Notably, this last communication channel uncovers a new insight, namely, NZP can be modes of both divestment and engagement. In addition, across these three channels, an important economic force is the competition effect among companies to stay in NZP, which injects an element of uncertainty into prices.

[1] See, for example, https://www.netzeroassetmanagers.org/; https://www.unepfi.org/net-zero-alliance/; and https://www.unepfi.org/net-zero-banking/.

[2] See https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32019R2089.

In our empirical analyses, we consider various implementations of *DTE*. Our first set of *DTE* assumes constant-rate decarbonization paths. In this setting, investors, at each point in time, decarbonize their portfolios to near-zero emissions by 2050, and thus reduce their carbon budget at a constant rate, subject to not exceeding the total cumulative budget up to 2050. Next, given the budget, investors select stocks for their portfolios using the following three decision schemes. In the first one, they use companies' current total emissions; in the second one, their predicted total emissions; and in the third one, their ambition to decarbonize. The last measure is expressed as a composite, *Ambition Score*, metric integrating three inputs: (1) current and past emission levels; (2) current and past emission intensities; and (3) forward-looking decarbonization plans, including decarbonization commitments, green innovation, green governance, or greenwashing incentives. For each of the three sorting variables, we also obtain industry-adjusted counterparts, which, in total, adds up to six different *DTE*.

Next, we study the main determinants of *DTE* using a large panel of global firms with emissions and other firm characteristics, sampled over the 2005-2021 period. All *DTE* are negatively correlated with firm emissions, book leverage, and monthly stock return volatility, consistent with the hypothesis that *DTE* captures equity risk. *DTE* are also negatively related to stock market capitalization and dollar trading volume, but the correlations here get weaker for *DTE* based on *Ambition Score*. In turn, all *DTE* are positively related to firms' measures of property, plant, and equipment and firm age. When it comes to other firm characteristics the results are more mixed. For example, *DTE* based on emissions are positively related to firms' *ROE*, investment-to-assets, and past stock returns, but the correlation is negative for *DTE* based on *Ambition Score*.

One concern when implementing the NZP framework is a potential for the portfolio to drift away from the market portfolio. We show that such drift in our sample is relatively modest. Even though, as expected, we find that the dynamics of NZP generates an uneven exclusion of certain sectors and stocks, the basic properties of the portfolios relative to the market portfolio are not very different. This finding is particularly true for *DTE* portfolios that account for industry-fixed effects. We also do not find any strong evidence that NZP underweight large companies and thus they are unlikely to bear significant transaction costs and illiquidity risk.

Next, we study the question of whether DTE are priced by investors in the stock market. We first relate DTE to next month's stock returns. Our empirical specification is based on a pooled cross-sectional regression framework of Bolton and Kacperczyk (2021), and includes a host of firm-level characteristics, as well as country-, industry-, and time-fixed effects. Across all specifications, we find a statistically strong negative association between DTE and stock returns. The results are economically large: a one-standard-deviation increase in DTE for a given cross-section of firms is associated with an approximate $3.5-4.5$ percentage-point reduction in next month's annualized stock returns. We further find that while the predictive power of DTE decreases into the future, it remains considerably significant, even for one-year-ahead stock returns. These results support the hypothesis that companies with lower DTE are more risky and investors require higher compensation from them.

A common challenge with the interpretation of stock returns data is the distinction between expected and realized returns. In line with previous studies, we provide additional evidence using valuation regressions. The benefit of using this approach is that valuation ratios are less noisy than stock returns. Further, we can control for future cash flows, and thus the interpretation of our results is more aligned with the pure discount rate effect. In our tests, we consider three measures of firm value, price-to-earnings, price-to-book, and price-to-sales. We find a strong positive correlation between DTE and almost all measures of values. These results are consistent with the view that companies subject to stronger NZP pressure are priced with lower multiples than those for which the pressure is lesser.

In another test, we examine whether the DTE premia also accrue on the extensive margin, that is, whether companies which never exit NZP are priced differently than those that do exit at any point up to and including 2050. We find a very strong statistical difference in stock returns between the two groups of stocks, for all measures of exit. The results are also economically large. Companies that exit have higher annualized returns by about $3.5-5$ percentage points. Thus, the pressure from institutional investors matters both at an intensive and extensive margin.

Our findings strongly support the risk-based explanation of the cross-sectional variation in stock returns. Given the nature of our exit measures, the most natural interpretation is that of transition risk. This interpretation is further supported by our next test in which we relate the size of the exit premium to a shift in transition risk due to Paris Agreement. This shock has been previously applied in studies of climate risk. Using our regression framework, we find that the cross-sectional premium in stock returns roughly doubles when we measure risk premia using either stock returns or price-to-earnings ratios. The results are statistically weaker for exit measures based on *Ambition Score*. Notably, most results are statistically significant even before 2015. Another finding that supports the transition-risk interpretation is the strong correlation between DTEs and other proxies of transition risk, such as emission levels, their growth, and *Ambition Score*. A natural question to ask is to what extent DTE capture the same variation as other climate-related measures. We answer this question using our basic regression model with additional controls for such measures. As expected, we find that some of the variation in DTE can be explained by the other variables. Nonetheless, the coefficients of DTE retain their sign and statistical significance. These results paint two important conclusions. First, DTE carry independent stock return variation. Second, the explanatory power of DTE stems from both the signals on which we sort stocks and the carbon budget that moderates the inclusion of stocks into NZP.

In the last part of the paper, we provide additional robustness to our findings. First, our results hold when we exclude scope 3 emissions, which are sometimes regarded as more noisy. Second, the effect of DTE on stock returns interacts with the firm-level decision to disclose their climate data directly, but if anything, the decision to disclose emissions amplifies rather than mitigates the size of the return premium. Third, our results are robust to different choices of decarbonization paths. Here, we consider a number of possibilities, such as: (a) the budget is kept constant for some time and then investors decarbonize their portfolios' footprint at a constant, but faster rate; (b) investors decarbonize their portfolios at a faster (slower) rate for the first half of the remaining period and then at a slower (faster) rate for the second half; (c) investors follow a more sophisticated science-based decarbonization path (of Andrew (2020)). We find very similar magnitudes of the return differences among firms across all the paths. Finally, we consider regressions excluding industry-fixed effects and stock characteristics related to firm size, and find that our results are not significantly affected by such choices. Overall, our results indicate a strong and robust relation between firms' DTEs and their equity values, consistent with the view that NZP are a source of transition risk for companies with different degrees of ambition to decarbonize.

Our paper is related to various strands of a recent literature on climate finance. First, we extend the literature on firm-level transition risk (e.g., Bolton and Kacperczyk, 2021, 2022b; Sautner et al., 2023) by proposing novel measures of such risk. In contrast to previous studies that either solely rely on the past emission data or use soft textual measures subjected to reporting biases, our DTE measures integrate both past and future climate-related information, and they are tightly linked to scientific evidence through the concept of decarbonization paths. Second, our paper parallels recent literature on NZP. The closest papers to ours are Bolton et al. (2022), which introduces the specifics of NZP, and Jondeau et al. (2021) and Cheng et al. (2022), which apply a similar methodology and extend it to corporate and sovereign bonds, respectively. We extend the basic framework of these studies in two critical dimensions: (a) by considering various paths of decarbonization, and (b) by using different signals that investors can use to sort companies into portfolios. Most important, we use the NZP framework to derive firm-specific measures of transition risk and show that they are related to the cross-section of stock returns and their equity valuation ratios.

Third, our paper relates to studies emphasizing the role of institutional investors for transition risk (e.g., Engle et al., 2020; Krueger et al., 2020; Pedersen et al., 2021; Pastor et al., 2023; Atta-Darkua et al., 2023). In contrast to these studies, we focus on the specific investment principle that institutional investors apply, net-zero portfolios, and link the resulting pressure to firm values. In this regard, our paper is the first one to formally integrate institutional investors' pressure in measures of transition risk. Fourth, our paper is related to studies that discuss the importance of institutional investors in the context of divestment (e.g., Heinkel et al., 2001; Andersson et al., 2016; De Angelis et al., 2022; Berk and van Binsbergen, 2022; Ceccarelli et al., 2023) and firm engagement (e.g., Gillan and Starks, 2000; Broccardo et al., 2022). These studies aim to show the different ways in which institutional investors can affect firm value and its cost of capital. Notably, they typically focus on one specific channel, or, in some ways, tend to assess the relative importance of divestment vs. engagement. Our study is different in at least two aspects. First, we study the economic importance of *both* expected and observed divestment, which means that our framework does not necessarily require significant exclusionary forces. Second, we argue that the threat of future divestment can be a form of engagement with firms to decarbonize their operations if they want to stay in the portfolio.

Finally, at a more general level, our paper can be interpreted as a new approach to testing duration-based asset pricing models (e.g., Lettau and Wachter (2007)). Different than the literature on the topic that resorts to measures based on time-series resolution of cash-flow risks, we show the timing differences that are directly built into discount rates through the DTE measures. The advantage of our approach is that it does not rely on specific assets, such as dividend strips, to generate differences in timing of risks; instead, it relies on the specific characteristic of stocks that are time dependent (DTE).

The rest of the paper proceeds as follows. In Section 2, we describe the details of our methodology to construct DTE, and summarize the data. Section 3 presents details on the empirical properties of DTEs. Section 4 reports results from the regression models relating DTE to stock returns and valuation ratios, and discusses various extensions and robustness. Section 5 concludes.

2 Methodology & Data

In this section, we describe the methodology and the data we use to construct DTE measures. The starting foundation for DTE is the concept of net-zero portfolios (NZP), adapted to our framework following the work of Bolton et al. (2022). Important in this concept are two elements: a) dynamic carbon budget, applied by investors in their portfolio decisions, which is informed by scientific projections about climate scenarios, and determines the maximum amount of emissions NZP can be exposed to at each point in time until the final period, and b) the rule by which investors select companies into NZP. Next, we describe the details to calculate DTE. Finally, we provide summary statistics related to the main variables we use in our analyses. Our data set covers a large sample of global firms with available historical and forward-looking carbon emissions metrics and other firm characteristics over the 2005-2020 period.

2.1 Net-Zero Portfolios

Net-zero portfolios (NZP) aim to reduce carbon footprint over time, typically until 2050, by mimicking scientific paths of decarbonization for the global economy. Even though NZP by themselves do not guarantee the decarbonization of the global economy, they aim to provide incentives for the companies to do so. Specifically, the idea is to reward companies that undertake emissions reduction, by including such companies in NZP, and to penalize companies that are behind the decarbonization curve, by excluding them from NZP.

2.1.1 Dynamic Carbon Budget

The starting point for constructing the portfolio budget is the global carbon budget. The global budget is defined as the amount of aggregate emissions that can be maximally produced to adhere to scientifically determined climate scenarios informed by temperature changes. In theory, many carbon budgets are possible, as long as different scenarios are being considered; in practice, some scenarios are more popular than others. In our paper, we focus on one such scenario, in which the Intergovernmental Panel on Climate Change (IPCC), the leading provider of climate data, estimates that in order to limit the global temperature rise to below 1.5°C compared to pre-industrial levels, with 83% probability, one would need to limit global emissions to 300 GtCO2 as of the beginning of 2020 (IPCC, 2021). To get a better sense of this number the following thought exercise can be useful. The Global Carbon Project, a consortium of scientists, estimates that global emissions in 2020 reached 39.3 GtCO2;[3] which means that the remaining budget as of beginning of 2021 is 260.7 GtCO2. Assuming a scenario in which emissions stay constant into the near future, the remaining budget would be depleted within 6.6 years (260.7/39.3). These findings underscore the urgency of addressing emissions reduction to sustainably manage the finite carbon budget and to attain critical climate objectives.

Given the global carbon budget, we can construct the portfolio carbon budget as follows. First, we define the investable universe, which includes stocks on all publicly traded firms in the Trucost data set, our source of emissions data. Second, we sum up scope 1–3 emissions

[3] See `https://globalcarbonbudget.org/`.

from all such firms in a given year (e.g., 24.8 GtCO2e in 2020). Third, assuming that the rate of portfolio decarbonization is proportional to the rate of global decarbonization, the cumulative portfolio budget is equal to the portfolio emissions in 2020 times the number of 6.6 years left to exhaust the world cumulative budget as of that date. This procedure yields an estimate of cumulative portfolio budget of 163.7 GtCO2e.

Having pinned down the size of the total carbon budget for NZP, the next step is to decide the pathway along which investors would decarbonize their portfolios. We consider several different choices of such decarbonization paths: (a) investors immediately decarbonize their portfolios' footprint at a constant rate, (b) the budget is kept constant for some time and then investors decarbonize their portfolios' footprint at a constant, but faster rate, (c) investors decarbonize their portfolios at a faster (slower) rate for the first half of the remaining period and then at a slower (faster) rate for the second half, (d) investors follow a more sophisticated science-based decarbonization path.

Figure 1 shows how these different decarbonization paths evolve over time, when choosing starting dates between 2006 and 2020. The green pathways, denoted as $Const$, assume that investors follow a constant reduction rate from the first year, such that the terminal emissions in 2050 are smaller than 0.1 GtCO2e.[4] The light blue pathways, $ZeroConst$, assume that investors delay the decarbonization process of their portfolios for a while by applying constant emissions, but then they apply faster, constant reduction rates. The yellow pathways, SF, assume that investors' carbon budget switches from a slow reduction rate of 1% to a faster reduction rate that is not larger than 30% (selected based on feasibility) after several years. The dark blue pathways, FS, switch from a faster reduction rate to a slow reduction rate of 1%. Here, the faster rate is applied to the maximum number of years possible to make the 2050 emission budget as low as possible while making sure that the total cumulative budget is fully used. Note that, for the cohort starting in 2006, the terminal 2050 emission budget can be as high as 12 GtCO2e. The orange pathways, $RAEM$, follow the emission mitigation pathway of Andrew (2020)[5] Here, emissions can increase initially and then decrease.

To provide a visual illustration of the portfolio budget's construction, Figure 2 zooms

[4]Notably, the immediate reduction in portfolio emissions does not lead to the depletion of the *global* budget.

[5]The mitigation curves were adapted from Raupach et al. (2014) by Andrew (2020).

in on a snapshot of decarbonization pathways for the cohort starting in 2020. Specifically, global emissions in 2020 amount to 39.3 GtCO2e, and the corresponding annual carbon footprint of the investable universe is 24.8 GtCO2e. Using the proportionality rule, the remaining *global* emissions budget of 260.3 GtCO2e translates into a cumulative *portfolio* budget of 163.7 GtCO2e. This proportionality rule applies not only to total emissions but also works for all individual yearly carbon budgets. This procedure gives rise to the entire portfolio decarbonization pathways, as is shown in the right panel of Figure 2. For example, if we followed the green pathway, *Const*, from 2020, global emissions would need to drop to 32.2 GtCO2e, and, correspondingly, our net-zero portfolio would allow for a carbon footprint of 20.3 GtCO2e in 2021.

As a final step to obtaining NZP, we select companies, such that their total emissions jointly do not exceed the yearly emission budget.

2.1.2 NZP Selection Rule

In this section, we describe the rules by which investors select companies into NZP. Our broad principle is that companies with greater decarbonization prospects should be given preference. We consider three different ranking schemes of such prospects. First, we use companies' current total emissions, following the idea that such emissions are the best predictor of future decarbonization efforts. Second, we sort companies based on their predicted total emissions. Here, the basic principle is that decarbonization may take time, so what matters is where companies will be later on with their efforts, and not necessarily where they are today. Third, we select companies according to their combined efforts to decarbonize their activities, measured by our novel composite, the *Ambition Score*. For the first two schemes, we consider measures based on unconditional sorts, as well as measures sorting within a given 4-digit Global Industry Classification Standard industry (GICS-4) cluster. In turn, the third scheme is always industry-neutral; nonetheless, we distinguish between carbon budgets based on current emissions and those based on forecasted emissions. All the measures utilize a wide range of data, starting with the emissions data, which we obtain from S&P Trucost, and then following with forward-looking climate-related indicators from the following databases: Refinitiv ESG, CDP, and Orbis Intellectual Property.

Rule 1: Historical Carbon Emissions. Our first selection rule is based on the sum of all firm-level emissions. Companies with lower total emissions are preferred to those, whose total emissions are higher. The construction of emissions data starts with all global firms in the S&P Trucost Environmental Data reported yearly between 2005 and 2020. Trucost reports firm-level absolute greenhouse gas emissions in tons of carbon dioxide equivalent (tCO2e) for scope 1, 2, and 3 upstream emissions.[6] According to the Greenhouse Gas Protocol, scope 1 emissions are emissions directly from sources that are owned or controlled by the company, scope 2 emissions refer to emissions generated by a company consuming purchased electricity, heat, or steam, and scope 3 emissions are indirect emissions produced by the company's value chain but occur from sources not owned or controlled by the company.

Rule 2: Forecasted Emissions. Our second scheme classifies companies based on the levels of their forecasted emissions. This means that for a given dynamic budget path, investors estimate total emissions for each point in time along the path taking a given decarbonization cohort as a starting point for making predictions. Since creating a sophisticated predictability framework is beyond the scope of this study, we rely on a fairly simple procedure to form predictions, a weighted average between pre-announced, self-reported firm commitments to decarbonize their efforts and past emissions trends. In the Appendix, we describe the details of our data and methods to source commitments data, and then present our method to incorporate trend data.

