Carbon-Transition Risk and Net-Zero Portfolios*

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November 25, 2023

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 hypothesis that DTE captures carbon-transition risk. The effect is stronger when climate pressure intensifies, and it is robust to various specification choices.

*We thank Nabeel Abdoula, Franklin Allen, Yakov Amihud, Juan Antolin-Diaz, Patrick Bolton, Iancu Daramus, Gavyn Davies, Asaf Manela, Lubos Pastor, Zach Sautner, Ivo Welch, David Zerbib, and seminar participants at Banque de France, Copenhagen Business School, Decarbonization Seminar at University of Mannheim, Fulcrum Asset Management, HEC Lausanne, HEC Paris, IESEG, Imperial College, Korea University, Luohan Academy, Norges Bank, Reichman University, UBS, University of Michigan, University of Porto, and WashU Finance Conference for helpful comments. We acknowledge research support from Inquire Europe. Contact: Gino Cenedese gino.cenedese@fulcrumasset.com; Shangqi Han shangqi.han@fulcrumasset.com; Marcin Kacperczyk mkacperc@ic.ac.uk.

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, partly because transition risk is often regarded as one of the main economic forces driving decarbonization efforts. 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 risk is priced in the cross-section of global stocks.

The starting point for building our measure 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 some 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 decarbonization paths reported by climate scientists 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 select stocks for their portfolios based on individual firms' revealed efforts to decarbonize

[1]See, for example, https://www.netzeroassetmanagers.org/; https://www.unepfi.org/net-zero-alliance/; and https://www.unepfi.org/net-zero-banking/. The specific initiatives need not be mutually exclusive; hence the economic value of the movement measures its upper bound.

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

their activities. 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 absolute and relative decarbonization efforts. 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.

There are at least three direct channels through which the pricing effect can operate. First, divestment by a significant fraction of investors can reduce risk sharing, and thus affect equilibrium prices and returns (e.g., Merton, 1987). Second, and novel to our study, is the pricing effect induced by investors' expectations of *future* divestment, which could be nontrivial even if one does not observe significant portfolio movements today. Finally, through net-zero portfolios, investors can communicate expectations of future divestment to corporates, and thus exert pressure on corporates to adjust their efforts to avoid potential penalties. This last communication channel suggests a new insight, namely, NZP can be modes of both divestment and engagement. Notably, the strength of the three forces does not only depend on the individual firm-level efforts but also on the behavior of other companies subject to similar pressures. This competition effect among companies is induced by the presence of an *aggregate* constraint imposed on the holdings.

In our empirical analyses, we discuss a step-by-step process of constructing *DTE*. The advantage of our approach is its flexibility of incorporating variants of decarbonization effort and the speed of implementing it. In the first part, we consider constant-rate decarbonization paths. In this setting, we assume that climate-oriented 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. We base their selection rule on the following three factors. The first one uses companies' current total emissions; the second one, their predicted total emissions; and the third one, their broad ambition to decarbonize. The last measure, expressed as a composite *Ambition Score*, is our most comprehensive measure of decarbonization efforts 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 the first two variables, we also obtain industry-standardized counterparts, while for the third measure we alternately consider budgets based on current and future emissions. In total, we examine six different DTE measures.

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 and monthly stock return volatility, consistent with the hypothesis that DTE captures equity risk. DTE are also negatively related to book leverage and dollar trading volume, but the correlations here get weaker for DTE based on *Ambition Score*. 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 negatively related to firms' stock market capitalization and book value of assets, but the correlation is positive for DTE based on *Ambition Score*.

One potential concern when implementing the NZP framework is that the portfolio may drift away from the market portfolio. This problem can be particularly important if the social planner implementing NZP aims to reach inclusive, broad-based decarbonization, rather than the outcome in which some economic sectors are excluded right at the beginning of the process. 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 portfolios based on DTE that are standardized within industry groups. 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 as well as they do not penalize companies that could be instrumental in driving the transition to green equilibrium.

In the second part of the tests, we study 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 2.5–4.6 percentage-point reduction in next month's annualized stock returns. We further find that while the predictive power of DTE declines with a longer lag, 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 the data is the distinction between expected and realized returns. In line with studies on large global data, 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 five out of six measures of exit. The results are also economically large. Companies that exit have higher annualized returns by about 2.6–6.2 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*. Another finding that supports the transition-risk interpretation is the strong correlation between DTE 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 baseline 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. Moreover, statistical significance is preserved for our most comprehensive measure based on *Ambition Score*. These results paint two important conclusions. First, DTE carry independent stock return variation, especially when we use the most comprehensive metric of decarbonization ambition. 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, as that in 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, 2023; 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 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 integrate formally 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; Cheng 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 the 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. Moreover, in these studies, divestment and engagement are ex-post phenomena. Our study is different in at least two aspects. First, we study the economic importance of *both* expected and present divestment, which means that our framework does not necessarily require significant exclusionary forces to be in force at present. Pricing effects can happen because investors rationally anticipate divestment may intensify in the future, as is the case in the NZP framework. 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). Differently from 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 2005-2021 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., 25.5 GtCO2e in 2020).[4] 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 168.3 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 2021. 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.[5] The light blue pathways, $Zero$, 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

[4] Our motivation to use the sum of all three scopes of emissions is to recognize the fact that investors in their decisions likely care about all aspects of corporate contribution to global warming, not just direct emissions. This notion has been supported by previous studies based on global data, which show that each scope of emissions independently contributes to pricing differences. Even though this approach has an element of double counting, we believe what drives the cross-sectional distribution in transition risk is the rate of decarbonization at the aggregate level and not necessarily the level of emissions. As a robustness, we also considered a less inclusive measure based on scope 1 and 2 and the results are qualitatively similar.

[5] Notably, the immediate reduction in portfolio emissions does not lead to the depletion of the *global* 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).[6] Here, emissions can increase initially and then decrease.

To provide a visual illustration of the portfolio budget's construction, Figure 2 zooms 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 25.5 GtCO2e. Using the proportionality rule, the remaining *global* emissions budget of 260.3 GtCO2e translates into a cumulative *portfolio* budget of 168.3 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 20.9 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 rankings of such prospects, each subsequent one building on the previous one and thus being more comprehensive and more realistic to the objective function of our exercise. As a first and simple illustration of our ideas, we use companies' current total emissions, following the idea that such emissions are the best predictor of future decarbonization efforts. Next, we acknowledge the importance of looking at future data and thus in our second approach 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, and most general, we select companies according to their combined efforts

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

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 group (GICS-4). 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 2021. Trucost reports firm-level absolute greenhouse gas emissions in tons of carbon dioxide equivalent (tCO2e) for scope 1, 2, and 3 upstream emissions.[7] 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.

[7] 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.

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. 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, and most comprehensive classification scheme aims to capture both 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.[8] 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, not directly linked to company size. Finally, forward-looking metrics summarize all the efforts undertaken by the company that relate to the companies' ambition to reduce future 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 com-

[8]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.

panies' 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.

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 sets of *DTE*, depending on the sorting variable used in their construction: (1) constant emissions, (2) forecasted emissions, and (3) *Ambition Score*. Within each of the first two sets, we define two variants of *DTE*: those that are based on the raw sorting variable, and those that standardize it within GICS-4 industry group. The third group based on *Ambition Score* also contains two variants of *DTE*, depending on whether we sum up constant or forecasted emissions to fill up the carbon budget. In total then, we have six different variants of *DTE*: constant emissions (*DTE-CE*); standardized constant emissions (*DTE-SCE*); forecasted emissions (*DTE-FE*); standardized forecasted emissions (*DTE-SFE*); *Ambition Score* plus constant emissions (*DTE-ACE*); *Ambition Score* plus forecasted emissions (*DTE-AFE*).

To illustrate the construction and basic properties of different DTE, we follow the example of Apple. We compute Apple's DTE by ranking all stocks based on their climate performance and calculating the number of years until Apple's stock is excluded from the net-zero portfolio. We repeat this process for every year from 2005 until 2021. The table below provides numerical results for the six DTE.

In the first panel, where we present results from sorting companies on their yearly emissions, Apple's DTE is decreasing from 2005 to 2021. 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

	Estimation Year															
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Panel A: DTE-CE																
Exit Year	2025	2024	2024	2023	2021	2020	2019	2020	2020	2020	2021	2021	2021	2022	2023	2024
Distance-to Exit	18	16	15	13	10	8	6	6	5	4	4	3	2	2	2	2
Panel B: DTE-SCE																
Exit Year	2014	2014	2015	2016	2014	2014	2014	2015	2016	2016	2017	2018	2019	2020	2021	2022
Distance-to Exit	7	6	6	6	3	2	1	1	1	0	0	0	0	0	0	0
Panel C: DT-FE																
Exit Year	2018	2014	2016	2016	2016	2016	2016	2023	2020	2020	2019	2020	2021	2022	2023	2024
Distance-to Exit	11	6	7	6	5	4	3	9	5	4	2	2	2	2	2	2
Panel D: DTE-SFE																
Exit Year	2012	2011	2012	2013	2013	2013	2013	2015	2016	2016	2017	2018	2019	2020	2021	2022
Distance-to Exit	5	3	3	3	2	1	0	1	1	0	0	0	0	0	0	0
Panel E: DTE-ACE																
Exit Year	2014	2016	2017	2017	2015	2013	2014	2015	2016	2016	2017	2018	2019	2020	2021	2022
Distance-to Exit	7	8	8	7	4	1	1	1	1	0	0	0	0	0	0	0
Panel F: DTE-AFE																
Exit Year	2012	2013	2015	2016	2015	2013	2013	2015	2016	2016	2017	2018	2019	2020	2021	2022
Distance-to Exit	5	5	6	6	4	1	0	1	1	0	0	0	0	0	0	0

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 or same 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 companies in our data, which allows us to generate 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.[9] 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 ratio, 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 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.

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

2.3 Summary Statistics

In this section, we summarize the variables used in our analysis based on the pooled sample of all companies observed in any period during the period 2005-2021. 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 sub-components. 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 23.2. 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, 2023).

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.[10] 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

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

constraint that induces additional variation in *DTE*.

In Panel B, we study 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 Score. 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.

3.2 Determinants of *DTE*

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

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

where $DTE_{i,t}$ is a generic term standing for various measures of distance-to-exit for firm i at time t. 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 regression model using pooled OLS. We 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 dimensions. 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 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. The effect turns positive when we relate size to DTE based on the *Ambition Score*. Third, across all specifications, DTE is positively related to firms' measures of property, plant, and equipment and firm age, but negatively related to firm volatility. The latter result supports the view that DTE is a risk-driven metric. Fourth, DTE is negatively related to firm trading volume and book leverage, 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 entertaining two-way comparisons between DTE-based portfolios and the benchmark portfolio including the universe of stocks in Trucost database. The two DTE groups of portfolios we consider are *DTE-SFE*) and *DTE-AFE*. To facilitate comparisons, we focus on the data in 2020. Within each group, 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 the Trucost benchmark. We present the results in Figure 3. The black dots in the figure represent market weights for the benchmark. Software and Services sector is the largest sector, followed by Capital Goods and Banks. Orange dots represent corresponding market weights of portfolios of companies with a minimum value of DTE equal to 5. In the left panel, we show the results for DTE portfolios based on industry-standardized future emissions. We note that most of the sector weights are not significantly different from those of the benchmark. Nonetheless, certain sectors are underweighted (Software and Services, Pharmaceuticals, Consumer Discretionary, and Media) and others are overweighted (Insurance, Financial Services, REITs, Food, and Materials). 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 those in the previous case. We further consider portfolios with DTE values of minimum 15 (blue dots) and the values greater than or equal 30 (green dots). While in each of the cases the deviations from the benchmark, as expected, increase slightly, there does not seem to be a very strong tilt away from the benchmark in our portfolios. In particular, we do not seem to observe several extreme cases in which certain sectors are fully excluded, with the exception of Energy, Telecom, and Utilities (in the left panel) and Energy (in the right panel), which are fully excluded in the case of the longest DTE portfolio.

Another dimension along which we compare DTE portfolios is the number of stocks held. This comparison allows us to allay the concern that DTE portfolios become thinly populated as the carbon budget gets tighter, and thus they may significantly deviate from the benchmark and become underdiversified. We show the results from this analysis in Figure 4. Two observations are noteworthy. First, the number of stocks in the portfolio that includes companies with $DTE \geq 5$ is not visibly different than that in the benchmark portfolio. This is true for both variants of DTE. Second, as we restrict the universe of companies towards the greater DTE values, the number of stocks in the portfolio drops, but the drop is really visible only for the extreme portfolio with companies that stay in the portfolio beyond 2050. Still, even 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.

Next, we examine the ability of our portfolios to reduce their exposure to carbon footprint within each sectoral activity. Figure 5 depicts the results from the analysis in which we compare the carbon footprint of portfolios in Figure 3 and 4 to the carbon footprint of the Trucost benchmark. As an example, a portfolio containing stocks with $DTE - AFE \geq 5$ observes reductions in its carbon footprint anywhere from 30% (Insurance) to 85% (Financial Services). 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 (estimated) emissions. Here, we predict emissions for 2025, 2035, and 2050 and show the proportion of carbon footprint of DTE portfolios relative to the Trucost universe. The results are quite consistent and show that in a 5-year period the DTE portfolios would reduce carbon footprint in each sector by anywhere between 40% and 80%. The numbers become significantly larger for emissions predicted for 2035. Based on our analysis, the expectation for 2050 is that we would decarbonize the portfolio by almost 100%, but this number is obviously not guaranteed.

As a final diagnostic, we assess the properties of DTE portfolios from the perspective of their factor/style exposure. In Figure 7, we look at the percentage deviations in style exposures from Trucost for each of the above-defined three 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. Our DTE portfolios are not significantly tilted away from the benchmark on the first three characteristics. The small deviations in size exposure are particularly comforting in light of potential concerns regarding transaction costs or exclusion of salient companies due to holding small stocks. In turn, we find more deviations from benchmark in terms of their momentum and ROE exposures, even though we note that the significance of the deviations is economically large only for portfolios with the largest values of DTE.

Overall, we conclude that while our DTE portfolios exhibit a significant reduction in their carbon footprint they do not observe significant deviations 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 constructed with constant decarbonization paths and sorts based on total emissions. We then proceed to show results on the specific drivers and additional 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, 2023), 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.[11] As shown in Bolton and Kacperczyk (2023), 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, 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 (2023). We double cluster standard errors

[11]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.

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 DTEs 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. Given the paths, we 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-standardized 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 -0.039 and the standard deviation of DTE in this specification is 9.8. This means that a one-standard-deviation increase in DTE is associated with 0.38% lower stock returns per month, or 4.6% annualized. Among other controls, $LOGMB$ and MOM are positively related to future stock returns and $LEVERAGE$ and $LOGMKTCAP$ 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.

We further assess the robustness of the above results to various specification choices. Specifically, in Table IA.4, we consider the regression specifications in which we alternately exclude industry-fixed effects (panel A) and stock characteristics related to firm size (panel B). Further, in Table IA.5, we estimate the regression models using alternative 4-digit GICS industry-group-fixed effects. Across all these tests, we find that our results remain qualitatively similar.

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 *LOGPE*. 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.[12] 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 as such they are priced differently. We explore such extensive-margin dimension by defining an indicator variable that is equal to one for companies that never exit net-zero portfolios, and is equal to zero for companies that exit at any point prior to and including the final year 2050. We replace our *DTE* measures with such indicator variables when estimating the relation for stock returns in specification (2). We report the results from estimating these alternative models in Table 7. The results show a large negative and statistically significant coefficient of each individual indicator variable, suggesting that companies that never exit have lower expected returns than those that do. The economic magnitude of the results is large, with the monthly differences in returns

[12] The results are not significantly affected when we use a more granular level of industry-fixed effects, as we show in Table IA.6.

ranging between 22 and 52 basis points, or $2.6\% - 6.2\%$, annualized.

Given that our DTE measures aim to capture transition risk, a natural question to ask is whether the premia we observe increase 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:

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

Our coefficient of interest is d_2. We report the results from our estimation in Table 8. In Panel A, returns are our 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 of DTE increases by a substantial fraction relative to the previous period. In four out of six specifications, we report a statistically significant effect. In Panel B, we test the hypothesis of increased risk premia from the perspective of companies' $LOGPE$. 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. More specific to our conceptual framework, they also support the view that the pressure from investors to align themselves with the NZP movement has increased in the post-2015 period, as it has been reflected in the emergence of various alignment initiatives.

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 this end, in Table 9, we report the results from estimating the returns regression model, in which we include as additional controls: in columns (1) and (2), the natural logarithm of total emissions, *Log Emissions*, the percentage change in total emissions, *Emissions Growth*; in columns (3) and (4), the natural logarithm of the three-year average of forecasted emissions, *Log Average Forecasted Emissions*, the three-year average of percentage change in forecasted emissions, *Average Forecasted Emissions Growth*; in columns (5) and (6), the *Ambition Score*.

We find that controlling for all the past information naturally reduces the magnitudes of each DTE measure. However, we still find some residual variation that can explain stock returns. 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. More specific, the coefficients of the other climate-related variables are in line with earlier findings in the literature (Bolton and Kacperczyk, 2023). The level and growth of emissions are positively associated with future stock returns. Notably, measures of Ambition Score are not significantly related to future returns. The last result is useful because 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 the model that combines scope 1, scope 2, and scope 3 emissions. One concern is that scope 3 are generally more difficult to measure and thus our DTE measures may be noisy. Another issue could be that of double counting emissions. We consider the latter issue to be less problematic given that we use total emissions as proxies for the contribution of each company to the carbon problem. 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 the 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 issue by conditioning our returns regressions on such information. We define an indicator variable, *Disclosure*, that is equal to one if a company directly discloses its emissions and is equal to zero if the information is estimated by the data provider. To assess 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 estimating this model in Table IA.3. 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 investor-level path of decarbonization. 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 fact, the only constraint they face is on the cumulative carbon budget and this can be satisfied through different paths. As a robustness, we consider four alternative paths. First, we assume that 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, as 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 for all the above decarbonization paths in Table 11. In Panel A, we look at the impact on next-month stock returns following specification (2); in Panel B, we look at valuation regressions following specification (3). The results in Panel A indicate a strong empirical robustness to the choice of different decarbonization paths. For all four decarbonization paths, we find a strong negative coefficient of DTE that is also statistically highly significant. In Panel B, when we use $LOGPE$ as a dependent variable, we again find results which are qualitatively similar to our baseline findings. Across all four alternative paths, the coefficient of DTE is positive and highly 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 measuring transition risk.

5 Conclusions

In the coming years and decades investors will be exposed to substantial risk resulting from a transition to green economy. What has emerged as a formidable driving factor of this process is social pressure imposed by various stakeholders globally. With the intensifying climate events, one can expect this pressure to become even stronger. Quantifying this pressure both in terms of investors' risks and companies' cost of capital has become of first-order economic importance largely because it could be part of the solution to the carbon problem. In this paper, we provide a formal framework of net-zero portfolios that allows one to quantify this economic force. Net-zero portfolios generate a shock to asset ownership structure and possibly can influence asset prices. Contrary to earlier studies on portfolio holdings that isolate pricing effects due to realized divestment, the mechanism we propose also operates through expected divestment and engagement coming through the interaction between asset holders and corporates themselves.

We operationalize this empirical mechanism using a novel measure of distance-to-exit (DTE) that blends climate forecasts into portfolio decisions. In a sample of global stocks, we show that companies that are more exposed to exit from net-zero portfolios have lower values and investors require higher returns for holding them. This result is economically large and is consistent with the view that DTE offers a useful framework for measuring transition risk. We further show that DTE isolate distinct variation to that captured by previously used measures based on corporate carbon emissions. Distinct from these, they also incorporate information that is forward-looking and is grounded in climate science.

At the broad level, 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. 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. In this regard, our results indicate 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 forces induced by tight carbon budget. Our study suggests 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 incorporates 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 composite 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.

References

Andersson, Mats, Patrick Bolton, and Frédéric Samama, 2016, Hedging climate risk, *Financial Analysts Journal* 72, 13–32.

Andrew, Robbie M., 2020, It's getting harder and harder to limit ourselves to 2°C, https://folk.universitetetioslo.no/roberan/t/global_mitigation_curves.shtml.

Asness, Clifford, and Andrea Frazzini, 2013, The devil in HML's details, *The Journal of Portfolio Management* 39, 49–68.

Atta-Darkua, Vaska, Simon Glossner, Philipp Krueger, and Pedro Matos, 2023, Decarbonizing institutional investor portfolios: helping to green the planet or Just greening your portfolio?, Working paper, University of Virginia.

Bali, Turan G., Robert F. Engle, and Scott Murray, 2016, *Empirical asset pricing: the cross section of stock returns* (John Wiley & Sons).

Berk, Jonathan, and Jules H. van Binsbergen, 2022, The impact of impact investing, Working paper, Stanford University.

Bolton, Patrick, and Marcin Kacperczyk, 2021, Do investors care about carbon risk?, *Journal of Financial Economics* 142, 517–549.

Bolton, Patrick, and Marcin Kacperczyk, 2023, Global pricing of carbon-transition risk, *The Journal of Finance* 78, 3677–3754.

Bolton, Patrick, Marcin Kacperczyk, and Frédéric Samama, 2022, Net-zero carbon portfolio alignment, *Financial Analysts Journal* 78, 19–33.

Bolton, Patrick, and Marcin T. Kacperczyk, 2022, Firm commitments, Working paper, Imperial College London.

Bolton, Patrick, Marcin T. Kacperczyk, and Moritz Wiedemann, 2023, The CO2 question: technical progress and the climate crisis, Working paper, Imperial College London.

Broccardo, Eleonora, Oliver Hart, and Luigi Zingales, 2022, Exit versus voice, *Journal of Political Economy* 130, 3101–3145.

Ceccarelli, Marco, Stefano Ramelli, and Alexander F. Wagner, 2023, Low carbon mutual funds, *Review of Finance* (forthcoming).

Chaieb, Ines, Hugues Langlois, and Olivier Scaillet, 2021, Factors and risk premia in individual international stock returns, *Journal of Financial Economics* 141, 669–692.

Cheng, Gong, Eric Jondeau, Benoit Mojon, and Dimitri Vayanos, 2023, The impact of green investors on stock prices, Working paper, Bank for International Settlements.

Cheng, Gong, Eric Jondeau, and Benoît Mojon, 2022, Building portfolios of sovereign securities with decreasing carbon footprints, Working paper, Bank for International Settlements.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *The Journal of Finance* 52, 1035–1058.

De Angelis, Tiziano, Peter Tankov, and Olivier David Zerbib, 2022, Climate impact investing, *Management Science* (forthcoming).

Engle, Robert, Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging climate change news, *The Review of Financial Studies* 33, 1184–1216.

GFANZ, 2023, Measuring portfolio alignment, Technical report.

Gillan, Stuart L., and Laura T. Starks, 2000, Corporate governance proposals and shareholder activism: the role of institutional investors, *Journal of Financial Economics* 57, 275–305.

Heinkel, Robert, Alan Kraus, and Josef Zechner, 2001, The effect of green investment on corporate behavior, *Journal of Financial and Quantitative Analysis* 36, 431–449, Publisher: Cambridge University Press.