The final forecasted emissions pathway is a weighted average of the decarbonization target-based path and the emissions trend path. Following the target credibility framework set out by the Glasgow Financial Alliance for Net Zero (GFANZ, 2023), we assign a 75% weight to a target-based path if a firm meets two criteria: (1) its targets are approved by the Science Based Targets initiative (SBTi), and (2) has targets for both short-term and medium-to-long-term horizon. In the case in which a firm only meets one of the above two criteria, we assign a 50% weight to the target-based path. We only assign a 25% weight to the target-based path if a firm only has medium-to-long-term targets that are not approved by SBTi. For all these three cases, we assign the rest of the weights to the trend path.

[6]To maintain consistency in our data across years, we use scope 3 emissions coming from upstream activities, as the emissions from downstream activities are only available from 2017 onwards.

Finally, if a firm only has short-term targets, or does not have targets at all, our forecasts rely fully on the trend path.

Rule 3: Ambition Score. Our third classification scheme aims to capture corporate intention and ability to decarbonize their future activities. The basic idea is to integrate information from past decarbonization efforts with information that speaks to future efforts to do so. To this end, we define a novel metric, the *Ambition Score*, defined as a weighted average of the following three categories of variables: (1) historical emissions levels and their growth rates (50%), (2) historical emissions intensities and their growth rates (25%), and (3) forward-looking climate-related activity metrics (25%). Within each category, we assign equal weights to individual characteristics.[7] All three categories aim to predict firm-level decarbonization outcomes. Carbon emissions levels and their growth rates are useful to extrapolate current emissions trends into the future. Intensity-level metrics add an additional dimension of efficiency of carbon production. Finally, forward-looking metrics summarize all the efforts undertaken by the company that relate to the companies' ambition to reduce emissions.

Specifically, within the first category, we include the size and the three-year moving-average simple growth rate of the company's absolute carbon emissions. Within the second category, we include the level and the three-year moving-average growth rate of the companies' carbon intensities, measured as tons of CO2 equivalent divided by the company's revenue in millions of dollars. Within the third category, we incorporate three aspects of decarbonization ambition measures: a) environmental variables from the company's Corporate Social Responsibility (CSR) report, b) patent variables on green and brown innovations, and c) variables on decarbonization commitments reported in the CDP survey. In the Appendix, we describe the details for the components forming each of the three categories.

[7] The weighting scheme we apply to construct the score is a choice variable and can be modified in a very flexible way. We chose these specific weights to reflect the importance of directly observed emissions in the prospects of decarbonization. The equal weights within each category are consistent with an uninformed prior regarding the importance of each individual corporate action.

2.1.3 Distance-to-Exit (DTE)

We define the distance-to-exit of a company i in year t, $DTE_{i,t}$, as the number of years a stock remains included in NZP. We consider three variants of DTE: (1) those based on constant emissions, (2) those based on forecasted emissions, and (3) those based on *Ambition Score*. The first two sets are further divided depending on whether the sorting variable, for a given firm, is normalized by the average of its GICS-4 industry peers, or not. For the *Ambition Score*, we conduct the exclusion by filling in the carbon budget using constant emissions and forecasted emissions, respectively.

To illustrate the basic properties of different DTE, we follow the example of Apple. Using the three climate alignment selection rules, we compute Apple's DTE by ranking stocks based on their climate performance and calculating the number of years its stock is not excluded from the net-zero portfolio, as discussed in Section 2.1. This process is repeated for every year from 2006 until 2020. We consider three sets of DTE measures: (1) those based on constant emissions; (2) those based on forecasted emissions; and (3) those based on the *Ambition Score*. The first two are further divided depending on whether the sorting variable is industry-adjusted or not. For the *Ambition Score*, we conduct the exclusion by filling the carbon budget using constant emissions and forecasted emissions, respectively. The table below provides numerical results for the six DTE.

Estimation Year	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Constant Emissions															
Exit Year	2025	2024	2024	2023	2021	2020	2019	2020	2020	2020	2021	2021	2022	2023	2024
DTE	18	16	15	13	10	8	6	6	5	4	4	3	3	3	3
Industry-Adjusted Constant Emissions															
Exit Year	2015	2014	2016	2016	2014	2014	2014	2015	2016	2016	2017	2018	2019	2020	2021
DTE	8	6	7	6	3	2	1	1	1	0	0	0	0	0	0
Forecasted Emissions															
Exit Year	2018	2012	2014	2016	2016	2016	2015	2023	2019	2020	2019	2020	2021	2022	2023
DTE	11	4	5	6	5	4	2	9	4	4	2	2	2	2	2
Industry-Adjusted Forecasted Emissions															
Exit Year	2013	2010	2011	2013	2013	2013	2013	2015	2016	2016	2017	2018	2019	2020	2021
DTE	6	2	2	3	2	1	0	1	1	0	0	0	0	0	0
Ambition Score Cum Constant Emissions															
Exit Year	2013	2016	2016	2019	2014	2014	2014	2015	2016	2016	2018	2018	2019	2020	2021
DTE	6	8	7	9	3	2	1	1	1	0	1	0	0	0	0
Ambition Score Cum Forecasted Emissions															
Exit Year	2011	2013	2014	2017	2014	2013	2013	2015	2016	2016	2018	2018	2019	2020	2021
DTE	4	5	5	7	3	1	0	1	1	0	1	0	0	0	0

In the first panel, where we sort companies on their yearly emissions, Apple's DTE is decreasing from 2006 to 2020. This could reflect both a tightening of the portfolio budget or a worsening of the company's decarbonization efforts, as measured by Apple's carbon emissions. Note that, by construction, it takes the smallest number of excluded firms to meet the yearly portfolio budget when firms are ranked by their emissions levels. Consistent with that intuition, in the second panel, Apple's DTE decreases when we rank companies by industry-adjusted emissions. At the same time, this finding could also mean that Apple is underperforming its peers in the same industry in terms of its emissions levels. The third panel shows Apple's DTE, based on its forecasted emissions. Compared to the first panel, we observe mostly lower DTE, except for 2013. When we construct DTE based on the *Ambition Score*, we observe values that are similar to the cases based on forecasted emissions, but lower than values based on constant emissions, suggesting that Apple is less ambitious in its decarbonization efforts when taking into account forward-looking information.

For the rest of the paper, we apply the same procedure for all other stocks in our data, which translates into a large panel of DTE.

2.2 Financial Data

Our firm-level financial data source is S&P Global Compustat. The dependent variables in our regressions are $RET_{i,t}$, which is the monthly return of an individual stock i in month t. To calculate returns, we follow the approach outlined in Chaieb et al. (2021), with necessary adjustments. We focus on securities categorized as common or ordinary shares (*tpci* = '0') in Compustat. Total return indexes are created by combining variables such as prices (*prccm*), adjustment factors (*ajexdm*), quotation units (*qunit*), exchange rates (*exratm*), and total return factors (*trfm*). We apply -30% delisting returns when delisting is performance related (based on the delisting reasons *dlrsn*), following Shumway (1997).

We define the book value of common equity, that is, as a difference between the book value of stockholder's equity, adjusted for tax effects, and the book value of preferred stock.[8] To construct the book value per share, we follow Asness and Frazzini (2013), and adjust book value for corporate actions between fiscal year-end and the date of portfolio formation. To construct price-to-book ration we divide current price by book value per share (both measured in local currency). The price-to-book ratio is updated monthly. Price-to-sales and price-to-earnings are built in an analogous way. $LOGMB_{i,t}$, is the natural logarithm of the

[8]See Bali et al. (2016), page 178.

price-to-book ration. Similarly, we take natural logarithms of price-to-earnings, $LOGPE_{i,t}$, and price-to-sales ratio, $LOGPS_{i,t}$.

Further, we define our control variables that we use in our cross-sectional regressions. Market capitalization is computed as a product of number of shares outstanding and stock prices (*prccm*). For North-American stocks, we use the last reported shares outstanding on the last trading day of the month (*cshom*), while for non-North American stocks, we use current shares outstanding (*cshoc*). $LOGMKTCAP_{i,t}$ is the natural logarithm of firm i's market capitalization at time t; $LEVERAGE_{i,t}$, which is the ratio of debt to book value of assets; momentum, $MOM_{i,t}$, which is given by the average of the most recent 12 months' returns on stock i, leading up to and including month t–1; capital expenditures, $INVEST/ASSETS_{i,t}$, which we measure as the firm's capital expenditures divided by the book value of its assets; $LOGPPE_{i,t}$, which is given by the natural logarithm, of the firm's property, plant, and equipment; the firm's earnings performance, $ROE_{i,t}$, which is given by the ratio of firm i's net yearly income divided by the value of its equity; the firm's total risk, $AGE_{i,t}$, which is the firm age in number of years, $VOLAT_{i,t}$, which is the standard deviation of returns based on the past 12 monthly returns; $SALESGR_{i,t}$, which is the annual growth rate in firm sales. To mitigate the impact of outliers, we winsorize $LEVERAGE$, $INVEST/ASSETS$, ROE, MOM, $VOLAT$, and $SALESGR$ at the 2.5% level.

2.3 Summary Statistics

In this section, we summarize the variables used in our analysis based on the pooled sample of companies observed over the period 2006-2020. We report basic statistics for each variable of interest, including their means, medians, 25th and 75th percentiles, and standard deviations. We present the information in Table 1.

In Panel A, we show information for emissions-related metrics. We present emission levels, their growth rates, intensities, and the growth rates thereof. Emissions are measured as a sum of scope 1, scope 2, and upstream scope 3 emissions, for which information is complete for the entire period of our analysis. Consistent with previous work, we find that emission levels are highly right skewed. While the mean value of firm-level emissions equals approximately 3 million tons of CO2e, the corresponding median is about 250,000. We also find that emissions are highly dispersed across firms, as indicated by a high value of standard deviation, which is almost 5 times larger than the mean value of emissions. Finally, both levels and emissions intensities exhibit, on average, a positive growth rate on an annual basis even though the values are highly dispersed across firms.

In Panel B, we report summary statistics for firm-level *Ambition Score* and its subcomponents. Summary statistics for the components are presented on an industry-adjusted basis and after being normalized. We note that different components exhibit different degree of cross-firm-level variation. The most dispersed metrics are those related to the level and intensity of emissions. In turn, variables related to forward-looking information are distributed in a fairly comparable way. Notably, unlike emission variables that are right skewed, most of the other metrics are left skewed, supporting the view that forward-looking information is generally less available.

In Panel C, we show summary statistics for the DTE that are derived using different metrics of sorting variables. Since some of the DTE measures are based on forecasted emissions we also report summary statistics of the emission forecasts one year and five years ahead. We observe some variation in the distribution of the different DTE. The metrics based on constant emissions have greater values, with an average of about 23.6. In turn, DTE based on *Ambition Scores* are significantly smaller with the average values of about 13. These differences indicate that companies, on average, are less ambitious in the way how they carry their decarbonization efforts when we take into consideration aspects that include not only hard emission data but also soft forward-looking metrics.

Finally, in Panel D, we summarize information on firm-level variables that enter our regression models in Section 4. The distribution of these variables is consistent with previous studies on global carbon-transition risk (e.g., Bolton and Kacperczyk, 2022b).

3 The Anatomy of DTE

In this section, we characterize the main properties of DTE. First, we show its relation to other measures of climate risk. Next, we study the time-series variation in DTE. Subsequently, we analyze the main determinants of DTE using pooled regression framework.

Finally, we provide evidence on the properties of NZP portfolios built on different DTEs in terms of their industry weighting and characteristic exposures.

3.1 Correlation Structure and Time-Series Variation of DTE

We begin by tabulating some of the properties of DTE. First, we relate different versions of DTE to each other and two main ingredients that underlie it: total emissions and *Ambition Scores*. Next, we show the time-series distributions of DTE. Both are reported in Table 2 below.

In Panel A, we report the correlation structure across various *DTE* and measures on which they are based.[9] We find that all *DTE* are positively correlated with each other but the correlations are far from perfect. In general, measures based on emission metrics are more correlated with each other but less correlated with measures based on *Ambition Score*. We also find that *DTE* are negatively correlated both with emission measures and with ambition scores but the correlations are fairly modest, especially for ambition scores, which suggests that *DTE* do not capture exactly same information as the raw metric from which they are derived. The likely driver of the difference is the dynamic carbon budget constraint that induces additional variation in *DTE*.

In Panel B, we illustrate the time-series variation of *DTE*. As expected, *DTE* decrease over time, consistent with the shrinking carbon budget and greater decarbonization pressure. At the same time, the declining values of *DTE* also indicate that companies are not able to reduce their emissions at the pace required by the carbon budget. We also note that *DTE* decrease more for metrics based on hard emission data as can be seen by comparing the average values between 2006 and 2020 and they decrease less for measures based on ambition scores. This pattern suggests that companies undertake additional measures beyond their emission adjustments to reduce the institutional pressure, even though those *DTE* are still relatively smaller than those based on hard data.

[9] Table IA.1 reports the correlation structure across additional DTEs constructed under different decarbonization pathways.

3.2 Determinants of *DTE*

We further provide additional information on *DTE* by relating its variation to various corporate characteristics. Formally, we estimate the following regression model:

$$\mathrm{DTE}_{i,t} = a_0 + a_1 \mathrm{Controls}_{i,t-1} + \mu_t + \varepsilon_{i,t}, \tag{1}$$

where $DTE_{i,t}$ is a generic term standing for various measures of distance-to-exit for firm i at time t constructed using our earlier framework. The vector of firm-level controls includes the firm-specific variables *LOGCO2*, *LOGMKTCAP*, *LOGASSETS*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*.

We estimate this cross-sectional regression model using pooled OLS. We also include country-fixed effects, as well as year-month-fixed effects. Finally, we also include industry-fixed effects to capture within-industry variation across firms. We double cluster standard errors at the firm and time dimension. We present the results in Table 3. Columns 1-2 show the results for measures based on constant emissions, columns 3-4 show the results for measures based on forecasted emissions, and columns 5-6 show the results for measures based on *Ambition Score*.

We document a number of interesting regularities. First, all *DTE* measures are negatively related to levels of total emissions, which reflects the fact that *DTE* partly reflect the variation in emissions. Second, we find that *DTE* based on emissions are negatively related to both firm assets size and market capitalization. Notably, the effect becomes much weaker or turns positive when we relate size to *DTE* based on the *Ambition Score*. Third, across all specifications, *DTE* is positively related to firm age and negatively related to firm volatility and firm leverage. The latter result supports the view that *DTE* is a risk-driven metric. Fourth, *DTE* is negatively related to firm trading volume, even though the result becomes statistically insignificant when we look at *DTE* based on the *Ambition Score*. Finally, the results for other variables, such as *LOGMB*, *MOM*, *INVEST/ASSETS*, and *ROE* are mixed and depend on the choice of the *DTE* measure.

3.3 Industry and Style Exposures of DTE Portfolios

In this section, we provide additional insights into the properties of DTE portfolios by looking at various comparisons between DTE-based portfolios and the universe of stocks in Trucost database. The two DTE portfolios we consider are one based on industry-adjusted forecasted emissions and another one based on the *Ambition Score* incorporating future emissions. In order to demonstrate some comparisons we focus on one snapshot of the data, 2020. Further, we consider three different investable sets: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE = 30$.

We begin by showing the GICS-4 market weights in our portfolios relative to those of the Trucost universe. The results are presented in Figure 3. As a benchmark, the black dots represent the market weights for all stocks in the Trucost universe. As is well known, Software and Services sector is the largest sector followed by Banks and Capital Goods. Next, we look at market weights of portfolios including companies with minimum DTE of 5, represented by orange dots. In the left panel, we show the results for DTE portfolios based on future emissions. We observe two following facts: most of the sector weights are not significantly different from those of the benchmark weights. Second, we observe that certain sectors are underweighted (Software and Services, Pharmaceuticals, Consumer Discretionary, and Media) and others are overweighted (Insurance, Financial Services, REITs, Food, and Marterials). These results conform to the general patterns of carbon footprints of these industries. In the right panel, we look at DTE portfolios based on *Ambition Score*. The deviations of the weights from the benchmark do not appear visibly different than in the previous case. We further compare the industry weights for portfolios with greater DTE values. While the deviations from the benchmark, as expected, increase slightly, there does not seem to be a very strong tilt away of our portfolios. Overall, we conclude that our portfolios do deviate slightly from the market weights but we do not seem to observe extreme cases in which certain sectors are fully excluded and others are significantly overweighted.

Another dimension on which we could compare the DTE portfolios is the number of stocks held. The primary concern is that DTE portfolios may become less and less populated due to tighter carbon budget and thus their properties in terms of tracking errors or risk may become unfavorable. We assess this dimension of our portfolios by looking at the number of stocks held by the benchmark portfolio and various DTE variants. We show the results from this analysis in Figure 4. Two observations are noteworthy. First, our analysis shows that the number of stocks in the portfolio that includes companies with $DTE \geq 5$ is not visible different than that for the benchmark portfolio. This is true for both DTE portfolios. Second, as we restrict the universe of companies towards the greater DTE values we can see that the number of stocks in the portfolio drops, but the drop is really visible only for the extreme portfolio with companies that survive in the portfolio in 2050. However, this example is somewhat stylized as it ignores the possibility that companies may improve their decarbonization profiles at the final periods of the investment horizon. At the very least, the uncertainty around this situation is too high to argue that the NZP in 2050 would include only a handful of stocks.