IPCC, 2021, Summary for Policymakers., in *Climate change 2021: the physical science basis. Contribution of Working Group I to the Sixth Assessment Report of the intergovernmental panel on climate change* (Cambridge University Press).

Jondeau, Eric, Benoît Mojon, and Luiz A. Pereira da Silva, 2021, Building benchmark portfolios with decreasing carbon footprints, Working paper, University of Lausanne.

Krueger, Philipp, Zacharias Sautner, and Laura T. Starks, 2020, The importance of climate risks for institutional investors, *Review of Financial Studies* 33, 1067–1111.

Lettau, Martin, and Jessica A. Wachter, 2007, Why is long-horizon equity less risky? A duration-based explanation of the value premium, *The Journal of Finance* 62, 55–92.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *The Journal of Finance* 42, 483–510.

Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor, 2023, Green tilts, Working paper, University of Chicago.

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski, 2021, Responsible investing: The ESG-efficient frontier, *Journal of Financial Economics* 142, 572–597.

Raupach, Michael R., Steven J. Davis, Glen P. Peters, Robbie M. Andrew, Josep G. Canadell, Philippe Ciais, Pierre Friedlingstein, Frank Jotzo, Detlef P. Van Vuuren, and Corinne Le Quéré, 2014, Sharing a quota on cumulative carbon emissions, *Nature Climate Change* 4, 873–879.

Sautner, Zacharias, Laurence Van Lent, Grigory Vilkov, and Ruishen Zhang, 2023, Firm-level climate change exposure, *The Journal of Finance* 78, 1449–1498.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *The Journal of Finance* 52, 327–340.

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 individual components of the *Ambition Score*.

A Commitments Data

We obtain all firm commitments tracked by the annual CDP survey from 2011 to 2021. CDP started asking its member companies to report their emissions reduction targets in 2011. Company commitments can take different forms, including carbon intensity improvements, absolute emissions reductions, or other forms like percentage of procurement. In our study, we focus on commitments to reduce absolute emissions only as they are considered to require the most effort, are more difficult to manipulate, and translate directly into a global decarbonization objective (Bolton and Kacperczyk, 2022). Since a company could be following the same commitment over multiple years, we define *survey year* as any year in which a specific emissions reduction target was observed in the CDP survey. Commitments also vary in terms of their *base year*, their *target year* defining how far the commitment extends into the future, as well as their *target ambition*, TGT, which is a percentage of emissions reduction over the target horizon. For comparability of targets within and across firms, we convert TGT into linear annual reductions, *Target LAR*, as follows:

$$\text{Target LAR} = \frac{TGT}{\text{target year} - \text{base year}}. \tag{6}$$

Target LAR measures the scope of annual emissions reduction over the entire time frame of the target (base year to target year).

Firms also tend to have multiple targets with different scope coverage in each survey year.[13] Within a given emissions scope, we define $CECOVER$ as the reported percentage of carbon emissions covered by the target; for example, 100% of combined scope 1 + 2 is covered by the target. The early vintages of the CDP surveys contain missing values of $CECOVER$ or data errors, such as $CECOVER \leq 1\%$ even if the level of target-covered emissions in tons 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 100%. We also perform manual checks if the same target is followed by a firm over multiple years, and we fill missing values of $CECOVER$ accordingly. Our final measure of the decarbonization abatement rate is the *Normalized Target LAR*:

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

[13]For example, Table IA.2 shows that 838 companies reported 1439 targets in 2020.

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

$$\begin{aligned} &\text{Targeted Reduction in Emissions Level } = \\ &\text{Normalized Target LAR} \times (\text{target year} - \text{base year}) \times \text{ base year emissions.} \end{aligned} \tag{8}$$

The *Targeted Reduction in Emissions Level* forms the foundation for one of the two main inputs in our measure of forecasted emissions.

B Forecasted Emissions

The forecasted emissions pathway is a weighted average of the decarbonization target-based path and the emissions trend path. Specifically, we construct the decarbonization target-based pathway by aggregating the CDP 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 also 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. We further 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. Next, in each survey year, we compute the *Targeted Reduction in Emissions Level* based on the *Normalized Target LAR* for every target, as defined earlier.

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 *Targeted Reduction in Emissions Level*. 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 into the overall scope 3 forecast. Note that this process ensures only one *Targeted Reduction in Emissions Level* per target year per scope group while allowing for processing and aggregating multiple targets.

In each survey year t, our forecast horizon is the longest among target years for a given firm. Within each of the seven scope groups, we calculate multiple *Targeted Emissions Checkpoints* spanning different target years by subtracting each *Targeted Reduction in Emissions Level* from their corresponding base year total emissions. Among the seven scope groups, our focus is to construct forecasts for scope $1+2$ and scope $1+2+3$ emissions. However, the *Targeted Emissions Checkpoints* for scope $1+2$ and scope $1+2+3$ might not be directly available from the reported targets, hence, we need to infer them by adding or subtracting other scope groups. We prioritize the targets that are better defined and tighter, that is, 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. As an example, to infer scope $1 + 2$, we first search for individual targets on scope 1 and scope 2, then we search for targets on scope $1 + 2$, followed by those on scope $1 + 2 + 3$ subtracting scope 1, and so on. To generate a full path of annual reductions, 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.

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 2021 across all firms. We apply the above long-term growth rate to data from $t + 15$ and hold it constant until 2050. Between years $t + 3$ and $t + 15$, we let the short-term growth rate converge to the long-term growth rate using exponential interpolation. This process is akin to methods used in forecasting of long-term cash flow growth rates. To simplify our measures, we use scope $1 + 2$ growth rate to proxy for scope $1 + 2 + 3$ growth rate for the short-term growth rate. For the long-term growth rate, we use the unconditional growth rate based on scope $1 + 2$ growth rate to forecast 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 pathways 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 2021. 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 additional factors that relate to firms' decarbonization commitments. Specifically, we focus on five metrics of such commitments.

We begin by evaluating the company's progress against its promise. A simple measure of *target underperformance* is the difference between *Normalized Target LAR* and the actual annual emissions reduction rate, calculated using a three-year moving average of emissions growth rate.

We then define the realized rate of emissions abatement. Assuming a constant *CECOVER* between the base year and the survey year, we define the actual linear annual reduction achieved, *Actual LAR*, as:

$$\text{Actual LAR} = \frac{\text{Emissions in base year} - \text{Emissions in survey year}}{\text{Emissions in base year} \times (\text{survey year} - \text{base year})}. \tag{9}$$

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

$$\begin{aligned}\text{Dynamic Abatement Rate} = {} & \frac{1}{\text{target year} - \text{survey year}} \times \\ & \Big(TGT - \text{Actual } LAR \times (\text{survey year} - \text{base year})\Big).\end{aligned} \tag{10}$$

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 *target impracticability*.

Next, we define the *target setting year* as the year when the target was initially set as reported by CDP. 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

$$\text{Greenwashing} = \frac{\text{Emissions in base year} - \text{Emissions in target setting year}}{\text{Emissions in base year}} \times \frac{1}{TGT}. \tag{11}$$

Finally, the CDP survey 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 focus on Apple, which made commitments to CDP. As of 2020, scope 1, 2, and 3 emissions of Apple are growing at a rate of 13.96% and its scope 1, and 2 emissions are growing at a rate of 17.80% based on a three-year moving average. Apple reports an active pre-existing target, dated back to 2012, committing to a 52% reduction covering 100% of scope 1 and 2 with 160,400 tons of base year absolute emissions over the 2012-2036 period. The *Normalized Target LAR* is 2.17% per year with a target horizon of 24 years. Apple also 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. The *Normalized Target LAR* is 5% per year with a target horizon of 15 years. The SBTi status for both targets is classified as committed but not yet approved. Thus, Apple is scored based on the new target as we prioritize the target with the highest level of SBTi validation, and with the highest target reduction, consistent with the framework for forecasted emissions. Regarding the new target, the target underperformance is thus 18.96% $(5.00\% - (-13.96\%))$, the *Actual LAR* is in total 34.64% from 2015 to 2020[14], the reduction

[14]The target-covered emissions are 38,400,000 tons in the base year 2015 and 25,100,000 tons in the survey year 2020 as reported by CDP. Thus the *Actual LAR* is 6.93% per year $\left(\frac{25{,}100{,}000-38{,}400{,}000}{38{,}400{,}000\times(2020-2015)}\right)$ or 34.64% in total from 2015 to 2020.

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 18.00% ($4.04\% - (-13.96\%)$). As for the greenwashing indicator, it is 0% for the existing target as 2012 is both the base year and the target-setting year. For the new target, the base year (2015) scope 1-3 emissions are 26,547,913 tCO2, and the target-setting year (2020) scope 1-3 emissions are 39,453,087 tCO2 as reported by Trucost, resulting in -64.81% emissions reduction already achieved. Thus, we use 0%—the maximum value—for the final greenwashing indicator.

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 hard data	50%	Trucost	Carbon emission	39,453,087.42	39,453,087.42	165.24
			Emission growth	0.14	0.14	0.68
Historical soft data	25%	Trucost	Carbon Intensity	143.72	143.72	-0.56
			Intensity growth	0.06	0.06	1.65
Forward-looking soft data	25%	CSR Report	Decarbonization target existence	Yes	0	-2.59
			Decarbonization policy existence	Yes	0	-1.75
			Emission disclosure	Reported	0	-1.94
			Sustainability committee existence	Yes	0	-2.08
			UNPRI signatory	No	1	NA
			SDG13 climate action	Yes	0	-2.63
		Orbis Patent	Green patent number	24	-24	-2.34
			Brown efficiency patent number	0	0	0.14
			Green patent citation number	264	-264	-16.1
			Brown efficiency patent citation number	0	0	0.11
			Green patent ratio	0.03	-0.03	0
			Brown efficiency patent ratio	0	0	0.08
		CDP Survey	SBTi participation	Submitted	1	-2.8
			Greenwashing indicator	0	0	3.18
			Abatement rate	5	-5	-6.35
			Target underperformance	18.96	18.96	-3.83
			Target impracticability	18.00	18.00	-3.78
					Final Score	40.93

We observe that Apple's *Ambition Score* is equal to 40.93. 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, and CDP target performance.