While the properties of the portfolio from the perspective of deviations from market portfolio are naturally important, another dimension of DTE concerns their ability to decarbonize NZP. We explore this question next. In Figure 5, we show the results from the analysis in which we compare the carbon footprint of portfolios defined in Figure 3 and 4 to the carbon footprint of a portfolio composed of all Trucost universe stocks. We show that depending on a given DTE profile, NZP portfolios reduce carbon footprint anywhere between 40% to 95%. These results are fairly impressive in conjunction with the fact that these are well-diversified portfolios. In Figure 6, we ask the same question from the perspective of future emissions. Here, we predict emissions for 2025, 2035, and 2050 and show the proportion of carbon footprint of DTE portfolios relative to the equivalent Trucost universe. The results are quite consistent and show that in a 5-year period the DTE portfolios would reduce carbon footprint by roughly $50\% - 60\%$ and the number gets significantly larger as we go towards 2035 and 2050. Of course, by construction in 2050, the expectation is we would decarbonize the portfolio by almost 100%.

Finally, it may be useful to assess the properties of DTE portfolios from the perspective of factor/style exposure. This is what we show in Figure 7. Here, we look at the percentage deviations from Trucost portfolios for the above-defined portfolios. Our style characteristics include $LOGASSETS$, $LEVERAGE$, $LOGMB$, MOM, and ROE. For comparisons, we also show the deviations in terms of emissions and forecasted emissions. We find that our DTE portfolios are not significantly tilted from the benchmark on the first three characteristics. Especially, the size balance is comforting as it indicates that our portfolios are likely shielded from potential transaction cost stories due to holding small stocks. On the other hand, we find more deviation our portfolios in terms of their momentum and ROE properties, even though we note that the significance of the deviation is economically large only for portfolios with the largest DTE.

Overall, we conclude that while our DTE portfolios exhibit a significant reduction of carbon footprint they do not lead to tilts that could indicate their significant deviation from what would represent a well-diversified and sectorally balanced portfolio.

4 DTE and Firm Values

In this section, we present our main findings on the pricing of carbon-transition risk using our novel measures of DTE. We begin by reporting results for the measures based on constant decarbonization paths and total emissions sorts. We then proceed to show additional results on the specific drivers and robustness.

4.1 Empirical Specification

Our analysis of carbon-transition risk centers on the cross-sectional regression model relating individual companies' stock returns to measures of DTE. Following the work of Bolton and Kacperczyk (2021, 2022b), we take a firm-characteristic-based approach along the lines of Daniel et al. (1997). This approach is particularly well suited given the rich cross-sectional variation in firm characteristics in our sample.[10] As shown in Bolton and Kacperczyk (2022b), the following characteristics are particularly relevant in carbon transition risk models: firm size; book-to-market; leverage; capital expenditures over assets; property, plant, and equipment; return on equity; sales growth; firm age; firm profitability,

[10]The risk factor-based approach has been a popular method to measure risk premia in a single-country, but in a fully global study, such as this one, this approach is problematic because of the difficulties in specifying appropriate factor-mimicking portfolios for a large number of countries with limited data, and because of cross-country comparability issues.

as measured by return on equity (*ROE*); dollar volume; and a measure of, respectively, stock price momentum and volatility. This characteristics-based approach also allows us to take full advantage of fixed effects along time, country, and industry dimensions. Further, we can better account for the potential dependence of residuals by using a clustering methodology. Finally, the advantage of taking a characteristics-based approach is that we do not need to take a stance on the underlying asset pricing model. Our aim is more limited: to provide a comprehensive picture of the cross-sectional variation in stock-level returns due to differences in *DTE*. Stated differently, our approach is to identify a company's transition risk beta.

We begin by linking companies' monthly stock returns to our measures of *DTE* and other characteristics, all lagged by one month. This regression model reflects the long-run, structural, firm-level impact of net-zero portfolios on stock returns. Specifically, we estimate the following model:

$$\mathrm{RET}_{i,t} = b_0 + b_1 \mathrm{DTE}_{i,t-1} + b_2 \mathrm{Controls}_{i,t-1} + \mu_t + \varepsilon_{i,t}, \tag{2}$$

where $RET_{i,t}$ measures the stock return of company i in month t, and *DTE* is a generic term standing for various measures of distance-to-exit constructed using our earlier framework. The vector of firm-level controls includes the firm-specific variables *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*.

We estimate this cross-sectional regression model using pooled OLS. We also include country-fixed effects, as well as year-month-fixed effects. Finally, we also include industry-fixed effects to capture within-industry variation across firms. Including industry-fixed effects is important in transition risk regressions due to significant cross-industry differences in emissions, as indicated by Bolton and Kacperczyk (2022b). We double cluster standard errors at the firm and year levels, which allows us to account for any cross-firm correlation in the residuals as well as capture the fact that some control variables, including *DTE*, are measured at an annual frequency. Our coefficient of interest in equation (2) is b_1, which measures the association between *DTE*s and returns.

4.2 Return Regressions with Constant Decarbonization Rates

We begin our analysis by comparing the results for our regression models under the assumption of constant-rate decarbonization paths. We further consider three sets of DTE measures: (1) those based on constant emissions sort; (2) those based on forecasted emissions sort; and (3) those based on *Ambition Score* sort. The first two of the three sets are further divided depending on whether the sorting variable is industry-adjusted or not. For the *Ambition Score* sort, we conduct the exclusion by filling the carbon budget using constant emissions and forecasted emissions, respectively. We report the results in Table 4. Throughout all six specifications, we find a strong negative predictive relation between measures of DTE and next-month stock returns, consistent with the view that companies with higher DTE face lower carbon transition risk and thus investors require lower returns for holding them. All six coefficients of DTE are statistically significant at the 1% level of statistical significance. The effects are also economically significant. To illustrate, a coefficient in column (1) equals -0.045 and the standard deviation of DTE in this specification is 10.1. This means that a one-standard-deviation increase in DTE is associated with 0.46 percentage-point lower stock returns per month, or 5.5% annualized. Among other controls, $LOGMB$ and momentum are positively related to future stock returns and leverage and size are negatively related. All other characteristics are statistically insignificant.

In the next test, we examine the persistence of the DTE signals. For that reason, we lag all DTE in our regressions by one year. We report the results in Table 5. As can be seen from the results, the predictive power of DTE weakens as we extend the horizon, which is expected given that the information from old DTE becomes stale after some time and investors possibly consider newer information in forming their demand. Still, we observe a negative relation between all measures of DTE and stock returns. Notably, two of the measures, based on constant emission sorts, still retain their statistical significance. At the same time, measures based on forecasted emissions and ambition scores are significantly weaker. These results suggest that DTE contain persistent information for stock returns.

4.3 Valuation Ratios

It is well known that stock returns are noisy proxies for expected returns. It is sometimes possible to get more precise measures of expected returns based on analyst forecasts. However, a major challenge with this approach is that (1) analyst forecasts are only available for a relatively small subset of global stocks; (2) analyst forecasts may be biased because of industry incentive structures; and (3) the metric of implied cost of equity critically depends on the postulated valuation model.

As an alternative, we look at the pricing of carbon emissions from a different perspective and relate our firm-level carbon emission measures to three different valuation ratios, which tend to be more stable over time and are available for a large set of firms. Looking at valuation ratios helps us to better distinguish the explanation of our results as one based on required expected returns vs. one due to luck. Accordingly, we estimate the following regression model:

$$\text{Valuation Ratio}_{i,t} = c_0 + c_1 \text{DTE}_{i,t-1} + c_2 \text{Controls}_{i,t-1} + \mu_t + \varepsilon_{i,t}. \tag{3}$$

Our dependent variables are three different firm-level valuation ratios all expressed in the natural log scale: price-to-earnings ratio, *LOGPE*, market-to-book ratio, *LOGMB*, and price-to-sales ratio, *LOGPS*. Our control variables include *MOM*, *VOLAT*, *AGE*, and *SALESGR*. In addition, we use one and two year-ahead measures of *SALESGR* to proxy for future cash-flow growth. Finally, in all specifications, we include country-, year-month-, and industry-fixed effects. As before we double-cluster standard errors at the firm and year level. The main independent variables of interest are six different variants of *DTE*. Our coefficient of interest is b_1. We present the results in Table 6.

In Panel A, we show the results for the price-to-earnings ratio. Consistent with our hypothesis of the presence of carbon-transition risk, we find that companies with high values of *DTE* have higher *LOGPE*. The effects are statistically significant at the 1% level of significance for all six measures of *DTE*. In Panel B, we show the results for *LOGMB*. We again find a positive and largely significant relation between *DTE*s and *LOGMB*; however, this time the results are statistically weaker for the *DTE* measures based on forecasted emissions. In Panel C, we report the results for $LOGPS$. The coefficients of all DTE measures are positive and highly statistically significant. Overall, the results indicate strong pricing effects for all six DTE measures. Given that we control for future sales growth (proxying for future cash flows), these results are more consistent with the risk-based explanations of returns rather than the cash-flow-based unexpected return story.

4.4 Additional Analyses

The results so far exploit the cross-sectional variation among companies that are subjected to net-zero portfolio exclusion and assign maximum DTE values to companies that never get excluded. However, one could argue that companies that are never excluded are potentially very different from the rest and they are priced differently. We explore the extensive margin dimension by defining an indicator variable that is equal to 1 for companies that never exit net-zero portfolios and is equal to zero for those companies that exit at any point prior to and including the final year 2050. We replace our DTE measures with such indicator variables in our specification (1). We report the results from estimating this alternative model in Table 7. The results show a very strong negative coefficient of each individual indicator function suggesting that companies that never exit have lower expected returns than those that exit. The economic magnitude of the results is quite large with the monthly differences in returns between 27 and 45 basis points, or 3.2-5.4 percentage points, annualized.

Given that our DTE measures aim to capture transition risk, a natural question to ask is whether the premia we observe increases in times when investors attach more importance to such risk. The literature on climate finance has been commonly using the structural break associated with the Paris Agreement of 2015, arguing that the transition risk has been elevated following that accord (e.g., Bolton and Kacperczyk, 2021). We follow this literature and define an indicator variable, which we label Paris, that is equal to one for the years starting from 2016 and equal to zero up to and including 2020. To measure the incremental pricing effect of the structural shift, we estimate the following regression model:

$$\text{RET}_{i,t} = d_0 + d_1\text{DTE}_{i,t-1} + d_2\text{DTE}_{i,t-1} \times \text{Paris}_{t-1} + d_3\text{Controls}_{i,t-1} + \mu_t + \varepsilon_{i,t}, \quad (4)$$

Our coefficient of interest is d_2. We report the results from our estimation in Table 8. In Panel A, we focus on returns as a dependent variable. Throughout all specifications we find a large and negative value of the coefficient suggesting that the risk premia increased for low-DTE companies following the Paris agreement. The coefficient on DTE increases by a substantial fraction relative to the previous period. In four out of six specifications we document a statistically highly significant effect. In Panel B, we test the hypothesis of increased risk premia from the perspective of companies' *LOGPE*. Consistent with the returns results we find a positive and economically significant effect of the Paris agreement on valuations of firms with different *DTE*. Like in the previous panel, in four out of six specifications, the coefficient of the interaction term is statistically significant. Overall, we conclude that the pricing of DTE is consistent with it being a measure of transition risk.

Our DTE measures aim to capture forward-looking transition risk. One could argue that some of the variation they capture also reflects past information. In fact, in constructing DTE we also rely on past climate-related information such as measures of emissions and forward-looking announcements. In addition, one may argue that DTE by themselves do not capture information beyond the signals on which companies are sorted for net-zero portfolios. To shed some evidence on these issues, in Table 9, we report the results from estimating the model in which we include *Ambition Score*, the natural logarithm of total emissions, $LOGCO2$, the percentage change in total emissions, *Emissions Growth*, and emission intensity, *Emission Intensity*, as additional controls in the returns regression model.

We find that controlling for all the past information naturally reduces the magnitudes of each DTE measure. However, we still find some independent variation that can explain stock returns over and above the past information. We draw two conclusions from these results. First, investors price in forward-looking information over and above the past information. Second, our DTE are not simple alternative measures of transition risk but they carry distinct information that is useful in pricing stocks. Further, the coefficients of the other climate-related variables are in line with earlier findings in the literature (Bolton and Kacperczyk, 2022b). The level and growth of emissions are positively associated with future stock returns and emission intensity is not significantly related with future returns. Notably, we also find that measures of ambition are not significantly related to future returns. The last result is useful because independently we show that *DTE* based on ambition score do predict future returns. Hence, the ability of *DTE* to predict future emissions does not simply derive from the sorting measures alone but rather from their interaction with the carbon budget.

A basic version of our *DTE* is based on emissions that combine scope 1, scope 2, and scope 3. One concern is that scope 3 could be more difficult to measure and thus our *DTE* measures may be noisy. Another issue is that of double counting. We consider the latter issue to be less problematic given that we care about the contribution of each firm to overall emissions. In this section, we assess the importance of these potential issues by using *DTE* that are based on the sum of scope 1 and scope 2 emissions only. With the alternative measures, we estimate the model in equation (2). We report the results in Table 10. The results of the model are qualitatively identical and quantitatively very similar to those in our baseline model. Again, we find strong negative association between all six measures of *DTE* and future stock returns. Thus, it is unlikely that our results are spurious or not robust to alternative specifications.

Another dimension of carbon transition risk relates to disclosure of climate-related information. As previous studies have argued information about carbon emissions is only disclosed by some and not all companies, and the decision to disclose is likely endogenous. As such it is possible that the pricing of individual companies may depend on whether information about their carbon footprint is self-disclosed or measured by third party, such as S&P Global. We examine the relevance of this process by conditioning our return regressions on such information source. We define an indicator variable Disclosure that is equal to one if the company directly discloses its emissions and is equal to zero if the information is estimated by the data provider. To estimate the marginal impact of such information we estimate the following regression model:

$$\mathrm{RET}_{i,t} = e_0 + d_1\mathrm{DTE}_{i,t-1} + e_2\mathrm{DTE}_{i,t-1} \times \mathrm{Disclosure}_{t-1} + e_3\mathrm{Controls}_{i,t-1} + \mu_t + \varepsilon_{i,t}, \quad (5)$$

We report the results from this model in Table 11. Across all specifications we find that the marginal effect of disclosure on stock returns is statistically significant. However, the direction of the effect differs across various categories of *DTE*. For the measures based on constant and forecasted emissions we find a negative coefficient and for the measures based on ambition score the coefficient is positive.

One of the key features underlying net-zero portfolios is the carbon budget. In our analysis so far, we have assumed that investors follow the path determined by the constant rate of decarbonization. However, in reality investors need not follow only such path. In this section, we consider four alternatives to this path. As a first alternative, we consider a situation in which investors wait the maximum number of years possible and after that begin decarbonizing at a constant rate. Second, we consider the possibility in which investors first decarbonize at a slower pace for the first half of their investment period and then they decarbonize at a faster pace until they reach residual emissions in 2050. We call this path an *SF* path. Third, we consider the opposite situation in which investors decarbonize first at a faster rate and then at a slower rate, an *FS* path. Finally, we consider a theory-motivated path from Andrew (2020). He follows mitigation curves of Raupach et al. (2014), which describe approximately exponential decay pathways such that the quota is never exceeded. These curves allow for some inertia in the early years of mitigation ("an oil tanker cannot turn on a dime"). Notably, these are not exponential pathways: the rate of mitigation is not the same every year. Finally, mitigation curves are defined such that the sum of historical cumulative emissions and cumulative emissions following the mitigation curves exactly meets the global emissions quota in 2100.

We report the results considering all the above decarbonization paths in Table 12. In Panel A, we look at the impact on next-month stock returns following specification (1); in Panel B we look at valuation regressions following specification (2). The results in Panel A indicate a strong empirical robustness to the choice of different carbon budgets. For all four decarbonization paths we estimate a strong negative coefficient of *DTE* that is highly statistically significant. In Panel B, we use *LOGPE* as a dependent variable. Again, we find results qualitatively similar to our baseline findings. Across all four alternative paths, the coefficient of *DTE* is positive and highly statistically significant. Overall, we establish a robust relationship between firms' DTE and their valuations. Companies with higher DTE have lower expected returns and higher valuations consistent with the interpretation of DTE being transition risk measures.

5 Conclusions

In the coming years and decades investors will be exposed to substantial transition risk. Many forces will be behind this risk, including the uncertain technological progress and ensuing legislation. What has emerged as a formidable factor is the role of social pressure manifested by various stakeholders globally. With the intensifying climate events, one can expect that this pressure can respond accordingly. Quantifying this pressure both in terms of investors' risks and companies' cost of capital becomes economically first-order. In this paper, we provide a formal framework of net-zero portfolios that allows us to quantify this economic force. Net-zero portfolios generate a shock to asset ownership structure and possibly have an ability to influence asset prices. Importantly, contrary to earlier studies on portfolio holdings that isolate pricing effects due to realized divestment, the mechanism we propose additionally operates through expected divestment forces and potential engagement coming through the interaction between asset holders and corporate themselves.

We operationalize this empirical mechanism using a novel measure of distance-to-exit (DTE). Using a global sample of stocks with cross sectionally and serially diverse DTE, we show that companies that are more exposed to exit from net-zero portfolios have lower values and require higher returns from investors holding them. This result is economically large and is consistent with the view that DTE are useful measures of transition risk. Notably, we show that DTE capture distinct variation to that captured by previously used measures based on corporate carbon emissions. Distinct from these, they capture information that is forward-looking and is grounded in climate science.

At the broad level, to our knowledge, our study is the first one to highlight the role of *expected divestment* and its role in asset prices. We are also one of the first studies in economics that formally links transition risk to scientific evidence grounded in IPCC projections. In fact, we show the importance of communicating such information to firms and investors, as it enters directly into portfolio decisions of institutional investors and cost of capital calculation and investment decisions of firms. Hence, we can argue that scientific evidence on climate can be a useful macro-level predictor of asset prices.

Even though our study aims to provide a comprehensive evidence on the asset pricing implication of net-zero portfolios, we believe it lends itself naturally to additional investigations, both theoretical and empirical. On the theory side, one of the promising avenues to explore is the game-theoretic foundation of the interactions between institutional investors and corporates through the competitive force induced by tight carbon budget. We show that it is not only individual companies' decarbonization efforts but also their competitors' actions that determine the equilibrium expected returns due to transition risk. On the empirical side, we provide a flexible framework that should allow to incorporate general climate-related information into transition risk framework. Unlike the typical studies that introduce such information on a case-by-case basis, our framework allows us to aggregate signals into one sufficient statistic, captured by DTE. All in, much more remains to be done, and we hope this study opens up the burgeoning literature on climate finance to new avenues of research.

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Appendices

This Appendix provides the details related to the construction of the variables we use to select stocks into NZP. First, we discuss the data on commitments. Next, we discuss the data entering forecasted emissions. Finally, we discuss the components of the *Ambition Score*.

A Commitments Data

We construct the CDP target-based emission pathway by aggregating decarbonization commitments with different ambitions and horizons at the firm level. We start by categorizing the targets into seven scope groups: (1) scope 1, (2) scope 2, (3) scope 3, (4) scope $1+2$, (5) scope $1+3$, (6) scope $2+3$, and (7) scope $1+2+3$. We then screen targets using the following criteria. For a specific target to be considered valid, both the survey year and target year should be greater than the base year. Additionally, targets up to and including the current survey year are not forward looking and hence are not considered valid. We categorize commitments with target years of up to 4 years from the survey year as short-term targets and the rest as medium-to-long-term. Next, in each survey year, we compute the targeted reduction in emissions level based on the reduction ambition abatement rate normalized by the boundary of the target as discussed earlier for every target.

Many firms report multiple targets within the same scope and time frame, which would lead to multiple target-based emissions pathways. In order to generate one representative forecast, we perform a series of filtering steps to arrive at a single pathway for each firm on its scope $1 + 2$ and scope $1 + 2 + 3$ forecasts, respectively. Within each scope group and time horizon, we select the target with the highest level of SBTi validation, with the progress status underway (instead of achieved), and with the highest target reduction in emission levels. Specific to scope 3, firms sometimes set up multiple targets regarding different segments of their emissions; for example, two scope 3 targets with the same target year on business travel and downstream transportation, respectively. In these cases, instead of selecting only one target, we aggregate the emission reduction implied by these two segments of targets for the overall scope 3 forecasts. Note that this process allows for only one target emissions checkpoint per target year, but it allows for multiple targets with different target years.

In each survey year t, our forecast horizon is the furthest target year of any firm. Within each of the seven scope groups, we translate multiple targets into the same amount of target emissions level checkpoints in different target years. Then, we construct forecasts for scope $1 + 2$ and scope $1 + 2 + 3$ emissions by inferring the target emissions from the seven scope groups. We prioritize the targets that are better defined and constraining such that we prefer individual scope targets (e.g., inferring scope $1 + 2$ target from individual targets on scope 1 and scope 2) over targets combining scopes (e.g., scope $1 + 2$, scope $1 + 2 + 3$, etc). With this preference hierarchy, we consider all the possible combinations to allow for a maximum amount of checkpoints for the scope $1 + 2$ and scope $1 + 2 + 3$ emissions pathways. For example, to infer scope $1 + 2$, we first search for individual targets on scope 1 and scope 2, then we search for scope $1 + 2$, third we try to use scope $1 + 2 + 3$ subtracting scope 1, and so on. We interpolate linearly between checkpoints. The horizon of the target pathway depends on the target year of the company's commitments. In the case of a company having a shorter horizon for scope $1+2+3$ emissions pathways than scope $1+2$, we try to infer the implied scope 3 emissions target by the difference between the two pathways and hold the latest implied scope 3 emissions constant to lengthen the scope $1+2+3$ emissions pathways. We do the reverse for scope $1+2$ pathways as well. If none of the above options are available to back out scope $1+2$ and scope $1+2+3$ emissions pathways, we also consider partially using constant emissions. For example, for the scope $1+2$ pathway, we hold the current scope 1 emissions constant if only scope 2 checkpoints are available.

B Forecasted Emissions

We obtain all the firm commitments data tracked by the annual CDP survey from 2011 to 2020. CDP started asking its member companies to report their emissions reduction targets from 2011. The format of the CDP survey evolved over the years and its structure has only been standardized recently. Company commitments can take different forms, including carbon intensity improvements, absolute emissions reductions, or other formats like percentage of procurement. In our study, we focus on commitments to reduce absolute emissions only as they are considered to require most effort, are more difficult to manipulate, and translate directly into a global decarbonization objective (Bolton and Kacperczyk, 2022a). Since a company could be following the same commitment over multiple reporting years, we define survey year as the year of the CDP survey for which a specific emissions reduction target was observed. Commitments also vary in terms of the choice of a base year for emissions, the horizon of the target, and the target ambition, expressed as a percentage of emissions reduction over the target horizon. For comparability of targets within and across firms, for each survey year, we convert the target ambition into linear annual reductions, *LAR*, as follows:

$$\text{LAR} = \frac{\text{\% Emissions reduction commitment from base year to target year}}{\text{target year} - \text{base year}}. \tag{6}$$

Notably, *LAR* measures the scope of emissions reduction over the entire time frame of the target (base year to target year), and not over the remaining portion of the commitment (current year to target year). As such, firms are not penalized by ignoring their early actions (CDP, 2020).

Firms also tend to have multiple targets with different scope coverage in each survey year.[11] Within a given emissions scope, we denote *CECOVER* as the reported percentage of carbon emissions that will be covered by the boundary of the target; for example, 100% of combined scope $1+2$ is covered by the target. The early vintage of the CDP surveys reports missing values of *CECOVER* or $CECOVER \leq 1\%$ even if the level of target-covered emissions exists and is sizable. In such cases, we back out *CECOVER* by taking the ratio of emissions in tons covered by the target reported by CDP, relative to total base year emissions in the corresponding scope, reported by Trucost. The maximum value we allow for *CECOVER* is

[11] For example, Table IA.2 shows that 840 companies reported 1451 targets in 2020.

100%. We also perform manual checks if the same target is followed by a firm over multiple years, and we fill missing *CECOVER*s accordingly. We try to maximize the availability of the emissions' coverage ratio *CECOVER* because it is an important normalizing factor for the calculation of the ambition of the target. Our final measure of the abatement rate is the normalized *LAR*:

$$\text{Normalized LAR} = \text{LAR} \times \text{CECOVER}. \tag{7}$$

Based on the above, we define the *Targeted Reduction in Emissions Level* as:

$$\text{Targeted Reduction in Emissions Level} = \tag{8}$$

$$\text{Normalized LAR} \times (\text{target year} - \text{base year}) \times \text{ baseyear emissions}. \tag{9}$$

The above measure is the first of the two main inputs in our measure of forecasted emissions.

The second element of our emissions forecasts is the past emissions trend-based pathway, with the forecast horizon from a given year t to 2050. We use a three-year moving average of the emissions growth rate to proxy for the short-term growth rate from t to $t+2$. We proxy for the long-term industry-level emissions growth rates using annual growth rates from 2006 to 2020 across all firms. We apply the above long-term growth rate to data from $t+15$ and hold it constant until 2051. Between years $t+3$ and $t+15$, we let the short-term growth rate converge to the long-term growth rate using exponential interpolation. Scope 3 emissions data may suffer from double-counting issues. Additionally, emissions data becoming more available in more segments of scope 3 and re-classification of the scopes may further introduce noise in the growth rates. Therefore, we use scope 1+2 growth rate to proxy for scope 1+2+3 growth rate for the short-term growth rate. Only in cases where scope $1+2$ growth rate is larger than 50%, we consult the scope $1+2+3$ growth rate and use the smaller value between the two. While it is possible for a fast-growing firm to have a 50% emissions growth rate, it is less intuitive to assume these sizable growth rates to persist far into the future. Regarding the long-term growth rate, we use the unconditional growth rate based on scope $1+2$ growth rate to forecast both scope $1+2$ and scope $1+2+3$ emissions. If a company has a decarbonization target, but its implied long-term growth rate is positive, we assume the long-term growth rate to be zero. We let the current emissions level evolve based on the interpolated growth rates to construct past trend-based emissions pathway for both scope $1+2$ and scope $1+2+3$ scenarios.

C Construction of the Ambition Score

Corporate Social Responsibility Indicators

We focus on six firm characteristics that are directly linked to a firm's potential decarbonization actions, obtained from Refinitiv. The primary underlying source for Refinitiv is the company's Corporate Social Responsibility (CSR) report. The six CSR indicators relate to the following questions: (i) does the company have any decarbonization target?; (ii) does the company have any decarbonization policy?; (iii) does the company report its emissions?; (iv) does the company have a CSR committee or team?; (v) has the company signed the

United Nation Principles for Responsible Investment (UNPRI)?; and (vi) does the company support the UN Sustainable Development Goal 13 (SDG 13) on Climate Action? Table IA.2 reports the percentage of firms with an environmentally positive answer to the above six questions. We can observe an increasing trend in the number of firms classified positively based on these CSR metrics. We note the drop in the percentage of positive answers between 2016 and 2017, which was predominantly driven by the expansion of the stock universe covered by Trucost into smaller firms.

Green and Brown Efficiency Innovation

In the second category, we quantify the scope of green patenting activity, both in terms of the volume as well as the impact of patents. Our source of patent data is Orbis Intellectual Property, which provides a comprehensive coverage of patent filings and corporate ownership of patents by listed and unlisted companies in 81 countries. This data set includes 136 million patents held by 2.3 million firms. It also provides patent citations, which are a good measure of the importance of the innovation protected by the patent. Following Bolton et al. (2023), we classify patents into green and brown-efficiency categories. Both types of patents aim to reduce carbon footprint. Subsequently, we define the following six variables that enter into construction of our *Ambition Score*: *Green patent number* is the number of green patents registered by a company in a given year, *Brown patent number* is the number of brown-efficiency patents registered by a company in a given year, *Green patent citation number* is the cumulative number of citations to green patents registered by a company in a given year, *Brown patent citation number* is the cumulative number of citations to brown-efficiency patents registered by a company in a given year, *Green patent ratio* is the number of green patents registered by a company in a given year scaled by the total number of patents of the same company in that year, and *Brown patent ratio* is the number of brown-efficiency patents registered by a company in a given year scaled by the total number of patents of the same company in that year. Table IA.2 reports the percentage coverage of firms with a positive number of green and brown-efficiency patents. In general, the patent coverage is stable over the time horizon from 2006 to 2020. The change in the coverage from 2016 to 2017 is driven by the inclusion of a substantial amount of small firms in our stock universe.

CDP Indicators

In the last category, we define factors that relate to firms' decarbonization commitments. Specifically, we focus on five metrics of such commitments.

We begin by measuring the rate of emissions abatement. Assuming a constant *CECOVER* between the base year and the survey year, we define the actual linear annual reduction achieved as:

$$\text{Actual LAR} = \frac{\text{Emissions in base year} - \text{Emissions in survey year}}{\text{Emissions in base year} \times (\text{survey year} - \text{base year})}. \tag{10}$$

Subsequently, in each survey year, we define the *Dynamic Abatement Rate* as the difference between the planned reduction target and the actual reduction achieved as:

$$\begin{aligned}\text{Dynamic Abatement Rate} = & \frac{1}{\text{target year} - \text{survey year}} \times \\ & \Big(\text{\% Emission reduction from base year to target year} - \\ & \text{Actual } LAR \times (\text{survey year} - \text{base year})\Big).\end{aligned} \tag{11}$$

This reflects the actual reduction effort required per year accounting for the target progress to date.

One could argue that the level of *Dynamic Abatement Rate* can go both ways, indicating either a more ambitious target or underperformance relative to the planned reduction. Therefore, we further transform the dynamic abatement rate into its difference with the actual annual emission reduction rate calculated using a three-year moving average of emissions growth rate. We interpret the difference as the degree of impracticability of the target.

Evaluating the company's progress against its promise is also important. A simple measure of underperformance is the difference between *Normalized* LAR and the actual annual emissions reduction rate, calculated using a three-year moving average of emissions growth rate. Alternatively, the CDP survey calculates target progress as the proportion of target achieved relative to the base year using reported base year and survey year emissions. Multiplying the target progress by LAR gives the actual percentage reduction achieved. Furthermore, we use the Trucost emissions when CDP data are missing.

CDP also reports the year when the target was initially set and we also track the first year a target appears, denoted as target setting year. Tracking the target progress when a target was initially set helps us to gauge if a firm deliberately selects a base year with high emissions for easy target completion. Our greenwashing indicator is defined as

$$\begin{aligned}\text{Greenwashing} = & \frac{\text{Emissions in base year} - \text{Emissions in target setting year}}{\text{Emissions in base year}} \times \\ & \frac{1}{\text{\% Emission reduction from base year to target year}}.\end{aligned} \tag{12}$$

Finally, the CDP survey also includes the SBTi status for each target from 2015. To join the SBTi a company must first sign a commitment letter. Then the company has to develop and submit a science-based emission reduction target for validation within 24 months. Once the target has been validated it is disclosed. We also classify targets into three groups in terms of their SBTi involvement: (1) SBTi approved, (2) SBTi committed, and (3) non-SBTi. We give more credit to the targets with SBTi validations when we forecast emissions and construct composite ambition scores.

To illustrate the mechanics of each of the above indicators, we again focus on Apple, which made commitments to CDP. In 2020, Apple set a new target of 75% reduction covering 100% of scope 1, 2, and 3 with $38,400,000$ tons of base year absolute emissions over the 2015-2030 period. As of 2020, scope 1, 2, and 3 emissions of Apple are not decreasing but growing at a rate of 2.70% based on a three-year moving average. The Normalized LAR is 5% per year with a target horizon of 15 years; the target underperformance is thus 7.70%. In this example, 2020 is both the survey year and the target-setting year. The reported 2020 emissions covered by the target is $25,100,000$ tons, indicating that the reduction achieved is already 34.64% between the base year 2015 and the target setting year 2020 and the greenwashing indicator is 46.18% ($\frac{34.64\%}{75\%}$). The reduction left is $75\% - 34.64\% = 40.36\%$ and that indicates a *Dynamic Abatement Rate* of 4.04% per year from 2020 to 2030, leading to a target impracticability measure of 6.74%. The SBTi status for this target is classified as committed but not yet approved.

To construct the composite *Ambition Score*, we follow the following three steps. First, we process the variables, including converting all the Boolean variables from the CSR report into numerical values, and computing and filtering the CDP target-related variables. All variables included in the score are expressed in units consistent with the assumption that a less climate-aligned firm receives a higher value. Except for the emissions-related variables for which we exclude missing values, we penalize the non-reporters by applying the worst possible value in a given industry. For example, we allocate a value of 2 if a firm only has non-SBTi targets or does not have a target at all, a value of 1 if a firm has SBTi committed targets, and a value of 0 if the targets are SBTi approved. Note that we do not penalize firms with no targets using the worst greenwashing indicator; instead, we assume zero greenwashing in the absence of any targets. Second, we apply the best-in-class method by standardizing each variable within GICS-4 industry groups using the z-score transformation. Third, we aggregate variables within each sub-category using equal weights and then construct the final composite score using appropriate weights.

Below, we present an example of the *Ambition Score* breakdown for Apple Inc., as of the end of 2020. The illustrative case is further extended into all companies and all years of our data. In column 1, we show the category label. In column 2, we report the weights assigned to each category. Column 3 reports the corresponding data source. Column 4 details each component within each category. Column 5 shows the data as reported by the company. Column 6 illustrates our transformation of the reported value into the score input. Column 7 presents the values that are first industry adjusted and then standardized using z-scores. In general, higher values of the score are associated with lower ambition of a company.