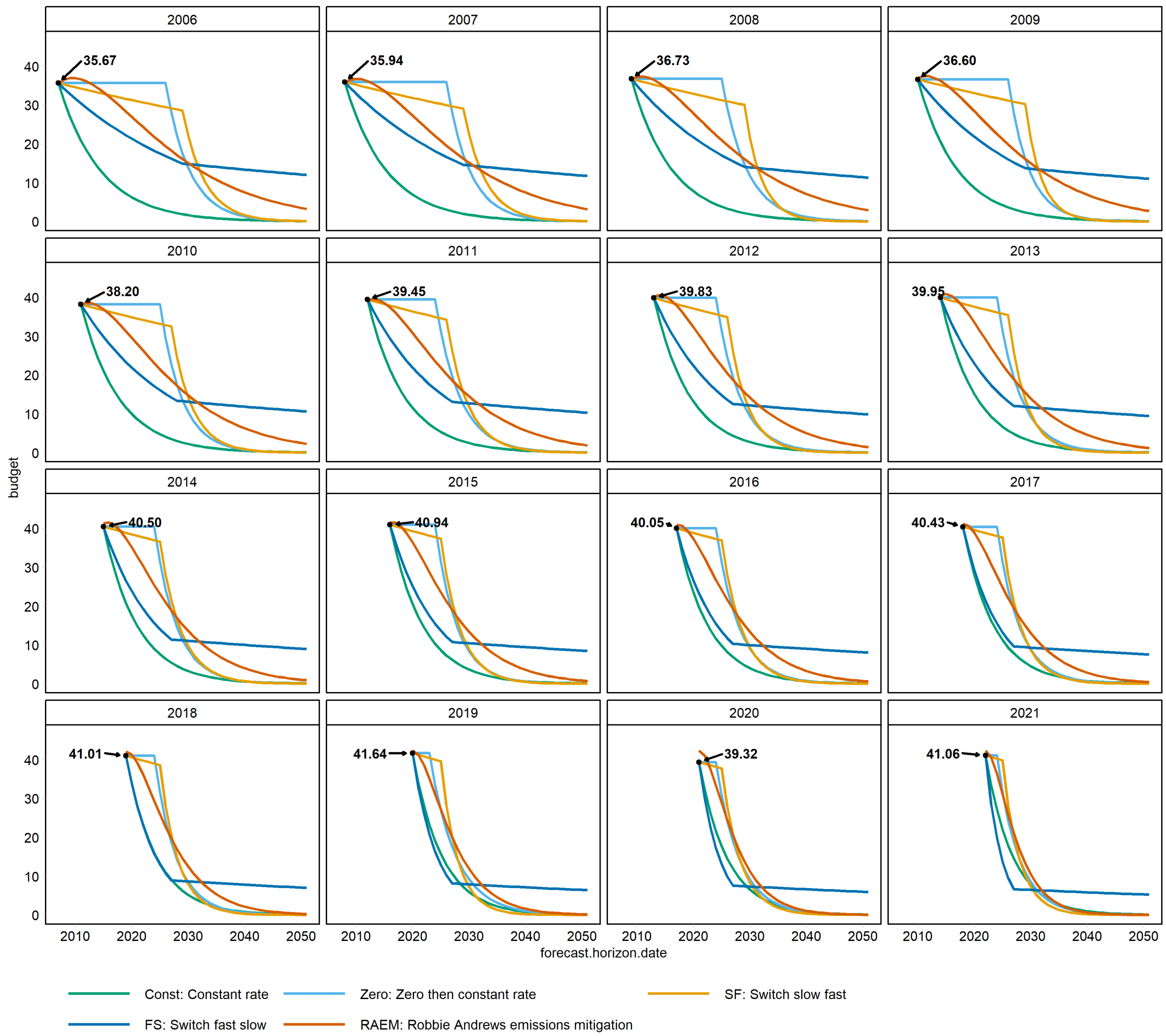

Figure 1: Global carbon budget.

This figure shows how the different choices of decarbonization paths evolve over time from 2006 to 2021. 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 *Zero*, 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).

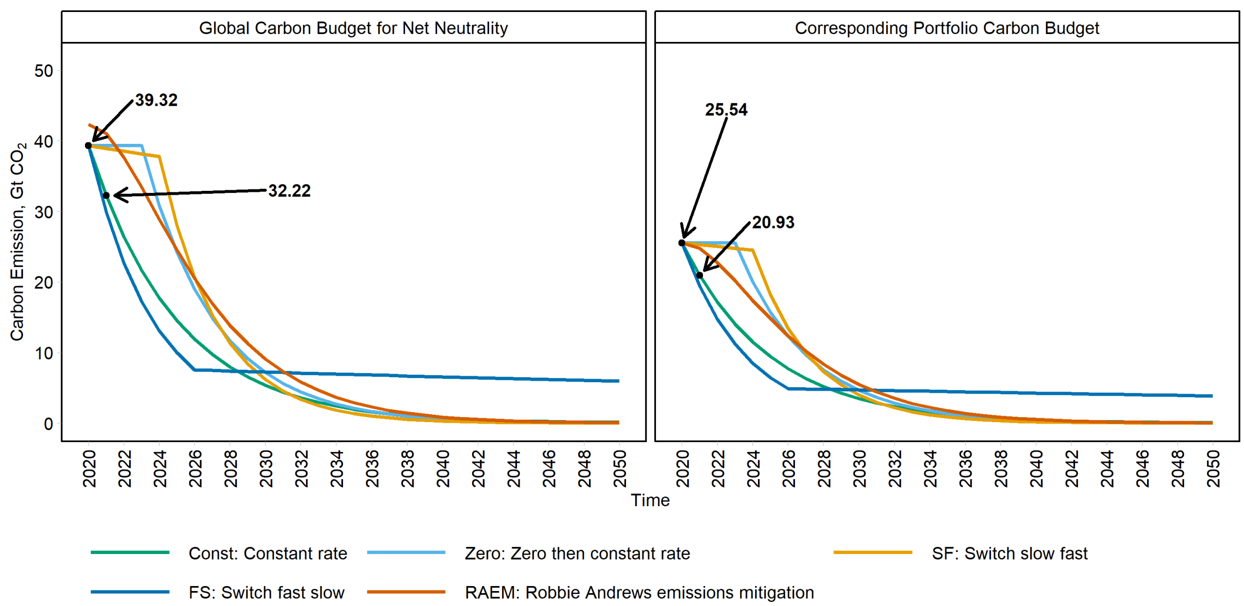

Figure 2: Net-Zero Portfolio carbon budget.

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).

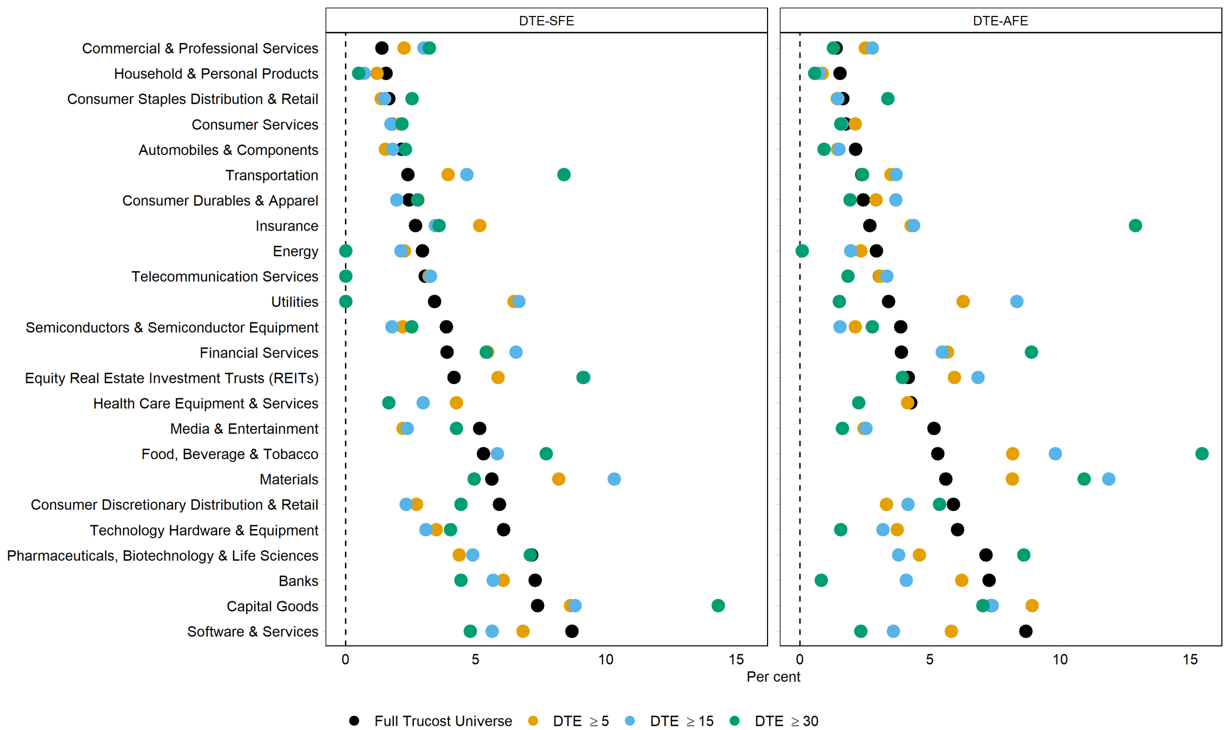

Figure 3: Industry exposures (in %) of the DTE-investable portfolios relative to the Trucost universe in 2020.

This figure shows industry exposures of DTE portfolios compared with those displayed by the universe of all stocks in the Trucost database. We show results for portfolios based on two variants of DTE. In the left panel, *DTE-SFE*, we sort firms by standardized forecasted emissions within GICS-4 industry group. In the right panel, *DTE-AFE*, we sort firms by *Ambition Score*. In both cases, we sum up forecasted emissions to fill up the carbon budget. We report the industry exposures of the DTE portfolios using a 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 $DTE \geq 30$.

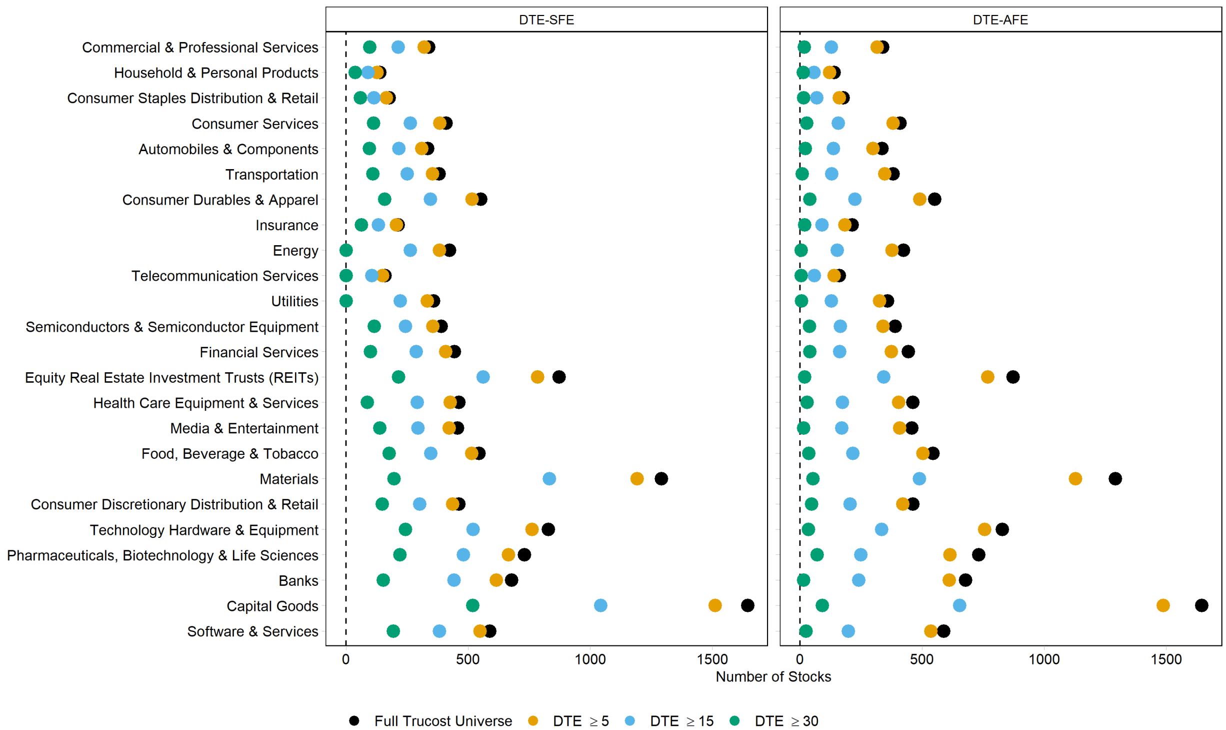

Figure 4: The number of DTE-investable stocks in 2020.

This figure shows the number of stocks held in *DTE* portfolios compared with that in the universe of all stocks in the Trucost database. We consider portfolios based on two variants of *DTE*. In the left panel, *DTE-SFE*, we sort firms by standardized forecasted emissions within GICS-4 industry group. In the right panel, *DTE-AFE*, we sort firms by *Ambition Score*. In both cases, we sum up forecasted emissions to fill up the carbon budget. We provide the number of stocks in *DTE* portfolios using a 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 $DTE \geq 30$.