Category	Category Weight	Data Source	Variables	Reported Value	Score Input	Standardized Value
Historical emissions data	50%	Trucost	Emissions level	30,119,516.91	30,119,516.91	128.31
			Emissions growth	0.03	0.03	0.09
Historical emissions intensity data	25%	Trucost	Emissions intensity	109.72	109.72	-0.94
			Intensity growth	-0.04	-0.04	-0.16
Forward-looking soft data	25%	CSR Report	Decarbonization target existence	Yes	0	-2.61
			Decarbonization policy existence	Yes	0	-1.75
			Emission disclosure	Reported	0	-1.93
			Sustainability committee existence	Yes	0	-2.08
			UNPRI signatory	No	1	NA
			SDG13 climate action	Yes	0	-2.64
		Orbis Patent	Green patent number	9	-9	-0.71
			Brown patent number	0	0	0.13
			Green patent citation number	20	-20	-5.39
			Brown patent citation number	0	0	0.1
			Green patent ratio	0.03	-0.03	0
			Brown patent ratio	0	0	0.07
		CDP Survey	SBTi participation	Submitted	1	-2.8
			Greenwashing indicator	46.18	46.18	3.18
			Abatement rate	5	-5	-6.35
			Target underperformance	7.7	7.7	-3.83
			Target impracticability	6.74	6.74	-3.78
					Final Score	31.47

We observe that Apple's *Ambition Score* is equal to 31.47. The main individual factors contributing negatively to the score are carbon emissions levels and greenwashing indicator. On the other hand, Apple's score is reduced by the impact of its green patents, abatement rate, CDP target performance.

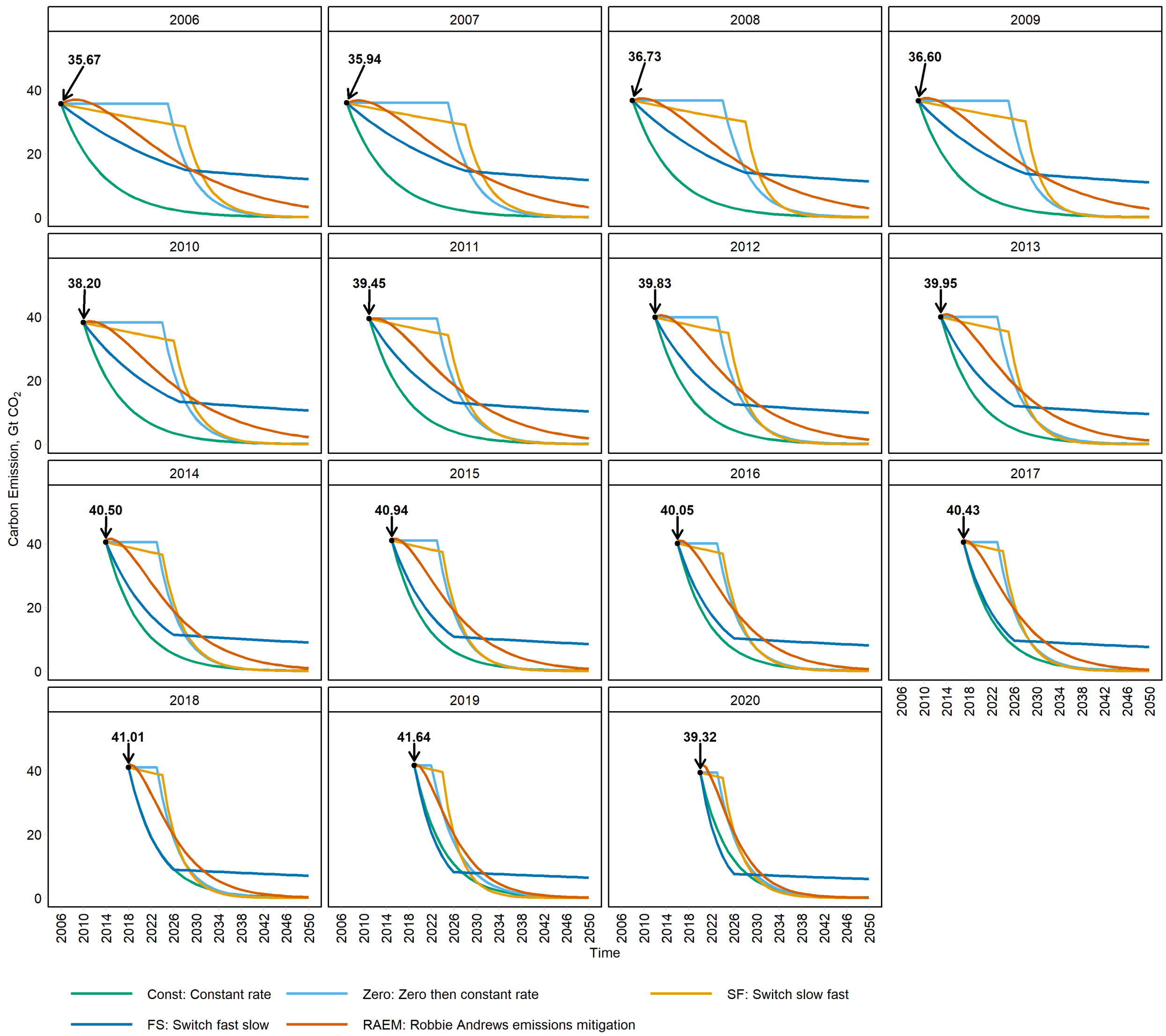

Figure 1: Global carbon budget.

This figure shows how the different choices of decarbonization paths evolve over time from 2006 to 2020. The green pathways, denoted as $Const$, assume that investors follow a constant reduction rate from the first year, so that the terminal emissions value in 2050 is smaller than 0.1 GtCO2e. The light blue pathways, denoted as $ZeroConst$, assume that investors delay the decarbonization process for a while by applying constant emissions, but then it assumes a faster constant reduction rate. The yellow pathways, denoted as SF, switch decarbonization rate from a slow reduction rate of 1% to a faster reduction rate that is not larger than 30% (selected based on feasibility) after several years. The dark blue pathways, denoted as FS, switch from a faster reduction rate to a slow reduction rate of 1%. Here, the faster rate is applied to the maximum number of years possible to make the 2050 emissions budget as low as possible while making sure we fully use up the total cumulative budget. The orange pathways, denoted as $RAEM$, follow the emissions mitigation pathway of Andrew (2020). The mitigation curves were adapted from Raupach et al. (2014) by Andrew (2020).

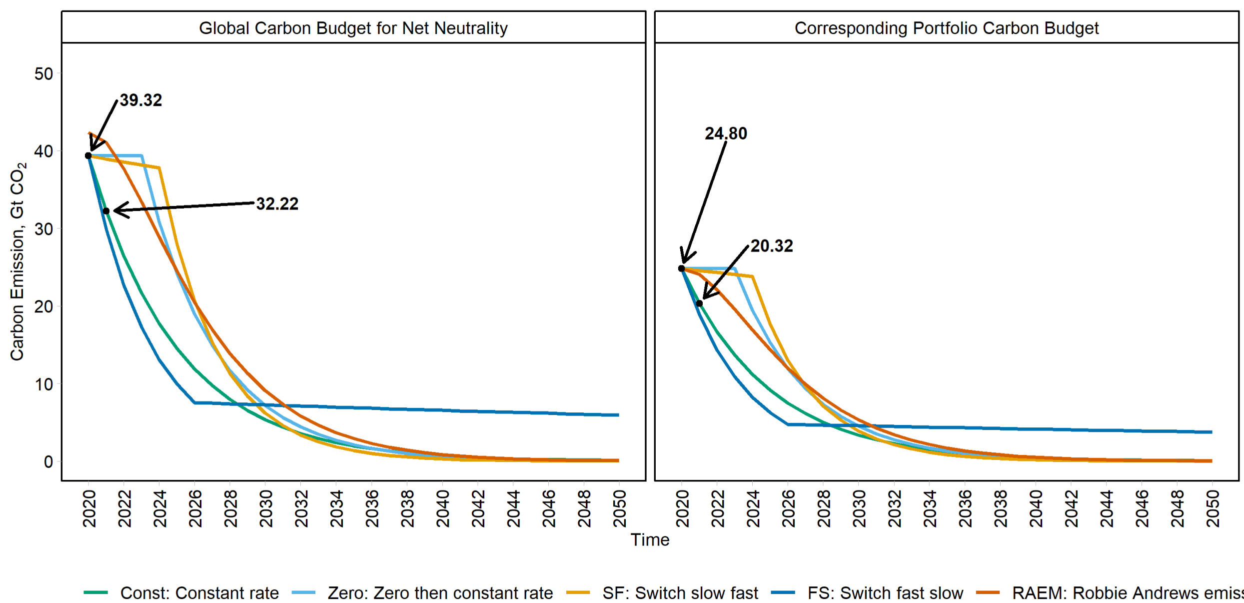

Figure 2: Net-Zero Portfolio carbon budget.

This figure illustrates the correspondence between the global decarbonization pathway and one applied at the portfolio level. The coefficient of proportionality between the two pathways is equal to the ratio of the portfolio emissions (24.80 GtCO2e) in 2020 over the world emissions (39.32 GtCO2e).

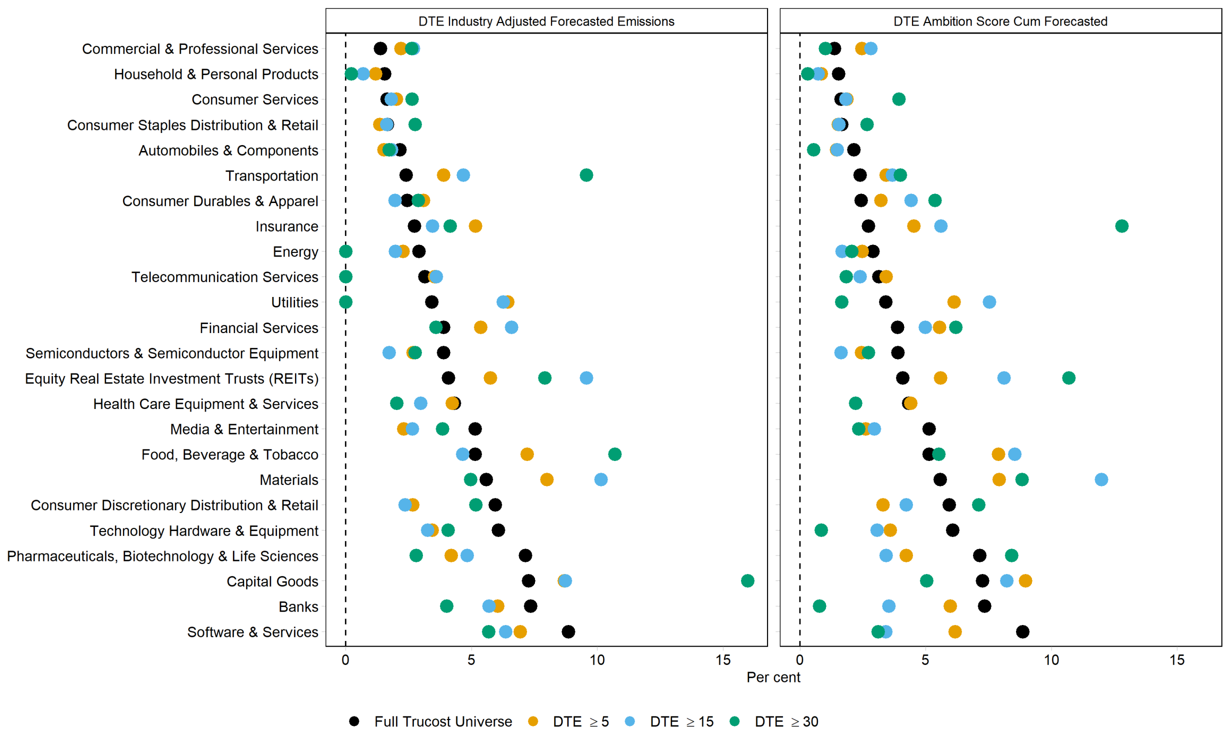

Figure 3: Industry exposure (in %) for the DTE-investable stocks relative to the Trucost universe as of 2020.

This figure shows industry exposures of DTE portfolios compared with those displayed by the universe of all stocks in the Trucost database. We show the DTE portfolios based on industry-adjusted forecasted emissions in the left panel and the DTE portfolios based on *Ambition Score* incorporating forecasted emissions in the right panel. We provide the industry exposure of DTE portfolios using the snapshot of observations in 2020. The three investable sets we consider are: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

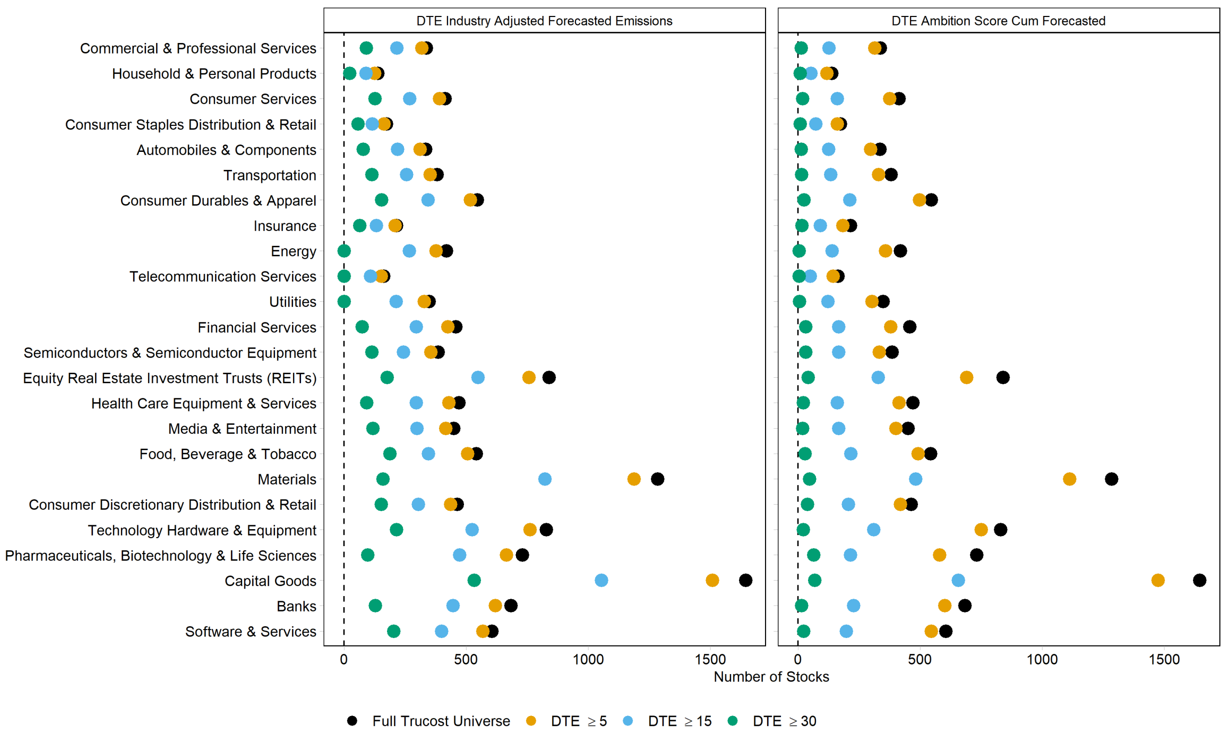

Figure 4: The number of DTE-investable stocks as of 2020.

This figure shows the number of stocks held in DTE portfolios compared with those in the universe of all stocks in the Trucost database. We show the DTE portfolios based on industry-adjusted forecasted emissions in the left panel, and the DTE portfolios based on *Ambition Score* incorporating forecasted emissions in the right panel. We provide the number of stocks in DTE portfolios using the snapshot of observations in 2020. The three investable sets we consider are: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

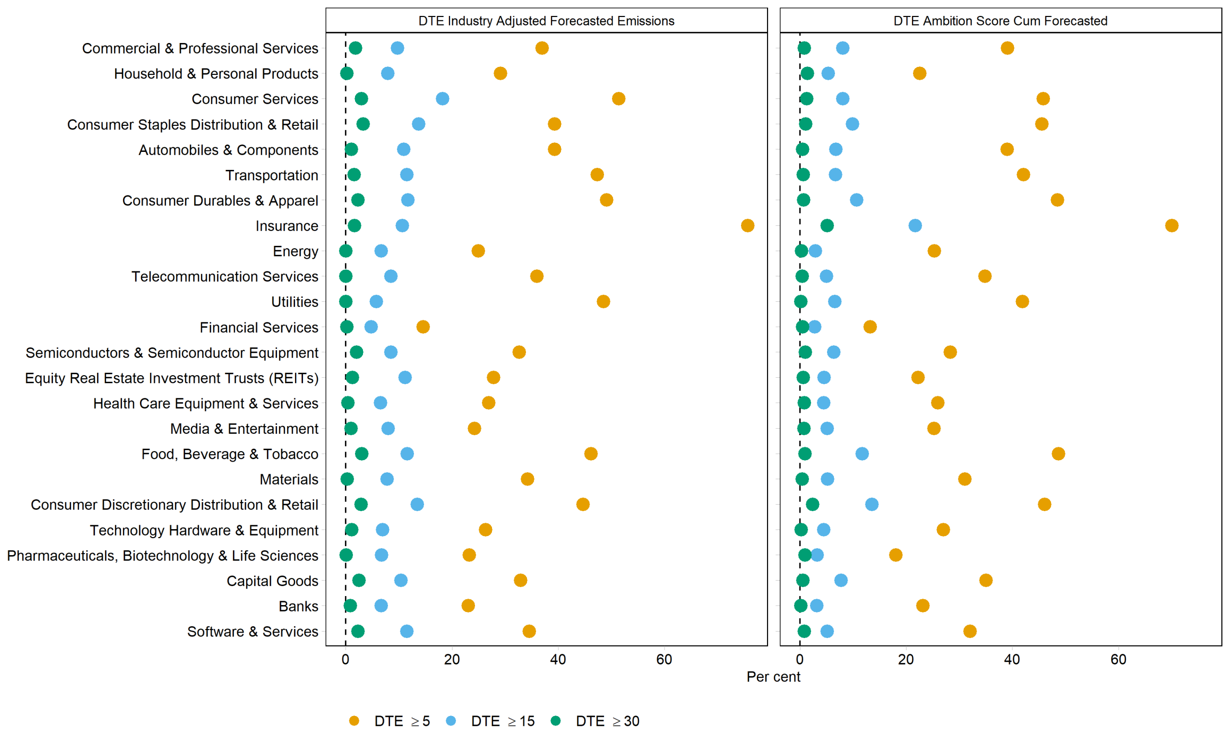

Figure 5: Carbon emissions of DTE-investable stocks relative to the Trucost universe as of 2020: constant-emissions model.