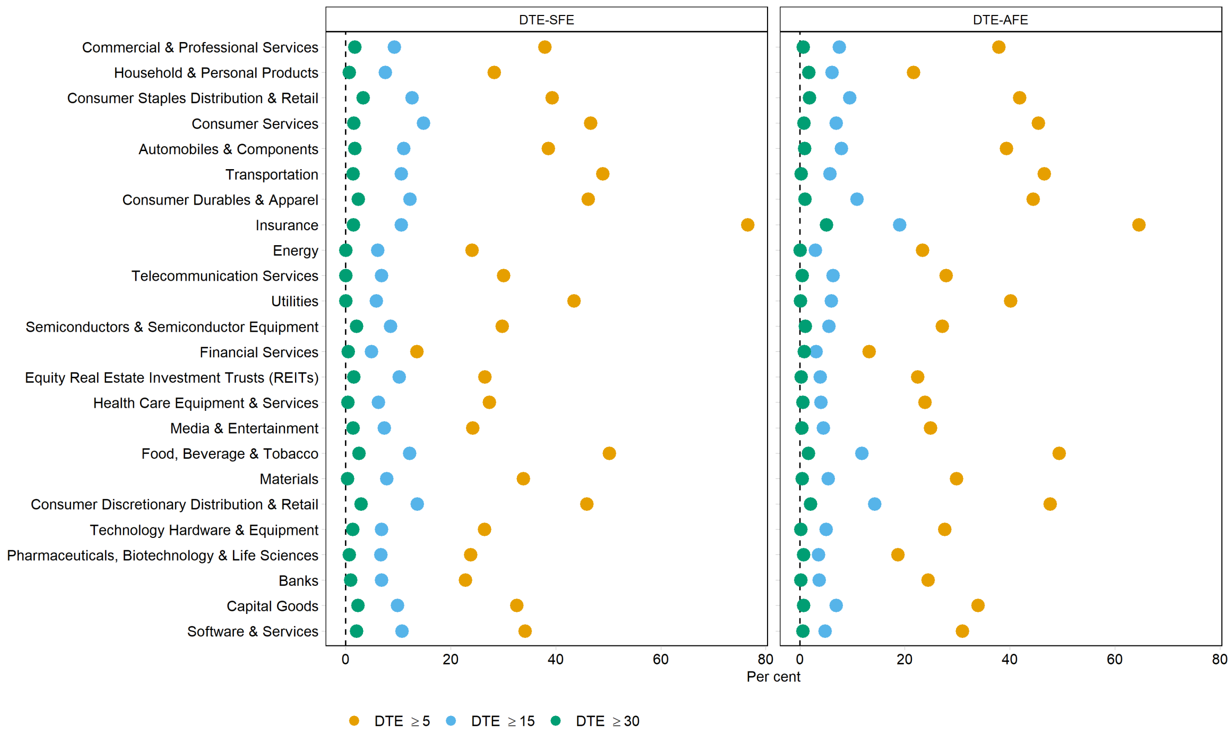

Figure 5: Carbon emissions of DTE-investable portfolios relative to the Trucost universe in 2020: constant-emissions model.

This figure shows the decarbonization performance of DTE portfolios compared with that in the universe of all stocks in the Trucost database. We show results for portfolios based on two variants of DTE. In the left panel, *DTE-SFE*, we sort firms by standardized forecasted emissions within GICS-4 industry group. In the right panel, *DTE-AFE*, we sort firms by *Ambition Score*. In both cases, we sum up forecasted emissions to fill up the carbon budget. We provide the percentage reduction in carbon footprint of a given DTE portfolio using a snapshot of observations in 2020. The carbon footprint is based on the observed annual total emissions in 2020. The three investable sets we consider are: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

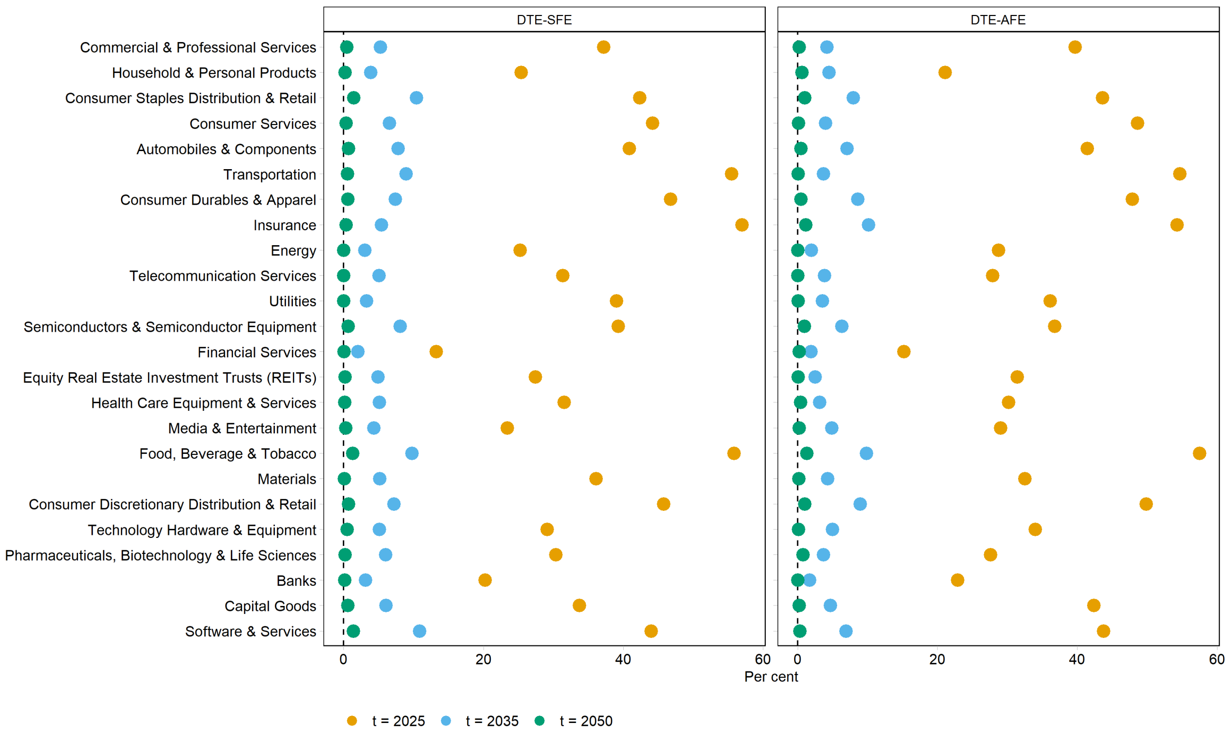

Figure 6: Carbon emissions of DTE-investable portfolios relative to the Trucost universe as of 2020: forecasted-emissions model.

This figure shows the decarbonization performance of DTE-investable portfolios compared with that in the universe of all stocks in the Trucost database. We characterize DTE-investable portfolios in three years: 2025, 2035, and 2050. We analyze the investable sets based on two variants of DTE. In the left panel, *DTE-SFE*, we sort firms by standardized forecasted emissions within GICS-4 industry group. In the right panel, *DTE-AFE*, we sort firms by *Ambition Score*. In both cases, we sum up forecasted emissions to fill up the carbon budget. We provide the percentage reduction in total carbon footprint of a given investable set using a snapshot of observations in 2020. The carbon footprint is based on the 2020 emissions forecasts over the horizon from 2020 to 2050.

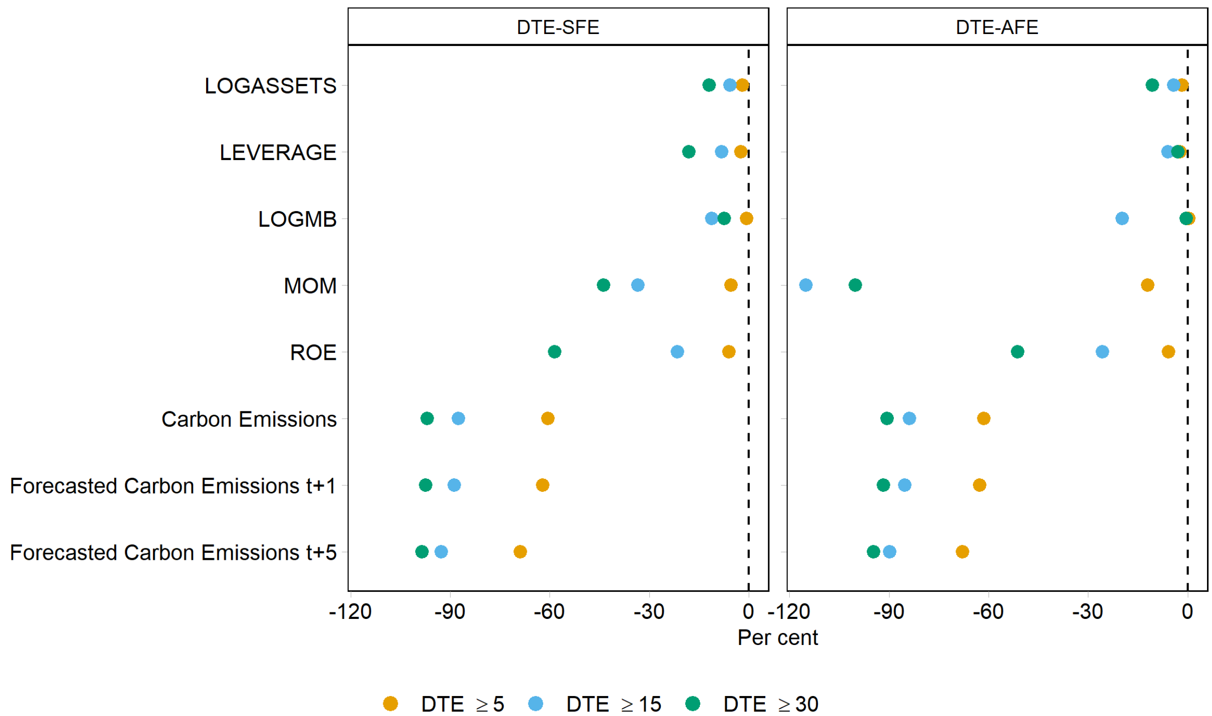

Figure 7: Percentage deviations in characteristics of DTE-investable portfolios from those of the Trucost universe in 2020.

This figure shows the style characteristics of DTE portfolios compared with those in the universe of all stocks in the Trucost database. We consider portfolios based on two variants of DTE. In the left panel, *DTE-SFE*, we sort firms by standardized forecasted emissions within GICS-4 industry group. In the right panel, *DTE-AFE*, we sort firms by *Ambition Score*. In both cases, we sum up forecasted emissions to fill up the carbon budget. We provide the percentage deviation for characteristics and carbon footprint of a given DTE portfolio from those of the Trucost portfolio using a 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) of the main variables. The sample period is 2005–2021. Panel A reports the emissions variables. Panel B shows the *Ambition Score* and its industry-standardized sub-components. Panel C reports the one-year and five-year ahead forecasted emissions, the three-year average of forecasted emissions, the three-year average of percentage change in forecasted emissions, and distance-to-exit (DTE) derived using different metrics of ranking. We consider three sets of DTE, depending on the sorting variable used in their construction: (1) constant emissions, (2) forecasted emissions, and (3) *Ambition Score*. Within each of the first two sets, we define two variants of DTE: those that are based on the raw sorting variable, and those that standardize it within GICS-4 industry group. The third group based on *Ambition Score* also contains two variants of DTE, depending on whether we sum up constant or forecasted emissions to fill up the carbon budget. We show six different variants of DTE: constant emissions (*DTE-CE*); standardized constant emissions (*DTE-SCE*); forecasted emissions (*DTE-FE*); standardized forecasted emissions (*DTE-SFE*); *Ambition Score* plus constant emissions (*DTE-ACE*); *Ambition Score* plus forecasted emissions (*DTE-AFE*). Panel D summarizes information on firm-level variables that enter our regression models. RET is the monthly stock return; $LOGPE$ is the natural logarithm of share price divided by earnings per share; $LOGMB$ is the natural logarithm of market cap divided by book value; $LOGPS$ is the natural logarithm of 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 previous year; $INVEST/ASSETS$ 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 billions; $SALESGR$ is the annual growth rate in firm sales; *Log Emissions* is the natural logarithm of scope 1, 2, 3 upstream total emissions; *Log Average Forecasted Emissions* is the natural logarithm of the three-year average of forecasted emissions.

	Mean	Std.Dev	Q25	Median	Q75
Panel A: Carbon Emissions					
Carbon Emissions (Scope 1, 2, 3 upstream)	2942181	14217611	45060	215385	1043975
Growth Rate in Carbon Emissions (Scope 1, 2, 3 upstream)	0.104	0.233	-0.022	0.056	0.173
Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	544.708	1606.150	88.187	194.123	422.612
Growth Rate in Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	-0.002	0.082	-0.039	-0.011	0.029
Panel B: Ambition Score Components (Industry-Group Standardized)					
Ambition Score	0.632	6.931	-0.083	0.151	0.574
Carbon Emissions (Scope 1, 2, 3 upstream)	1.517	14.817	-0.216	-0.004	0.742
Growth Rate in Carbon Emissions (Scope 1, 2, 3 upstream)	0.227	1.163	-0.398	0.002	0.588
Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	1.348	44.814	-0.296	0.000	0.622
Growth Rate in Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	0.203	2.955	-0.431	0.000	0.517
Decarbonization Target	0.014	0.988	0.299	0.428	0.551
Decarbonization Policy	0.017	0.995	-1.052	0.568	0.764
Reported Emissions	0.019	0.992	-1.069	0.532	0.696
CSR Committee	0.019	0.990	-1.056	0.508	0.684
UNPRI Signatory	0.011	0.971	0.039	0.045	0.096
SDG 13 Climate Action	0.016	0.998	0.043	0.368	0.471
# Patent (Brown)	0.002	0.982	0.077	0.111	0.149
# Patent Citation (Green)	0.000	0.981	0.068	0.120	0.178
# Patent Citation	0.002	0.982	0.071	0.105	0.154
Ratio of # Green Patents over # Patents	-0.004	1.000	0.083	0.186	0.289
Ratio of # Brown Patent over # Patent	0.002	0.976	0.068	0.103	0.185
SBTi Status	0.007	0.987	0.129	0.173	0.211
Greenwash Indicator	0.001	1.000	-0.059	-0.022	0.026
Abatement rate	0.009	0.976	0.150	0.182	0.229
Underperformance	0.007	0.988	0.199	0.247	0.301
Infeasible Indicator	0.006	0.992	0.193	0.230	0.284
Panel C: DTE-Related Variables					
Forecasted Emissions $t+1$	3072844	15163928	47137	225664	1088088
Forecasted Emissions $t+5$	4139646	26636130	53327	273622	1364004
Average Forecasted Emissions ($t+1$ to $t+3$)	3274122	16862846	49223	238820	1151497
Average Forecasted Emissions Growth ($t+1$ to $t+3$)	0.053	0.142	-0.033	0.043	0.126
DTE-CE	23.199	9.839	16.000	24.000	31.000
DTE-SCE	19.260	10.108	11.000	19.000	28.000
DTE-FE	22.615	10.656	14.000	24.000	31.000
DTE-SFE	18.766	10.792	9.000	18.000	29.000
DTE-ACE	13.047	7.446	8.000	12.000	17.000
DTE-AFE	13.173	8.480	7.000	12.000	18.000
Panel D: Additional Regression Variables					
RET	1.167	30.418	-4.951	0.458	6.185
LOGPE	3.072	0.949	2.520	2.985	3.501
LOGMB	0.728	1.027	0.084	0.676	1.330
LOGPS	0.349	1.358	-0.506	0.318	1.142
LOGSIZE	9.601	2.585	7.881	9.410	11.218
LOGASSETS	9.606	2.698	7.801	9.359	11.311
LEVERAGE (winsorized at 2.5%)	0.226	0.184	0.068	0.204	0.344
MOM (winsorized at 2.5%)	0.143	0.445	-0.146	0.070	0.330
INVEST/ASSETS (winsorized at 2.5%)	0.046	0.045	0.014	0.032	0.062
LOGPPE	7.864	3.217	5.754	7.766	9.948
VOLAT (winsorized at 2.5%)	0.103	0.056	0.063	0.089	0.127
ROE (winsorized at 2.5%)	0.193	0.243	0.071	0.163	0.283
AGE	56.474	48.470	23.000	41.000	75.000
DOLVOL in Billion (winsorized at 2.5%)	18.420	53.300	0.149	1.008	6.138
SALESGR (winsorized at 2.5%)	0.083	0.212	-0.009	0.046	0.148
Log Emissions	12.291	2.393	10.716	12.280	13.859
Log Average Forecasted Emissions ($t+1$ to $t+3$)	12.379	2.412	10.804	12.383	13.957

Table 2: DTE: Basic Properties

Panel A reports Pearson correlation coefficients across carbon emissions, the *Ambition Score*, and the six variants of DTE, as defined in Table 1. Panel B shows the time-series variation of the stock universe and the average DTE.

	Emissions	Ambition Score	DTE-CE	DTE-SCE	DTE-FE	DTE-SFE	DTE-ACE
Panel A: Correlations							
Ambition Score	0.124	1.000					
DTE-CE	-0.372	-0.098	1.000				
DTE-SCE	-0.282	-0.113	0.745	1.000			
DTE-FE	-0.340	-0.104	0.884	0.674	1.000		
DTE-SFE	-0.257	-0.116	0.635	0.833	0.772	1.000	
DTE-ACE	-0.210	-0.164	0.362	0.452	0.474	0.579	1.000
DTE-AFE	-0.197	-0.153	0.346	0.440	0.474	0.585	0.987

Year	No. Firms	DTE-CE	DTE-SCE	DTE-FE	DTE-SFE	DTE-ACE	DTE-AFE
Panel B: Stock universe and average DTEs by year							
2006	2494	28.985	23.041	27.274	21.982	15.123	13.330
2007	2686	28.185	22.574	25.344	19.813	14.331	13.518
2008	2665	27.474	22.389	25.911	21.002	14.067	13.871
2009	2789	26.595	21.478	26.309	22.226	13.516	14.272
2010	2931	26.038	21.282	26.092	21.769	12.954	14.022
2011	3162	25.460	20.797	25.157	20.013	13.650	14.213
2012	3332	24.902	20.187	24.094	18.583	12.982	12.589
2013	3357	24.211	19.406	24.021	18.769	12.728	13.269
2014	3967	23.632	19.251	23.146	19.154	13.106	13.557
2015	4297	23.101	18.998	23.458	19.313	12.999	14.707
2016	4490	22.405	18.389	22.713	18.657	12.474	14.047
2017	10435	23.355	19.533	21.913	17.824	13.363	12.425
2018	11339	22.749	19.080	21.077	17.375	13.749	13.191
2019	12050	22.100	18.596	21.515	18.275	13.026	12.618
2020	12904	21.451	18.134	21.895	18.860	12.443	13.317
2021	14227	20.975	17.823	20.871	17.945	12.085	12.472

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

The dependent variables are DTE, defined in Table 1. The independent variables are defined in Table 1. These include *Log Emissions*, *LOGMKTCAP*, *LOGASSETS*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*. The sample period is 2005–2021. 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 GICS-6 industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1) DTE-CE	(2) DTE-SCE	(3) DTE-FE	(4) DTE-SFE	(5) DTE-ACE	(6) DTE-AFE
Log Emissions	-3.667***	-4.220***	-3.936***	-4.378***	-2.697***	-3.027***
	(0.256)	(0.237)	(0.263)	(0.233)	(0.099)	(0.117)
LOGMKTCAP	-0.193**	-0.494***	-0.356***	-0.624***	0.255**	0.290**
	(0.066)	(0.066)	(0.084)	(0.094)	(0.097)	(0.111)
LOGASSETS	-0.470***	-0.523***	-0.212**	-0.241**	0.703***	0.780***
	(0.057)	(0.079)	(0.091)	(0.099)	(0.098)	(0.113)
LOGMB	-0.119	0.035	-0.473***	-0.460***	-0.520***	-0.620***
	(0.068)	(0.073)	(0.091)	(0.093)	(0.098)	(0.111)
LEVERAGE	-0.656***	-1.085***	-1.102***	-1.114***	0.229	0.191
	(0.202)	(0.245)	(0.256)	(0.293)	(0.343)	(0.383)
MOM	0.304***	0.320***	0.059	0.131	-0.559***	-0.672***
	(0.058)	(0.098)	(0.142)	(0.141)	(0.174)	(0.206)
INVEST/ASSETS	0.810	0.238	-10.791***	-11.085***	-12.398***	-14.514***
	(0.669)	(0.820)	(1.484)	(1.393)	(1.337)	(1.556)
LOGPPE	0.267***	0.104*	0.509***	0.416***	0.119**	0.163**
	(0.051)	(0.053)	(0.071)	(0.060)	(0.053)	(0.060)
VOLAT	-5.080***	-5.508***	-6.775***	-8.335***	-4.563***	-5.560***
	(0.584)	(0.960)	(0.925)	(1.135)	(0.601)	(0.660)
ROE	1.636***	1.528***	0.594**	0.260	0.530**	0.550*
	(0.255)	(0.308)	(0.263)	(0.276)	(0.233)	(0.265)
DOLVOL	-0.006***	-0.005***	-0.007***	-0.005***	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
AGE	2.553***	3.601***	13.316***	15.446***	17.745***	20.472***
	(0.862)	(1.120)	(1.969)	(2.255)	(1.910)	(2.307)
Constant	72.863***	81.795***	74.490***	81.263***	38.784***	42.039***
	(2.756)	(2.888)	(2.864)	(2.851)	(1.176)	(1.299)
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	932,391	932,391	932,391	932,391	932,391	932,391
R-squared	0.886	0.830	0.726	0.652	0.309	0.298

Table 4: Returns and DTE

The dependent variable is firm-level return, $RET_{i,t+1}$, measured monthly. The main independent variables are $DTE_{i,t}$ constructed with different ranking variables, as defined in Table 1. Control variables include *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*, as defined in Table 1. The sample period is 2005–2021. 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 GICS-6 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-CE	-0.039***					
	(0.009)					
DTE-SCE		-0.037***				
		(0.010)				
DTE-FE			-0.031***			
			(0.008)			
DTE-SFE				-0.030***		
				(0.008)		
DTE-ACE					-0.028***	
					(0.006)	
DTE-AFE						-0.025***
						(0.006)
LOGMKTCAP	-0.331***	-0.350***	-0.313***	-0.329***	-0.250***	-0.250***
	(0.070)	(0.075)	(0.066)	(0.071)	(0.057)	(0.058)
LOGMB	-0.113*	-0.103*	-0.143**	-0.138**	-0.174**	-0.175**
	(0.058)	(0.055)	(0.063)	(0.061)	(0.068)	(0.068)
LEVERAGE	-0.349*	-0.380*	-0.326	-0.342*	-0.208	-0.210
	(0.189)	(0.183)	(0.192)	(0.190)	(0.197)	(0.197)
MOM	0.600***	0.599**	0.587**	0.588**	0.571**	0.569**
	(0.203)	(0.204)	(0.201)	(0.202)	(0.203)	(0.203)
INVEST/ASSETS	-0.022	-0.016	-0.480	-0.455	-0.703	-0.718
	(1.081)	(1.075)	(1.041)	(1.041)	(1.028)	(1.026)
LOGPPE	0.040	0.029	0.056	0.049	0.068*	0.069*
	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.033)
VOLAT	3.105	3.123	3.095	3.074	3.129	3.119
	(3.857)	(3.862)	(3.857)	(3.855)	(3.870)	(3.867)
DOLVOL	-0.012	-0.011	-0.011	-0.011	-0.010	-0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
AGE	-0.300	-0.289	0.039	0.076	0.199	0.214
	(1.047)	(1.037)	(0.996)	(0.990)	(0.976)	(0.975)
Constant	4.637***	4.746***	4.180***	4.295***	3.193***	3.160***
	(0.488)	(0.561)	(0.427)	(0.468)	(0.338)	(0.343)
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	922,365	922,365	922,365	922,365	922,365	922,365
R-squared	0.120	0.120	0.120	0.120	0.120	0.120