This figure shows the decarbonization performance of DTE portfolios compared with those in the universe of all stocks in the Trucost database. We show the DTE portfolios based on industry-adjusted forecasted emissions in the left panel and the DTE portfolios based on *Ambition Score* incorporating forecasted emissions in the right panel. We provide the percentage reduction in carbon footprint on a given DTE portfolio using the snapshot of observations in 2020. The carbon footprint is based on the observed annual emissions in 2020. The three investable sets we consider are: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

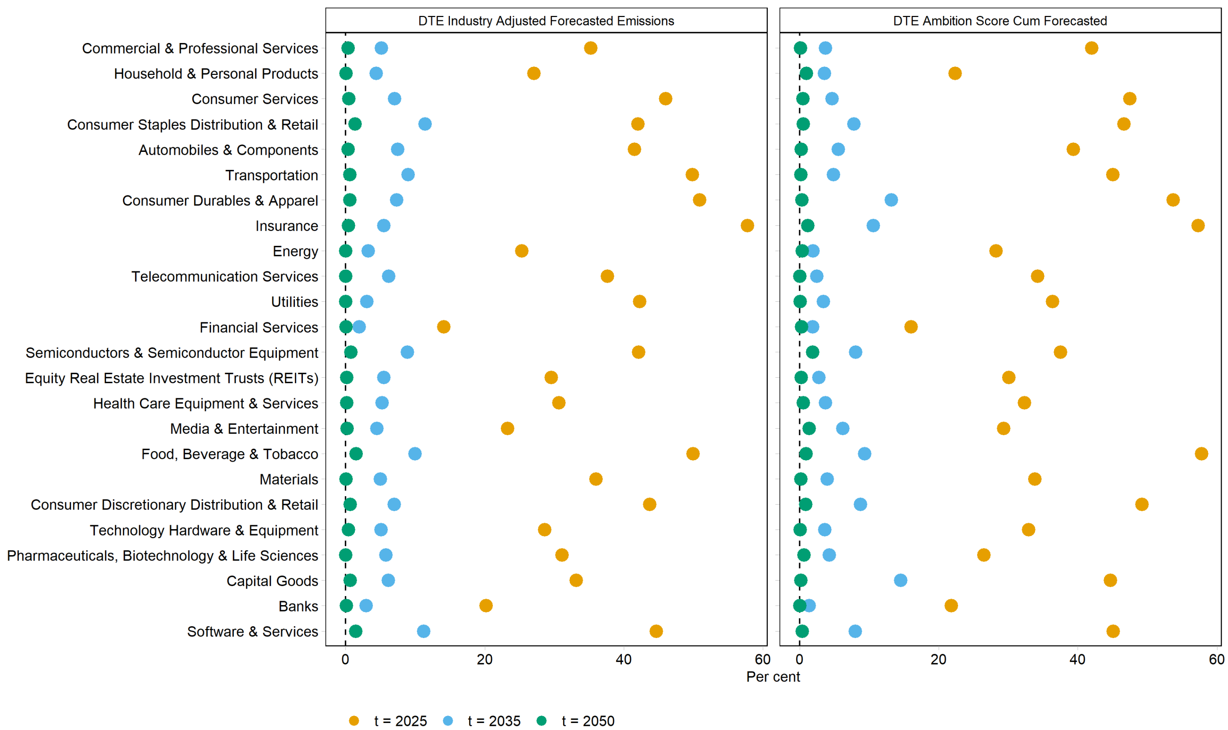

Figure 6: Carbon emissions of DTE-investable stocks relative to the Trucost universe as of 2020: forecasted-emissions model.

This figure shows the decarbonization performance of DTE-investable stocks compared with those in the universe of all stocks in the Trucost database. We present DTE-investable stocks at three time stamps: 2025, 2035, and 2050. We show the investable sets based on industry-adjusted forecasted emissions in the left panel and the investable sets based on *Ambition Score* incorporating forecasted emissions in the right panel. We provide the percentage reduction in carbon footprint on a given investable set using the snapshot of observations in 2020. The carbon footprint is based on the 2020 emissions forecasts over the horizon from 2020 to 2050.

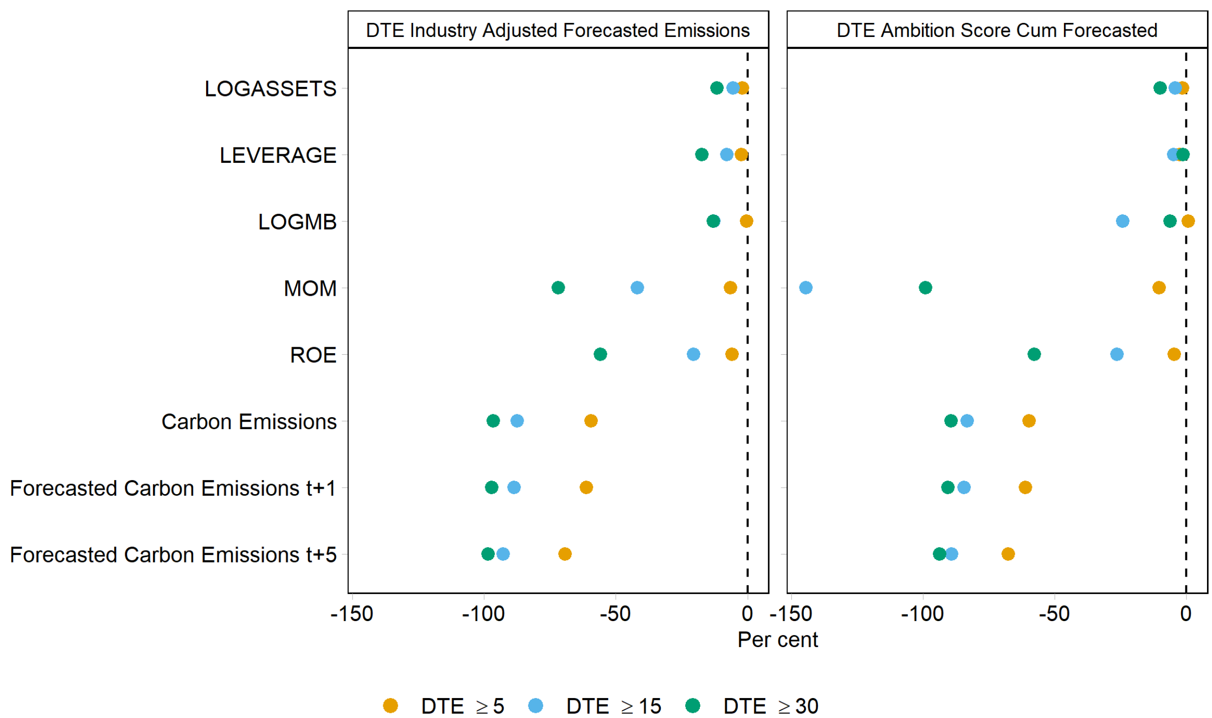

Figure 7: Percentage deviations of DTE-investable stock characteristics from the Trucost universe as of 2020.

This figure shows the style characteristics of DTE portfolios compared with those in the universe of all stocks in the Trucost database. We show the DTE portfolios based on industry-adjusted forecasted emissions in the left panel and the DTE portfolios based on *Ambition Score* incorporating forecasted emissions in the right panel. We provide the percentage deviation for characteristics and carbon footprint on a given DTE portfolio from the Trucost portfolio using the snapshot of observations in 2020. The characteristics we consider include $LOGASSETS$, $LEVERAGE$, $LOGMB$, MOM, and ROE. Carbon footprint is based on both 2020 emissions and emission forecasts. The three investable sets we consider are: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

Table 1: Summary Statistics

This table reports summary statistics (mean, standard deviation, the 25th, 50th, and 75th percentile) for the variables used in regressions. The sample period is 2006-2020. Panel A reports the emission variables. Panel B shows the Ambition Score and its industry-adjusted sub-components. Panel C reports the one-year and five-year ahead forecasted emissions and DTEs derived using different metrics of ranking variables. We show three sets of DTE measures: (1) two based on constant emissions sort; (2) two based on forecasted emissions sort; and (3) two based on *Ambition Score* sort. The first two of the three sets are further divided depending on whether the sorting variable is industry-adjusted or not. For the *Ambition Score* sort, we conduct the exclusion by filling the carbon budget using constant emissions and forecasted emissions, respectively. Panel D summarizes information on firm-level variables that enter our regression models. RET is the monthly stock return; $LOGPE$ is share price divided by earnings per share; $LOGMB$ is market cap divided by its book value; $LOGPS$ is the share price divided by sales per share; $LOGSIZE$ is the natural logarithm of market capitalization; $LOGASSETS$ is the natural logarithm of asset value; $LEVERAGE$ is the ratio of debt to book value of assets; MOM is the average stock returns over the one-year period; $INVEST/ASSETS$ is capital expenditures divided by the book value of its assets; $LOGPPE$ is the natural logarithm of the property, plant, and equipment; $VOLAT$ is the standard deviation of returns based on the past 12 monthly returns; ROE is the ratio of net yearly income divided by the value of equity; AGE is firm age; $DOLVOL$ is the dollar volume in billion; $SALESGR$ is the annual growth rate in firm sales.

	Mean	Std.Dev	Q25	Median	Q75
Panel A: Carbon Emissions					
Carbon Emissions (Scope 1, 2, 3 upstream)	3094098	14507951	50600	239626	1135341
Growth Rate in Carbon Emissions (Scope 1, 2, 3 upstream)	0.134	0.416	-0.023	0.053	0.167
Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	550.287	1708.348	87.231	193.004	423.004
Growth Rate in Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	0.007	0.142	-0.042	-0.014	0.028
Panel B: Ambition Score Variables (Industry-Group Standardized)					
Ambition Score	0.701	8.100	-0.088	0.146	0.583
Carbon Emissions (Scope 1, 2, 3 upstream)	1.460	14.629	-0.218	-0.004	0.735
Growth Rate in Carbon Emissions (Scope 1, 2, 3 upstream)	0.386	2.063	-0.401	0.000	0.579
Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	1.409	55.598	-0.287	0.000	0.622
Growth Rate in Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	0.497	5.655	-0.464	0.000	0.471
Decarbonization Target	0.010	0.991	0.292	0.402	0.543
Decarbonization Policy	0.016	0.994	-1.029	0.556	0.755
Reported Emissions	0.017	0.992	-1.056	0.525	0.708
CSR Committee	0.017	0.991	-1.042	0.490	0.668
UNPRI Signatory	0.009	0.973	0.039	0.044	0.089
SDG 13 Climate Action	0.013	1.006	0.043	0.323	0.422
# Patents (Green)	0.001	0.980	0.080	0.110	0.186
# Patents (Brown)	0.007	0.933	0.076	0.113	0.153
# Patent Citations (Green)	0.003	0.979	0.070	0.130	0.209
# Patent Citations (Brown)	0.004	0.974	0.072	0.104	0.162
Ratio of # Green Patents over # Patents	-0.004	1.003	0.083	0.188	0.294
Ratio of # Brown Patents over # Patents	0.002	0.984	0.067	0.106	0.200
SBTi Status	0.006	0.989	0.123	0.151	0.190
Greenwash Indicator	0.002	1.003	-0.097	-0.060	-0.022
Abatement Rate	0.005	0.991	0.144	0.178	0.214
Underperformance	0.006	0.988	0.197	0.244	0.293
Infeasible Indicator	0.004	0.996	0.187	0.216	0.253
Panel C: DTE-Related Variables					
Forecasted Emissions t1	3248288	15635351	53408	253908	1192281
Forecasted Emissions t5	4657073	35491481	61523	313218	1528164
DTE Constant Emissions	23.571	10.096	16.000	24.000	31.000
DTE Industry-Adjusted Constant Emissions	19.474	10.320	11.000	19.000	28.000
DTE Forecasted emissions	22.834	11.029	13.000	24.000	32.000
DTE Industry-Adjusted Forecasted Emissions	18.774	11.029	9.000	18.000	29.000
DTE Ambition Score Cum Constant	13.026	7.721	8.000	12.000	17.000
DTE Ambition Score Cum Forecasted	13.082	8.732	6.000	12.000	18.000
Panel D: Additional Regression Variables					
RET	1.012	13.143	-4.945	0.452	6.108
LOGPE	3.033	0.927	2.504	2.960	3.451
LOGMB	0.710	1.013	0.082	0.663	1.306
LOGPS	0.302	1.328	-0.532	0.282	1.087
LOGSIZE	9.619	2.606	7.869	9.413	11.273
LOGASSETS	9.644	2.717	7.809	9.385	11.387
LEVERAGE (winsorized at 2.5%)	0.225	0.182	0.068	0.203	0.340
MOM (winsorized at 2.5%)	0.100	0.402	-0.164	0.047	0.286
INVEST/ASSETS (winsorized at 2.5%)	0.047	0.046	0.015	0.034	0.064
LOGPPE	7.906	3.243	5.759	7.798	10.029
VOLAT (winsorized at 2.5%)	0.098	0.053	0.061	0.086	0.121
ROE (winsorized at 2.5%)	0.198	0.240	0.075	0.166	0.286
AGE	57.304	48.361	23.000	42.000	78.000
DOLVOL in Billion (winsorized at 2.5%)	17.991	51.326	0.148	0.987	6.115
SALESGR (winsorized at 2.5%)	0.091	0.208	-0.001	0.052	0.152

Table 2: Table 2 DTE: Basic Properties

Panel A reports Pearson correlation across various DTEs as defined earlier, carbon emissions and the Ambition Score. Panel B shows the time-series variation of the stock universe and DTEs. We show the number of firms with available data for the computation of DTEs in the first column. We then show the average DTEs overtime.