Table 5: Returns and Lagged DTE

The dependent variable is RET measured monthly. The main independent variables are 12-month lagged DTE, constructed with different ranking variables, as defined in Table 1. All regressions include the same set of control variables as in Table 4. The sample period is 2005–2021. 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 GICS-6 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-CE	-0.015***					
	(0.005)					
DTE-SCE		-0.014**				
		(0.006)				
DTE-FE			-0.002			
			(0.006)			
DTE-SFE				-0.007		
				(0.006)		
DTE-ACE					-0.004	
					(0.003)	
DTE-AFE						-0.003
						(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	801,763	801,763	801,763	801,763	801,763	801,763
R-squared	0.132	0.132	0.132	0.132	0.132	0.132

Table 6: Valuation Ratios and DTE

The dependent variables are $LOGPE$ in Panel A, $LOGMB$ in Panel B, and $LOGPS$ in Panel C, all defined in Table 1. The main independent variables are DTE constructed with different ranking variables, defined in Table 1. Control variables include MOM, $VOLAT$, AGE, and $SALESGR$, defined in 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 2005–2021. 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 GICS-6 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-CE	0.009***					
	(0.001)					
DTE-SCE		0.007***				
		(0.001)				
DTE-FE			0.006***			
			(0.001)			
DTE-SFE				0.005***		
				(0.001)		
DTE-ACE					0.006***	
					(0.001)	
DTE-AFE						0.005***
						(0.001)
Observations	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.232	0.232	0.230	0.230	0.229	0.228
Panel B. Dependent Variable: LOGMB						
DTE-CE	0.007***					
	(0.001)					
DTE-SCE		0.005***				
		(0.001)				
DTE-FE			0.003**			
			(0.001)			
DTE-SFE				0.002**		
				(0.001)		
DTE-ACE					0.004***	
					(0.001)	
DTE-AFE						0.003***
						(0.001)
Observations	651,621	651,621	651,621	651,621	651,621	651,621
R-squared	0.385	0.385	0.383	0.383	0.383	0.383
Panel C. Dependent Variable: LOGPS						
DTE-CE	0.037***					
	(0.002)					
DTE-SCE		0.030***				
		(0.002)				
DTE-FE			0.026***			
			(0.002)			
DTE-SFE				0.022***		
				(0.002)		
DTE-ACE					0.014***	
					(0.002)	
DTE-SFE						0.012***
						(0.002)
Observations	658,913	658,913	658,913	658,913	658,913	658,913
R-squared	0.482	0.482	0.465	0.465	0.439	0.438
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 DTE: Extensive Margin

The dependent variable is RET, measured monthly. The independent variables (EXT) are transformations of DTEs (as defined in 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 2005–2021. 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 GICS-6 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 DTE-CE	-0.449***					
	(0.075)					
EXT DTE-SCE		-0.429***				
		(0.124)				
EXT DTE-FE			-0.518***			
			(0.097)			
EXT DTE-SFE				-0.441***		
				(0.102)		
EXT DTE-ACE					-0.216	
					(0.154)	
EXT DTE-AFE						-0.261***
						(0.078)
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	963,697	963,697	963,697	963,697	963,697	963,697
R-squared	0.121	0.121	0.121	0.121	0.121	0.121

Table 8: Returns and DTE: Paris Agreement

The dependent variable is RET, measured monthly. We define an indicator variable, $Paris$, that is equal to one for the years starting from 2016 onwards, and equal to zero up to and including 2015. The main independent variables are DTE, constructed with different ranking variables, as defined in Table 1, and the interaction terms between DTEs and $Paris$. All regressions include the same set of control variables as in Table 4. The sample period is 2005–2021. 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 GICS-6 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-CE	-0.030***					
	(0.008)					
DTE-CE × Paris	-0.029***					
	(0.010)					
DTE-SCE		-0.024**				
		(0.009)				
DTE-SCE × Paris		-0.031***				
		(0.008)				
DTE-FE			-0.020**			
			(0.008)			
DTE-FE × Paris			-0.026**			
			(0.009)			
DTE-SFE				-0.017**		
				(0.007)		
DTE-SFE × Paris				-0.027***		
				(0.007)		
DTE-ACE					-0.017**	
					(0.006)	
DTE-ACE × Paris					-0.018*	
					(0.010)	
DTE-AFE						-0.015**
						(0.005)
DTE-AFE× Paris						-0.018*
						(0.010)
Observations	922,365	922,365	922,365	922,365	922,365	922,365
R-squared	0.120	0.121	0.121	0.121	0.120	0.120
Panel B. Dependent Variable: LOGPE						
DTE-CE	0.006***					
	(0.001)					
DTE-CE × Paris	0.007***					
	(0.002)					
DTE-SCE		0.004***				
		(0.001)				
DTE-SCE × Paris		0.005***				
		(0.001)				
DTE-FE			0.004***			
			(0.001)			
DTE-FE × Paris			0.005***			
			(0.001)			
DTE-SFE				0.003***		
				(0.001)		
DTE-SFE × Paris				0.004***		
				(0.001)		
DTE-ACE					0.005***	
					(0.001)	
DTE-ACE × Paris					0.001	
					(0.002)	
DTE-AFE						0.004***
						(0.001)
DTE-AFE × Paris						0.001
						(0.001)
Observations	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.233	0.233	0.231	0.231	0.229	0.229
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 DTE: Controlling for Climate Variables

The dependent variable is RET, measured monthly. The main independent variables are DTEs constructed with different ranking variables as defined in Table 1. In addition to the same set of control variables as in Table 4, we also include the natural logarithm of total emissions, *Log Emissions*, the percentage change in total emissions, *Emissions Growth* in columns (1) and (2); the natural logarithm of the three-year average of forecasted emissions, *Log Average Forecasted Emissions*, the three-year average of percentage change in forecasted emissions, *Average Forecasted Emissions Growth* in columns (3) and (4); *Ambition Score* in columns (5) and (6). The sample period is 2005–2021. 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 GICS-6 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-CE	0.002					
	(0.017)					
DTE-SCE		-0.010				
		(0.014)				
DTE-FE			0.001			
			(0.011)			
DTE-SFE				-0.008		
				(0.010)		
DTE-ACE					-0.028***	
					(0.006)	
DTE-AFE						-0.025***
						(0.006)
Log Emissions	0.224**	0.176**				
	(0.092)	(0.080)				
Emissions Growth	1.458***	1.458***				
	(0.236)	(0.234)				
Log Average Forecasted Emissions			0.265***	0.229***		
			(0.070)	(0.064)		
Average Forecasted Emissions Growth			0.327*	0.101		
			(0.177)	(0.196)		
Ambition Score					-0.087	-0.067
					(0.112)	(0.111)
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	922,365	922,365	922,365	922,365	922,365	922,365
R-squared	0.122	0.122	0.121	0.121	0.120	0.120

Table 10: Returns and DTE: Scope 1 and 2

The dependent variable is RET, measured monthly. The main independent variables are DTE defined as in Table 1, but excluding scope 3 emissions. Control variables mimic those in Table 4. The sample period is 2005–2021. 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 GICS-6 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-CE	-0.024***					
	(0.007)					
DTE-SCE		-0.023***				
		(0.007)				
DTE-FE			-0.022***			
			(0.007)			
DTE-SFE				-0.023***		
				(0.007)		
DTE-ACE					-0.014***	
					(0.004)	
DTE-AFE						-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	922,365	922,365	922,365	922,365	922,365	922,365
R-squared	0.120	0.120	0.120	0.120	0.120	0.120

Table 11: Returns and DTE: Alternative Decarbonization Pathways

We consider alternative portfolio decarbonization pathways. Pathway $ZeroConst$ assumes that investors delay the decarbonization process 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 $RAEM$ follows the emission mitigation pathway of Andrew (2020). The main independent variables are DTE, defined as in Table 1, but assuming alternative pathways. The dependent variable in panels 1 is RET, measured monthly. The dependent variable in panels 2 is $LOGPE$. Control variables mimic those from respective tables. The sample period is 2005–2021. 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 GICS-6 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-CE	-0.066***						0.013***					
	(0.014)						(0.001)					
DTE-SCE		-0.056***						0.010***				
		(0.012)						(0.001)				
DTE-FE			-0.046***						0.009***			
			(0.011)						(0.001)			
DTE-SFE				-0.041***						0.007***		
				(0.010)						(0.001)		
DTE-ACE					-0.038***						0.008***	
					(0.008)						(0.001)	
DTE-AFE						-0.030***						0.006***
						(0.007)						(0.001)
Observations	922,365	922,365	922,365	922,365	922,365	922,365	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.120	0.121	0.121	0.121	0.120	0.120	0.233	0.232	0.231	0.231	0.229	0.229
	Panel B1. Dependent Variable: RET. Pathway: SF						Panel B2. Dependent Variable: LOGPE. Pathway: SF					
DTE-CE	-0.082***						0.015***					
	(0.014)						(0.002)					
DTE-SCE		-0.061***						0.011***				
		(0.012)						(0.002)				
DTE-FE			-0.054***						0.010***			
			(0.011)						(0.001)			
DTE-SFE				-0.044***						0.008***		
				(0.010)						(0.001)		
DTE-ACE					-0.042***						0.009***	
					(0.010)						(0.001)	
DTE-AFE						-0.033***						0.007***
						(0.008)						(0.001)
Observations	922,365	922,365	922,365	922,365	922,365	922,365	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.121	0.121	0.121	0.121	0.120	0.120	0.233	0.232	0.231	0.231	0.229	0.229
	Panel C1. Dependent Variable: RET. Pathway: FS						Panel C2. Dependent Variable: LOGPE. Pathway: FS					
DTE-CE	-0.009**						0.006***					
	(0.004)						(0.001)					
DTE-SCE		-0.017***						0.005***				
		(0.004)						(0.000)				
DTE-FE			-0.010**						0.006***			
			(0.004)						(0.001)			
DTE-SFE				-0.016***						0.004***		
				(0.005)						(0.000)		
DTE-ACE					-0.014***						0.004***	
					(0.004)						(0.000)	
DTE-AFE						-0.013***						0.003***
						(0.004)						(0.000)
Observations	922,365	922,365	922,365	922,365	922,365	922,365	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.120	0.120	0.120	0.120	0.120	0.120	0.229	0.230	0.230	0.230	0.229	0.229
	Panel D1. Dependent Variable: RET. Pathway: RAEM						Panel D2. Dependent Variable: LOGPE. Pathway: RAEM					
DTE-CE	-0.041***						0.010***					
	(0.012)						(0.001)					
DTE-SCE		-0.045***						0.008***				
		(0.010)						(0.001)				
DTE-FE			-0.032***						0.008***			
			(0.010)						(0.001)			
DTE-SFE				-0.031***						0.006***		
				(0.008)						(0.001)		
DTE-ACE					-0.025***						0.006***	
					(0.006)						(0.001)	
DTE-AFE						-0.020***						0.005***
						(0.006)						(0.001)
Observations	922,365	922,365	922,365	922,365	922,365	922,365	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.120	0.120	0.120	0.120	0.120	0.120	0.232	0.232	0.231	0.231	0.229	0.229
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"