	Carbon Emissions (Scope 1, 2, 3 upstream)	Ambition Score	DTE Constant Emissions	DTE Industry Adjusted Constant Emissions	DTE Forecasted emissions	DTE Industry Adjusted Forecasted Emissions	DTE Ambition Score Cum Constant
Panel A: Correlations							
Ambition Score	0.099	1.000					
DTE Const. Emissions	-0.380	-0.080	1.000				
DTE Ind. Adj. Const. Emissions	-0.287	-0.093	0.741	1.000			
DTE Forecasted Emissions	-0.341	-0.089	0.871	0.662	1.000		
DTE Ind. Adj. Forecasted Emissions	-0.257	-0.099	0.621	0.822	0.770	1.000	
DTE Ambition Score Cum Const.	-0.205	-0.156	0.342	0.432	0.466	0.566	1.000
DTE Ambition Score Cum Forecasted	-0.193	-0.146	0.329	0.422	0.469	0.575	0.986

Year	No. Firms	DTE Constant Emissions	DTE Industry-Adjusted Constant Emissions	DTE Forecasted emissions	DTE Industry-Adjusted Forecasted Emissions	DTE Ambition Score Cum Constant	DTE Ambition Score Cum Forecasted
Panel B: Stock universe and average DTEs by year							
2006	2510	29.087	23.007	27.393	22.091	14.894	13.093
2007	2696	28.251	22.692	25.188	18.801	14.142	13.393
2008	2672	27.539	22.313	25.743	20.874	14.118	13.675
2009	2789	26.652	21.428	26.272	21.918	12.971	13.706
2010	2931	26.041	21.251	25.989	21.458	12.932	14.108
2011	3154	25.456	20.653	25.088	20.043	13.437	14.102
2012	3328	24.882	20.110	24.023	18.388	12.858	12.347
2013	3351	24.199	19.361	23.998	18.568	12.770	13.209
2014	3958	23.610	19.175	23.127	19.056	12.983	13.439
2015	4280	23.050	18.893	23.375	19.316	12.928	14.554
2016	4483	22.369	18.376	22.679	18.585	12.330	14.014
2017	10401	23.321	19.522	21.887	17.836	13.138	12.227
2018	11300	22.715	19.048	20.801	17.081	13.546	12.758
2019	12032	22.079	18.624	21.420	18.183	12.778	12.501
2020	12855	21.423	18.065	21.873	18.831	12.219	13.024

Table 3: Determinants of the Distance-to-Exit (DTE)

This table reports estimates of Equation (1). The dependent variables are DTEs as defined in Panel C of Table 1. The independent variables are defined in Panel D of Table 1, including *LOGCO2*, *LOGMKTCAP*, *LOGASSETS*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Constant Emissions		Forecasted emissions		Ambition Score	
	(1) DTE Constant Emissions	(2) DTE Industry-Adjusted Constant Emissions	(3) DTE Forecasted Emissions	(4) DTE Industry-Adjusted Forecasted Emissions	(5) DTE Ambition Score Cum Constant	(6) DTE Ambition Score Cum Forecasted
LOGCO2	-3.695***	-3.952***	-4.098***	-4.196***	-2.182***	-2.418***
	(0.296)	(0.208)	(0.298)	(0.212)	(0.084)	(0.104)
LOGMKTCAP	-0.258***	-0.778***	-0.409***	-0.858***	0.050	0.049
	(0.076)	(0.076)	(0.085)	(0.100)	(0.107)	(0.123)
LOGASSETS	-0.475***	-0.914***	-0.149	-0.587***	0.057	0.056
	(0.065)	(0.101)	(0.090)	(0.103)	(0.104)	(0.118)
LOGMB	-0.072	0.118	-0.446***	-0.388***	-0.412***	-0.486***
	(0.070)	(0.075)	(0.104)	(0.102)	(0.097)	(0.109)
LEVERAGE	-0.397	-1.074***	-0.842***	-1.225***	-0.056	-0.072
	(0.237)	(0.326)	(0.277)	(0.385)	(0.338)	(0.380)
MOM	0.367***	0.508***	0.031	0.202	-0.689***	-0.809***
	(0.075)	(0.099)	(0.181)	(0.194)	(0.166)	(0.203)
INVEST/ASSETS	0.204	0.965	-11.544***	-10.524***	-11.750***	-13.678***
	(0.693)	(0.882)	(1.803)	(1.664)	(1.468)	(1.678)
LOGPPE	0.237***	0.409***	0.525***	0.746***	0.497***	0.577***
	(0.064)	(0.076)	(0.090)	(0.089)	(0.073)	(0.084)
VOLAT	-5.687***	-6.517***	-8.331***	-9.911***	-3.718***	-4.457***
	(0.580)	(0.764)	(1.158)	(1.297)	(0.743)	(0.842)
ROE	1.341***	1.044***	0.540*	0.076	-0.131	-0.233
	(0.273)	(0.301)	(0.277)	(0.291)	(0.231)	(0.262)
DOLVOL	-0.007***	-0.005***	-0.007***	-0.006***	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
AGE	2.027*	3.503**	13.479***	15.239***	17.090***	19.314***
	(1.005)	(1.531)	(1.893)	(2.110)	(1.937)	(2.292)
Constant	74.848***	83.264***	77.005***	82.560***	37.643***	40.417***
	(2.996)	(2.781)	(3.048)	(2.709)	(1.127)	(1.266)
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	794,266	794,266	794,266	794,266	794,266	794,266
R-squared	0.897	0.802	0.722	0.617	0.280	0.275

Table 4: Returns and *DTE*s

This table presents the estimation results of equation (2). The dependent variable is *RET* measured monthly. The main independent variables are *DTE*s constructed with different ranking variables as defined in Panel C of Table 1. Control variables include *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*, as defined in Panel D of Table 1. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
DTE Constant Emissions	-0.048***					
	(0.012)					
DTE Industry-Adjusted Constant Emissions		-0.040***				
		(0.010)				
DTE Forecasted Emissions			-0.031***			
			(0.009)			
DTE Industry-Adjusted Forecasted Emissions				-0.029***		
				(0.008)		
DTE Ambition Score Cum Constant					-0.026***	
					(0.006)	
DTE Ambition Score Cum Forecasted						-0.023***
						(0.006)
LOGMKTCAP	-0.370***	-0.383***	-0.327***	-0.343***	-0.265***	-0.265***
	(0.084)	(0.081)	(0.075)	(0.078)	(0.063)	(0.063)
LOGMB	-0.072	-0.068	-0.114	-0.110	-0.141*	-0.142*
	(0.064)	(0.063)	(0.070)	(0.068)	(0.075)	(0.075)
LEVERAGE	-0.488**	-0.507***	-0.432**	-0.450**	-0.333*	-0.333*
	(0.167)	(0.165)	(0.167)	(0.166)	(0.179)	(0.179)
MOM	0.692**	0.695**	0.671**	0.677**	0.651**	0.650**
	(0.235)	(0.235)	(0.234)	(0.234)	(0.236)	(0.236)
INVEST/ASSETS	-0.069	-0.018	-0.591	-0.496	-0.679	-0.691
	(0.870)	(0.877)	(0.826)	(0.834)	(0.831)	(0.828)
LOGPPE	0.033	0.038	0.060**	0.061**	0.079**	0.079**
	(0.023)	(0.025)	(0.026)	(0.026)	(0.027)	(0.027)
VOLAT	3.928	3.936	3.932	3.903	4.056	4.050
	(4.292)	(4.298)	(4.301)	(4.295)	(4.320)	(4.319)
DOLVOL	-0.007	-0.006	-0.006	-0.005	-0.004	-0.004
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)
AGE	-0.426	-0.357	-0.045	-0.013	0.084	0.087
	(0.696)	(0.681)	(0.627)	(0.615)	(0.586)	(0.586)
Constant	5.097***	4.876***	4.119***	4.134***	3.041***	3.000***
	(0.601)	(0.479)	(0.433)	(0.410)	(0.294)	(0.291)
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	786,787	786,787	786,787	786,787	786,787	786,787
R-squared	0.142	0.142	0.142	0.142	0.142	0.142

Table 5: Returns and Lagged DTEs

This table presents the estimation results of equation (2) with lagged DTE signals. The dependent variable is RET measured monthly. The main independent variables are 12-month lagged DTEs, constructed with different ranking variables, as defined in Panel C of Table 1. All regressions include the same set of control variables as in Table 4, defined in Panel D of Table 1. The sample period is 2005-2020. We report the results of the pooled regression model with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
DTE Constant Emissions	-0.021***					
	(0.006)					
DTE Industry-Adjusted Constant Emissions		-0.018***				
		(0.006)				
DTE Forecasted Emissions			-0.003			
			(0.006)			
DTE Industry-Adjusted Forecasted Emissions				-0.008		
				(0.006)		
DTE Ambition Score Cum Constant					-0.003	
					(0.004)	
DTE Ambition Score Cum Forecasted						-0.002
						-0.003
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	709,424	709,424	709,424	709,424	709,424	709,424
R-squared	0.148	0.148	0.148	0.148	0.148	0.148

Table 6: Valuation Ratios and DTEs

This table presents the estimation results of equation (3). The dependent variables are $LOGPE$ in Panel A, $LOGMB$ in Panel B, and $LOGPS$ in Panel C, all defined in Panel D of Table 1. The main independent variables are DTEs constructed with different ranking variables, defined in Panel C of Table 1. Control variables include MOM, $VOLAT$, AGE, and $SALESGR$, defined in Panel D of 1. In addition, we include one-year and two year-ahead measures of $SALESGR$ to proxy for future cash-flow growth. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dependent Variable: LOGPE						
DTE Constant Emissions	0.008***					
	(0.001)					
DTE Industry-Adjusted Constant Emissions		0.006***				
		(0.001)				
DTE Forecasted Emissions			0.005***			
			(0.001)			
DTE Industry-Adjusted Forecasted Emissions				0.004***		
				(0.001)		
DTE Ambition Score Cum Constant					0.004***	
					(0.001)	
DTE Ambition Score Cum Forecasted						0.003***
						(0.001)
Observations	499,903	499,903	499,903	499,903	499,903	499,903
R-squared	0.245	0.244	0.244	0.243	0.242	0.242
Panel B. Dependent Variable: LOGMB						
DTE Constant Emissions	0.006***					
	(0.001)					
DTE Industry-Adjusted Constant Emissions		0.004***				
		(0.001)				
DTE Forecasted Emissions			0.002**			
			(0.001)			
DTE Industry-Adjusted Forecasted Emissions				0.001		
				(0.001)		
DTE Ambition Score Cum Constant					0.002**	
					(0.001)	
DTE Ambition Score Cum Forecasted						0.002*
						(0.001)
Observations	560,288	560,288	560,288	560,288	560,288	560,288
R-squared	0.412	0.412	0.411	0.411	0.411	0.411
Panel C. Dependent Variable: LOGPS						
DTE Constant Emissions	0.036***					
	(0.002)					
DTE Industry-Adjusted Constant Emissions		0.025***				
		(0.002)				
DTE Forecasted Emissions			0.023***			
			(0.003)			
DTE Industry-Adjusted Forecasted Emissions				0.017***		
				(0.002)		
DTE Ambition Score Cum Constant					0.007***	
					(0.002)	
DTE Ambition Score Cum Forecasted						0.006***
						(0.001)
Observations	566,729	566,729	566,729	566,729	566,729	566,729
R-squared	0.522	0.512	0.505	0.499	0.482	0.482
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Returns and DTEs: Extensive Margin

This table presents the estimation results on the extensive margin. The dependent variable is RET, measured monthly. The independent variables (EXTs) are transformations of DTEs (as defined in Panel C of Table 1) that are equal to one for companies that never exit net-zero portfolios, and equal to zero for companies that exit net-zero portfolios at any point prior to and including the final year 2050. Control variables are the same as in Table 4. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
EXT Constant Emissions	-0.359***					
	(0.111)					
EXT Industry-Adjusted Constant Emissions		-0.321***				
		(0.100)				
EXT Forecasted Emissions			-0.451***			
			(0.122)			
EXT Industry-Adjusted Forecasted Emissions				-0.320***		
				(0.104)		
EXT Ambition Score Cum Constant					-0.269**	
					(0.115)	
EXT Ambition Score Cum Forecasted						-0.268**
						(0.103)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	864,334	864,334	864,334	864,334	864,334	864,334
R-squared	0.137	0.137	0.137	0.137	0.137	0.137

Table 8: Returns and DTEs: Paris Agreement

This table presents the estimation results of equation (4). The dependent variable is RET measured monthly. We define an indicator variable, $Paris$, that is equal to one for the years starting from 2016, and equal to zero up to and including 2015. The main independent variables are DTEs, constructed with different ranking variables, as defined in Panel C of Table 1, and the interaction terms between DTEs and $Paris$. All regressions include the same set of control variables as in Table 4, defined in Panel D of Table 1. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dependent Variable: RET						
DTE Constant Emissions	-0.043***					
	(0.011)					
DTE Constant Emissions × Paris	-0.025***					
	(0.008)					
DTE Industry-Adjusted Constant Emissions		-0.030***				
		(0.009)				
DTE Industry-Adjusted Constant Emissions × Paris		-0.028***				
		(0.007)				
DTE Forecasted Emissions			-0.023**			
			(0.008)			
DTE Forecasted Emissions × Paris			-0.021**			
			(0.009)			
DTE Industry-Adjusted Forecasted Emissions				-0.019**		
				(0.008)		
DTE Industry-Adjusted Forecasted Emissions × Paris				-0.025***		
				(0.007)		
DTE Ambition Score Cum Constant					-0.018***	
					(0.006)	
DTE Ambition Score Cum Constant × Paris					-0.016	
					(0.012)	
DTE Ambition Score Cum Forecasted						-0.016***
						(0.005)
DTE Ambition Score Cum Forecasted × Paris						-0.016
						(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	786,787	786,787	786,787	786,787	786,787	786,787
R-squared	0.142	0.142	0.142	0.142	0.142	0.142
Panel B. Dependent Variable: LOGPE						
DTE Constant Emissions	0.006***					
	(0.001)					
DTE Constant Emissions × Paris	0.006**					
	(0.002)					
DTE Industry-Adjusted Constant Emissions		0.004***				
		(0.001)				
DTE Industry-Adjusted Constant Emissions × Paris		0.004***				
		(0.001)				
DTE Forecasted Emissions			0.004***			
			(0.001)			
DTE Forecasted Emissions × Paris			0.005***			
			(0.001)			
DTE Industry-Adjusted Forecasted Emissions				0.003***		
				(0.001)		
DTE Industry-Adjusted Forecasted Emissions × Paris				0.003***		
				(0.001)		
DTE Ambition Score Cum Constant					0.004***	
					(0.001)	
DTE Ambition Score Cum Constant × Paris					0.001	
					(0.001)	
DTE Ambition Score Cum Forecasted						0.003***
						(0.001)
DTE Ambition Score Cum Forecasted × Paris						0.001
						(0.001)
Observations	499,903	499,903	499,903	499,903	499,903	499,903
R-squared	0.246	0.245	0.244	0.243	0.242	0.242
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Returns and DTEs: Controlling for Climate Variables

This table presents the estimation results with additional control variables on climate. The dependent variable is RET measured monthly. The main independent variables are DTEs constructed with different ranking variables as defined in Panel C of Table 1. In addition to the same set of control variables as in Table 4, we also include *Ambition Score*, the natural logarithm of total emissions, $LOGCO2$, the percentage change in total emissions, *Emissions Growth*, and emission intensity, *Emissions Intensity*, as additional controls in the returns regression model. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
DTE Constant Emissions	-0.011					
	(0.015)					
DTE Industry-Adjusted Constant Emissions		-0.018				
		(0.010)				
DTE Forecasted Emissions			-0.011			
			(0.009)			
DTE Industry-Adjusted Forecasted Emissions				-0.014*		
				(0.008)		
DTE Ambition Score Cum Constant					-0.013**	
					(0.005)	
DTE Ambition Score Cum Forecasted						-0.012**
						(0.004)
Ambition Score	0.056	0.056	0.040	0.035	-0.039	-0.033
	(0.134)	(0.141)	(0.134)	(0.136)	(0.153)	(0.150)
LOGCO2	0.302***	0.270***	0.296***	0.281***	0.314***	0.314***
	(0.057)	(0.045)	(0.044)	(0.038)	(0.034)	(0.034)
Emissions Growth	0.245**	0.246**	0.236**	0.234**	0.225**	0.225**
	(0.090)	(0.089)	(0.085)	(0.083)	(0.085)	(0.085)
Emission Intensity	-0.014**	-0.014**	-0.014**	-0.014**	-0.014***	-0.014***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	786,577	786,577	786,577	786,577	786,577	786,577
R-squared	0.142	0.142	0.142	0.142	0.142	0.142

Table 10: Returns and DTEs: Scope 1 and 2

This table presents the estimation results of equation (2) but with the sum of scope 1 and scope 2 emissions only. The dependent variable is RET, measured monthly. The main independent variables are DTEs constructed using the same methodology as those defined in Panel C of Table 1, but excluding scope 3 emissions. We also include the same set of control variables as in Table 4, defined in Panel D of Table 1. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
DTE Constant Emissions	-0.032***					
	(0.008)					
DTE Industry-Adjusted Constant Emissions		-0.027***				
		(0.006)				
DTE Forecasted Emissions			-0.024***			
			(0.007)			
DTE Industry-Adjusted Forecasted Emissions				-0.023***		
				(0.006)		
DTE Ambition Score Cum Constant					-0.014***	
					(0.004)	
DTE Ambition Score Cum Forecasted						-0.013***
						(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	786,787	786,787	786,787	786,787	786,787	786,787
R-squared	0.142	0.142	0.142	0.142	0.142	0.142

Table 11: Returns and DTEs: The Role of Carbon Disclosure

This table presents the estimation results of equation (5). The dependent variable is RET, measured monthly. We define an indicator variable $Disclosure$ that is equal to one if the company directly discloses its emissions, and it is equal to zero if the information is estimated by the data provider. The main independent variables are DTEs, constructed with different ranking variables, as defined in Panel C of Table 1 and the interaction terms between DTEs and $Disclosure$. We include the same set of control variables as in Table 4, defined in Panel D of Table 1. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
DTE Constant Emissions	-0.046***					
	(0.012)					
DTE Constant Emissions × Disclosure	-0.016**					
	(0.005)					
DTE Industry-Adjusted Constant Emissions		-0.037***				
		(0.010)				
DTE Industry-Adjusted Constant Emissions × Disclosure		-0.018***				
		(0.005)				
DTE Forecasted Emissions			-0.030***			
			(0.009)			
DTE Forecasted Emissions × Disclosure			-0.006			
			(0.004)			
DTE Industry-Adjusted Forecasted Emissions				-0.027***		
				(0.009)		
DTE Industry-Adjusted Forecasted Emissions × Disclosure				-0.009**		
				(0.004)		
DTE Ambition Score Cum Constant					-0.032***	
					(0.008)	
DTE Ambition Score Cum Constant × Disclosure					0.017**	
					(0.006)	
DTE Ambition Score Cum Forecasted						-0.028***
						(0.007)
DTE Ambition Score Cum Forecasted × Disclosure						0.014**
						(0.005)
Disclosure	0.222*	0.242**	0.087	0.140	-0.191*	-0.164*
	(0.116)	(0.097)	(0.105)	(0.096)	(0.097)	(0.092)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	786,787	786,787	786,787	786,787	786,787	786,787
R-squared	0.142	0.142	0.142	0.142	0.142	0.142

Table 12: Returns and DTEs: Additional Decarbonization Pathways

This table presents the estimation results of equation (2) and equation (3) with alternative portfolio decarbonization pathways. Pathway $ZeroConst$ assumes investors delay the decarbonization process for a while by applying constant emissions, but then they follow a faster constant-reduction rate. Pathway SF switches from a slow reduction rate of 1% to a faster reduction rate that is not larger than 30% after several years. Pathway FS switches from a faster reduction rate to a slow reduction rate of 1%. Pathway denoted $RAEM$ follows the emission mitigation pathway of Andrew (2020). The main independent variables are DTEs, constructed using the same methodology as in Panel C of Table 1, but under the alternative pathways. The dependent variable in Panels 1 is RET, measured monthly with the same set of control variables as in Table 4. The dependent variable in Panels 2 is $LOGPE$ with the same set of control variables as in Table 6. The sample period is 2005-2020. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects, country-fixed effects, and Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Constant Emissions		Forecasted Emissions		Ambition Score		Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A1. Dependent Variable: RET. Pathway: Zero						Panel A2. Dependent Variable: LOGPE. Pathway: Zero					
DTE Constant Emissions	-0.077***						0.006***					
	(0.018)						(0.001)					
DTE Industry-Adjusted Constant Emissions		-0.060***						0.005***				
		(0.011)						(0.001)				
DTE Forecasted Emissions			-0.045***						0.013***			
			(0.012)						(0.001)			
DTE Industry-Adjusted Forecasted Emissions				-0.039***						0.008***		
				(0.010)						(0.001)		
DTE Ambition Score Cum Constant					-0.037***						0.009***	
					(0.009)						(0.001)	
DTE Ambition Score Cum Forecasted						-0.028***						0.006***
						(0.007)						(0.001)
Observations	786,787	786,787	786,787	786,787	786,787	786,787	499,903	499,903	499,903	499,903	499,903	499,903
R-squared	0.142	0.142	0.142	0.142	0.142	0.142	0.242	0.242	0.246	0.244	0.245	0.243
	Panel B1. Dependent Variable: RET. Pathway: SF						Panel B2. Dependent Variable: LOGPE. Pathway: SF					
DTE Constant Emissions	-0.093***						0.006***					
	(0.016)						(0.001)					
DTE Industry-Adjusted Constant Emissions		-0.064***						0.005***				
		(0.011)						(0.001)				
DTE Forecasted Emissions			-0.052***						0.014***			
			(0.013)						(0.002)			
DTE Industry-Adjusted Forecasted Emissions				-0.040***						0.009***		
				(0.010)						(0.001)		
DTE Ambition Score Cum Constant					-0.040***						0.010***	
					(0.009)						(0.001)	
DTE Ambition Score Cum Forecasted						-0.029***						0.006***
						(0.007)						(0.001)
Observations	786,787	786,787	786,787	786,787	786,787	786,787	499,903	499,903	499,903	499,903	499,903	499,903
R-squared	0.142	0.142	0.142	0.142	0.142	0.142	0.242	0.242	0.247	0.244	0.245	0.243
	Panel C1. Dependent Variable: RET. Pathway: FS						Panel C2. Dependent Variable: LOGPE. Pathway: FS					
DTE Constant Emissions	-0.008*						0.003***					
	(0.004)						(0.000)					
DTE Industry-Adjusted Constant Emissions		-0.017***						0.003***				
		(0.003)						(0.000)				
DTE Forecasted Emissions			-0.010**						0.005***			
			(0.004)						(0.001)			
DTE Industry-Adjusted Forecasted Emissions				-0.015***						0.004***		
				(0.004)						(0.001)		
DTE Ambition Score Cum Constant					-0.012***						0.005***	
					(0.004)						(0.000)	
DTE Ambition Score Cum Forecasted						-0.011***						0.004***
						(0.004)						(0.000)
Observations	786,787	786,787	786,787	786,787	786,787	786,787	499,903	499,903	499,903	499,903	499,903	499,903
R-squared	0.142	0.142	0.142	0.142	0.142	0.142	0.243	0.243	0.242	0.243	0.244	0.243
	Panel D1. Dependent Variable: RET. Pathway: RAEM						Panel D2. Dependent Variable: LOGPE. Pathway: RAEM					
DTE Constant Emissions	-0.043***						0.005***					
	(0.011)						(0.001)					
DTE Industry-Adjusted Constant Emissions		-0.047***						0.004***				
		(0.009)						(0.001)				
DTE Forecasted Emissions			-0.030***						0.009***			
			(0.009)						(0.001)			
DTE Industry-Adjusted Forecasted Emissions				-0.029***						0.006***		
				(0.008)						(0.001)		
DTE Ambition Score Cum Constant					-0.023***						0.007***	
					(0.006)						(0.001)	
DTE Ambition Score Cum Forecasted						-0.019***						0.005***
						(0.005)						(0.001)
Observations	786,787	786,787	786,787	786,787	786,787	786,787	499,903	499,903	499,903	499,903	499,903	499,903
R-squared	0.142	0.142	0.142	0.142	0.142	0.142	0.243	0.243	0.244	0.244	0.245	0.244
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Online Appendix to "Carbon-Transition Risk and Net-Zero Portfolios"

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IA Additional Tables and Figures

Table IA.1: Correlations between Carbon Emissions, Ambition Score, and DTEs.

This table presents the correlation matrix between carbon emissions, ambition score, and $DTEs$. The DTEs are constructed using different ranking measures and portfolio decarbonization pathways. In terms of ranking measures, we consider three sets of DTE measures: (1) two based on constant emissions sort; (2) two based on forecasted emissions sort; and (3) two based on *Ambition Score* sort. The first two of the three sets are further divided depending on whether the sorting variable is industry-adjusted or not. For the *Ambition Score* sort, we conduct the exclusion by filling the carbon budget using constant emissions and forecasted emissions, respectively. Reagrding pathways, $ZeroConst$ assumes investors delay the decarbonization process for a while by applying constant emission, but then it assumes a faster constant reduction rate. Pathways SF switch from a slow reduction rate of 1% to a faster reduction rate that is not larger than 30% after several years. Pathways FS switch from a faster reduction rate to a slow reduction rate of 1%. Pathways denoted $RAEM$ follow the emission mitigation pathway constructed by Andrew (2020).

	Carbon Emissions	Ambition Score	DTE Const. Emissions	DTE Ind. Adj. Const. Emissions	DTE Forecasted emissions	DTE Ind. Adj. Forecasted Emissions	DTE Ambition Score Cum Const.	DTE Ambition Score Cum Forecasted	DTE Const. Emissions	DTE Ind. Adj. Const. Emissions	DTE Forecasted emissions	DTE Ind. Adj. Forecasted Emissions	DTE Ambition Score Cum Const.	DTE Ambition Score Cum Forecasted	DTE Const. Emissions	DTE Ind. Adj. Const. Emissions	DTE Forecasted emissions	DTE Ind. Adj. Forecasted Emissions	DTE Ambition Score Cum Const.	DTE Ambition Score Cum Forecasted	DTE Const. Emissions	DTE Ind. Adj. Const. Emissions	DTE Forecasted emissions	DTE Ind. Adj. Forecasted Emissions	DTE Ambition Score Cum Const.
			Switch Zero-Const. Reduction Pathway						Switch Slow-Fast Reduction Pathway						Switch Fast-Slow Reduction Pathway						Robbie Andrews Reduction Pathway				
Ambition Score	0.10	1.00																							
Switch Zero-Constant Reduction Pathway																									
DTE Const. Emissions	-0.30	-0.08	1.00																						
DTE Ind. Adj. Const. Emissions	-0.21	-0.09	0.79	1.00																					
DTE Forecasted emissions	-0.31	-0.09	0.89	0.72	1.00																				
DTE Ind. Adj. Forecasted Emissions	-0.23	-0.11	0.68	0.84	0.81	1.00																			
DTE Ambition Score Cum Const.	-0.12	-0.14	0.51	0.57	0.58	0.65	1.00																		
DTE Ambition Score Cum Forecasted	-0.17	-0.16	0.47	0.54	0.58	0.66	0.95	1.00																	
Switch Slow-Fast Reduction Pathway																									
DTE Const. Emissions	-0.26	-0.07	0.97	0.80	0.87	0.68	0.54	0.49	1.00																
DTE Ind. Adj. Const. Emissions	-0.19	-0.09	0.79	0.97	0.71	0.82	0.61	0.56	0.82	1.00															
DTE Forecasted emissions	-0.29	-0.08	0.88	0.73	0.97	0.81	0.61	0.60	0.90	0.75	1.00														
DTE Ind. Adj. Forecasted Emissions	-0.21	-0.11	0.68	0.83	0.80	0.97	0.68	0.68	0.71	0.86	0.83	1.00													
DTE Ambition Score Cum Const.	-0.10	-0.15	0.52	0.57	0.58	0.63	0.97	0.92	0.58	0.65	0.63	0.69	1.00												
DTE Ambition Score Cum Forecasted	-0.16	-0.15	0.49	0.55	0.58	0.65	0.94	0.98	0.53	0.60	0.62	0.70	0.94	1.00											
Switch Fast-Slow Reduction Pathway																									
DTE Const. Emissions	-0.50	-0.10	0.63	0.53	0.59	0.48	0.48	0.44	0.63	0.57	0.61	0.52	0.52	0.48	1.00										
DTE Ind. Adj. Const. Emissions	-0.33	-0.13	0.61	0.69	0.57	0.63	0.54	0.55	0.60	0.68	0.57	0.64	0.55	0.57	0.62	1.00									
DTE Forecasted emissions	-0.42	-0.10	0.61	0.51	0.67	0.56	0.48	0.48	0.61	0.53	0.66	0.59	0.51	0.50	0.78	0.55	1.00								
DTE Ind. Adj. Forecasted Emissions	-0.27	-0.12	0.54	0.61	0.66	0.73	0.55	0.58	0.53	0.61	0.64	0.73	0.55	0.59	0.50	0.73	0.62	1.00							
DTE Ambition Score Cum Const.	-0.22	-0.17	0.44	0.50	0.51	0.58	0.71	0.77	0.44	0.51	0.51	0.58	0.69	0.76	0.45	0.62	0.49	0.64	1.00						
DTE Ambition Score Cum Forecasted	-0.22	-0.16	0.41	0.48	0.51	0.57	0.69	0.77	0.41	0.48	0.50	0.57	0.65	0.75	0.40	0.59	0.47	0.64	0.94	1.00					
Robbie Andrews Reduction Pathway																									
DTE Const. Emissions	-0.36	-0.08	0.89	0.73	0.81	0.64	0.57	0.51	0.90	0.77	0.83	0.68	0.61	0.56	0.79	0.67	0.72	0.57	0.49	0.45	1.00				
DTE Ind. Adj. Const. Emissions	-0.26	-0.11	0.77	0.91	0.70	0.80	0.62	0.60	0.79	0.92	0.73	0.82	0.65	0.63	0.62	0.81	0.58	0.70	0.58	0.55	0.81	1.00			
DTE Forecasted emissions	-0.35	-0.10	0.81	0.67	0.90	0.75	0.60	0.58	0.81	0.70	0.89	0.77	0.63	0.61	0.72	0.61	0.82	0.70	0.55	0.53	0.89	0.73	1.00		
DTE Ind. Adj. Forecasted Emissions	-0.24	-0.11	0.67	0.79	0.79	0.92	0.66	0.68	0.69	0.79	0.81	0.92	0.67	0.70	0.55	0.71	0.64	0.85	0.64	0.63	0.70	0.85	0.81	1.00	
DTE Ambition Score Cum Const.	-0.16	-0.15	0.51	0.58	0.59	0.66	0.93	0.94	0.55	0.63	0.63	0.71	0.93	0.96	0.51	0.60	0.52	0.61	0.80	0.78	0.60	0.67	0.64	0.72	1.00
DTE Ambition Score Cum Forecasted	-0.18	-0.15	0.48	0.55	0.58	0.66	0.88	0.94	0.51	0.59	0.61	0.69	0.87	0.94	0.47	0.59	0.51	0.62	0.83	0.84	0.55	0.64	0.62	0.72	0.97

Table IA.2: Detailed Summary Statistics of Ambition Score Variables

This table presents further details on the forward-looking sub-components of the Ambition Score. Panel A reports the percentage of firms with environmentally positive answers to the six ESG variables. Panel B reports the percentage coverage of firms with green and brown efficiency patents, respectively. Across firms with green (brown efficiency) patents, we also report the average number of green (brown efficiency) patents registered by a company in a given year, the cumulative number of citations to green (brown efficiency) patents registered by a company in a given year, and the number of green (brown efficiency) patents registered by a company in a given year scaled by the total number of patents of the same company in that year. Panel C reports the number of targets, number of firms with targets, number of firms with targets on Scope 1 emission, number of firms with targets on Scope 2 emission, number of firms with targets on Scope 3 emission, number of firms with SBTi approved targets, and number of firms with SBTi committed targets.

Year	# Firms	Decarbonization Target	Decarbonization Policy	Reported Emissions	CSR Committee	UNPRI Signatory	SDG 13 Climate Action
Panel A: Refinitiv ESG							
2006	2510	13.71	14.34	19.20	11.04		
2007	2696	20.47	26.34	23.55	16.14		
2008	2672	25.56	36.38	27.88	25.11		
2009	2789	28.68	39.58	34.60	35.14	0.04	
2010	2931	30.16	44.59	40.09	41.73	0.03	
2011	3154	30.15	44.67	40.20	42.77	0.03	
2012	3328	29.84	46.45	41.71	44.62	0.03	
2013	3351	28.98	46.82	43.30	45.33	0.03	
2014	3958	24.48	42.62	39.19	39.62	0.03	
2015	4280	24.44	43.43	40.14	37.83	0.02	
2016	4483	24.09	45.33	42.67	38.46	0.96	0.02
2017	10401	12.05	24.09	22.30	19.76	0.48	0.01
2018	11300	13.61	26.71	24.72	21.24	0.19	0.15
2019	12032	16.15	31.48	28.13	24.70	0.14	11.06
2020	12855	18.41	35.01	29.68	28.41	0.88	18.22
Overall	13277	19.79	34.28	30.94	28.92	0.30	6.67

Year	# Firms	% Coverage	# Patents	# Patents Citations	# Green Patents to # Patents Ratio	% Coverage	# Patents	# Patent Citations	# Brown Patents to # Patents Ratio
Panel B: Patents									
		Green Patents				Brown Efficiency Patents			
2006	2510	15.34	8.28	180.46	0.21	8.96	7.17	98.26	0.19
2007	2696	15.80	8.58	144.30	0.22	8.23	7.55	218.47	0.17
2008	2672	17.51	7.87	156.34	0.23	8.12	7.87	69.17	0.17
2009	2789	16.24	8.62	194.62	0.24	7.21	8.47	73.17	0.19
2010	2931	16.58	9.21	200.38	0.24	7.92	7.94	62.86	0.17
2011	3154	15.82	10.86	192.61	0.24	7.80	7.22	69.19	0.19
2012	3328	17.22	11.47	140.82	0.26	7.84	7.50	68.02	0.20
2013	3351	17.07	12.31	140.28	0.26	7.76	8.42	48.89	0.19
2014	3958	16.42	12.81	180.18	0.28	7.40	8.27	52.26	0.18
2015	4280	15.77	12.63	92.87	0.27	7.17	8.25	36.89	0.18
2016	4483	15.77	12.70	140.79	0.27	7.41	8.63	33.26	0.16
2017	10401	8.86	10.71	74.54	0.32	3.71	8.30	21.83	0.21
2018	11300	8.24	10.34	41.39	0.32	3.65	8.08	16.58	0.23
2019	12032	8.38	10.44	26.42	0.34	3.38	7.79	11.79	0.21
2020	12855	7.88	9.26	55.91	0.35	3.08	6.82	10.25	0.21
Overall	13277	11.81	10.56	117.64	0.28	5.31	7.89	53.08	0.19

Year	# Firms	# Targets	Firms with Valid Target	Firms with Scope 1 Related Target	Firms with Scope 2 Related Target	Firms with Scope 3 Related Target	Firms with SBTi Approved Target	Firms with SBTi Considered Target
Panel C: CDP Targets								
2011	3154	389	269	251	243	94		
2012	3328	381	264	239	232	76		
2013	3351	474	322	295	285	94		
2014	3958	558	378	341	335	106		
2015	4280	509	356	308	309	97		
2016	4483	741	476	424	426	114		103
2017	10401	1027	599	533	532	150	52	113
2018	11300	1119	652	589	594	164	89	182
2019	12032	1335	777	718	715	212	153	201
2020	12855	1451	840	796	791	277	234	266
Overall	13277	7984	1250	1167	1179	457	264	471