by Gino Cenedese, Shangqi Han, Marcin Kacperczyk

IA Additional Tables and Figures

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

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

			Switch Zero-Const. Reduction Pathway						Switch Slow-Fast Reduction Pathway						Switch Fast-Slow Reduction Pathway						Robbie Andrews Reduction Pathway				
	Carbon Emissions	Ambition Score	DTE-CE	DTE-SCE	DTE-FE	DTE-SFE	DTE-ACE	DTE-AFE	DTE-CE	DTE-SCE	DTE-FE	DTE-SFE	DTE-ACE	DTE-AFE	DTE-CE	DTE-SCE	DTE-FE	DTE-SFE	DTE-ACE	DTE-AFE	DTE-CE	DTE-SCE	DTE-FE	DTE-SFE	DTE-ACE
Ambition Score	0.12	1.00																							
Switch Zero-Constant Reduction Pathway																									
DTE-CE	-0.28	-0.09	1.00																						
DTE-SCE	-0.21	-0.11	0.80	1.00																					
DTE-FE	-0.30	-0.10	0.90	0.73	1.00																				
DTE-SFE	-0.22	-0.12	0.70	0.85	0.82	1.00																			
DTE-ACE	-0.12	-0.15	0.53	0.59	0.60	0.66	1.00																		
DTE-AFE	-0.17	-0.16	0.50	0.57	0.59	0.68	0.96	1.00																	
Switch Slow-Fast Reduction Pathway																									
DTE-CE	-0.25	-0.08	0.97	0.80	0.88	0.70	0.56	0.52	1.00																
DTE-SCE	-0.18	-0.11	0.79	0.97	0.73	0.83	0.63	0.60	0.83	1.00															
DTE-FE	-0.27	-0.09	0.90	0.74	0.97	0.82	0.63	0.62	0.91	0.77	1.00														
DTE-SFE	-0.20	-0.12	0.71	0.85	0.81	0.97	0.70	0.70	0.74	0.87	0.84	1.00													
DTE-ACE	-0.10	-0.15	0.55	0.60	0.59	0.64	0.97	0.93	0.60	0.67	0.65	0.71	1.00												
DTE-AFE	-0.16	-0.15	0.52	0.58	0.59	0.67	0.95	0.98	0.56	0.64	0.64	0.72	0.95	1.00											
Switch Fast-Slow Reduction Pathway																									
DTE-CE	-0.47	-0.12	0.64	0.54	0.61	0.50	0.51	0.47	0.64	0.58	0.62	0.54	0.55	0.51	1.00										
DTE-SCE	-0.31	-0.15	0.63	0.70	0.58	0.65	0.57	0.58	0.62	0.69	0.58	0.65	0.57	0.59	0.62	1.00									
DTE-FE	-0.42	-0.12	0.63	0.53	0.67	0.56	0.50	0.49	0.62	0.55	0.66	0.59	0.53	0.52	0.80	0.57	1.00								
DTE-SFE	-0.27	-0.14	0.57	0.64	0.66	0.73	0.57	0.59	0.56	0.63	0.64	0.72	0.56	0.60	0.53	0.75	0.63	1.00							
DTE-ACE	-0.22	-0.17	0.47	0.53	0.53	0.59	0.72	0.76	0.47	0.53	0.53	0.60	0.69	0.75	0.47	0.65	0.50	0.66	1.00						
DTE-AFE	-0.22	-0.16	0.44	0.50	0.52	0.58	0.69	0.76	0.44	0.50	0.51	0.58	0.66	0.74	0.43	0.61	0.48	0.65	0.96	1.00					
Robbie Andrews Reduction Pathway																									
DTE-CE	-0.33	-0.10	0.90	0.75	0.83	0.66	0.60	0.55	0.91	0.79	0.85	0.71	0.65	0.60	0.78	0.67	0.74	0.59	0.52	0.48	1.00				
DTE-SCE	-0.24	-0.12	0.78	0.92	0.72	0.81	0.65	0.63	0.81	0.93	0.75	0.84	0.68	0.67	0.63	0.80	0.60	0.71	0.61	0.57	0.82	1.00			
DTE-FE	-0.32	-0.11	0.84	0.70	0.91	0.76	0.63	0.61	0.84	0.73	0.90	0.78	0.66	0.64	0.73	0.63	0.80	0.70	0.56	0.54	0.91	0.76	1.00		
DTE-SFE	-0.23	-0.12	0.70	0.81	0.80	0.92	0.69	0.70	0.72	0.82	0.82	0.93	0.70	0.72	0.57	0.72	0.64	0.83	0.65	0.64	0.73	0.87	0.82	1.00	
DTE-ACE	-0.15	-0.15	0.54	0.60	0.60	0.67	0.94	0.94	0.59	0.66	0.65	0.72	0.94	0.96	0.54	0.62	0.54	0.62	0.78	0.76	0.64	0.71	0.67	0.75	1.00
DTE-AFE	-0.17	-0.15	0.52	0.58	0.60	0.67	0.90	0.94	0.55	0.62	0.63	0.71	0.89	0.94	0.51	0.61	0.53	0.63	0.81	0.82	0.60	0.68	0.65	0.74	0.98

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	2494	13.67	14.31	19.17	10.95		
2007	2686	20.44	26.25	23.42	16.08		
2008	2665	25.55	36.17	27.77	25.03		
2009	2789	28.47	39.40	34.31	34.89	0.04	
2010	2931	29.99	44.39	39.82	41.49	0.03	
2011	3162	29.98	44.37	39.94	42.44	0.03	
2012	3332	29.59	46.22	41.48	44.21	0.03	
2013	3357	28.75	46.65	42.98	44.92	0.03	
2014	3967	24.22	42.37	38.87	39.22	0.03	
2015	4297	24.18	43.17	39.80	37.49	0.02	
2016	4490	23.99	45.21	42.41	38.20	0.89	0.02
2017	10435	11.98	23.98	22.16	19.57	0.42	0.01
2018	11339	13.52	26.62	24.66	21.13	0.19	0.15
2019	12050	16.12	31.50	28.08	24.71	0.13	11.07
2020	12904	18.37	34.90	29.58	28.33	0.81	18.20
2021	14227	21.61	36.63	29.00	31.54	0.69	21.85
Overall	14693	19.96	34.52	30.53	29.16	0.34	9.77

		Green Patents				Brown Efficiency Patents			
Year	# Firms	% Coverage	# Patents	# Patents Citations	# Green Patents to # Patents Ratio	% Coverage	# Patents	# Patent Citations	# Brown Patents to # Patents Ratio
Panel B: Patents									
2006	2494	15.72	7.60	277.48	0.21	8.10	8.12	109.86	0.18
2007	2686	15.75	7.53	259.84	0.22	7.45	7.70	155.80	0.17
2008	2665	17.04	7.10	543.20	0.22	8.37	8.52	1849.03	0.19
2009	2789	17.03	7.87	399.26	0.23	7.10	8.61	257.09	0.17
2010	2931	17.23	8.55	306.88	0.24	7.81	8.46	99.66	0.17
2011	3162	17.17	8.95	282.94	0.23	6.93	7.81	82.09	0.18
2012	3332	17.29	10.38	305.01	0.25	7.44	8.48	85.59	0.16
2013	3357	17.72	11.75	324.09	0.25	7.72	9.09	78.51	0.16
2014	3967	16.69	11.67	340.83	0.28	7.39	8.17	73.20	0.19
2015	4297	16.66	12.66	159.63	0.27	7.21	9.24	62.59	0.18
2016	4490	16.66	13.29	289.68	0.28	7.48	9.52	53.31	0.16
2017	10435	9.48	10.85	155.91	0.33	3.73	8.94	39.70	0.20
2018	11339	8.57	10.26	90.72	0.33	3.69	9.01	30.07	0.21
2019	12050	8.78	10.19	73.00	0.34	3.41	10.98	27.72	0.22
2020	12904	8.50	10.14	290.24	0.35	2.99	8.77	20.99	0.20
2021	14227	7.66	10.36	42.96	0.35	2.48	8.10	16.63	0.20
Overall	14693	11.63	10.26	230.06	0.29	4.81	8.85	152.14	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	3162	386	268	250	243	94		
2012	3332	376	262	237	231	77		
2013	3357	465	319	291	282	95		
2014	3967	549	374	340	333	105		
2015	4297	499	350	304	305	94		
2016	4490	740	475	424	426	113		106
2017	10435	1033	600	536	535	148	52	116
2018	11339	1121	654	591	597	164	91	181
2019	12050	1336	774	715	713	211	156	200
2020	12904	1439	838	792	788	275	239	262
2021	14227	2161	1190	1148	1134	457	336	427
Overall	14693	10105	1510	1437	1439	631	382	666

Table IA.3: Returns and DTE: The Role of Carbon Disclosure

The dependent variable is RET, measured monthly. $Disclosure$ is an indicator variable 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 DTE, constructed with different ranking variables, as defined in Table 1, and the interaction terms between DTE and $Disclosure$. We include the same set of control variables as in Table 4. The sample period is 2005–2021. 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 GICS-6 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-CE	-0.036***					
	(0.009)					
DTE-CE × Disclosure	-0.015***					
	(0.004)					
DTE-SCE		-0.034***				
		(0.010)				
DTE-SCE × Disclosure		-0.018***				
		(0.004)				
DTE-FE			-0.029***			
			(0.009)			
DTE-FE × Disclosure			-0.006*			
			(0.003)			
DTE-SFE				-0.028***		
				(0.008)		
DTE-SFE × Disclosure				-0.009**		
				(0.003)		
DTE-ACE					-0.033***	
					(0.008)	
DTE-ACE × Disclosure					0.015**	
					(0.006)	
DTE-AFE						-0.029***
						(0.007)
DTE-AFE × Disclosure						0.014**
						(0.005)
Disclosure	0.270**	0.287***	0.134	0.175*	-0.139	-0.120
	(0.096)	(0.088)	(0.091)	(0.085)	(0.092)	(0.084)
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	922,365	922,365	922,365	922,365	922,365	922,365
R-squared	0.120	0.120	0.120	0.121	0.120	0.120

Table IA.4: Returns and DTE: Exclude Controls

The dependent variable is RET, measured monthly. The main independent variables are DTE constructed with different ranking variables, as defined in Table 1. Panel A includes the same set of control variables as in Table 4, while Panel B excludes $LOGMKTCAP$ and $LOGPPE$. Panel A excludes GICS-6 industry-fixed effects while Panel B includes GICS-6 industry-fixed effects. All regressions include year-month-fixed effects and country-fixed effects. The sample period is 2005–2021. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. ***1% significance; **5% significance; *10% significance.

	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Dependent Variable: RET. Excluding Industry-Fixed Effect.						
DTE-CE	-0.021**					
	(0.009)					
DTE-SCE		-0.035***				
		(0.009)				
DTE-FE			-0.022**			
			(0.008)			
DTE-SFE				-0.029***		
				(0.008)		
DTE-ACE					-0.026***	
					(0.006)	
DTE-AFE						-0.023***
						(0.005)
Observations	922,945	922,945	922,945	922,945	922,945	922,945
R-squared	0.120	0.120	0.120	0.120	0.120	0.120
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	No	No	No
Year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Panel B. Dependent Variable: RET. Excluding Firm Size.						
DTE-CE	-0.006					
	(0.005)					
DTE-SCE		-0.006				
		(0.004)				
DTE-FE			-0.011**			
			(0.005)			
DTE-SFE				-0.011**		
				(0.005)		
DTE-ACE					-0.020***	
					(0.006)	
DTE-AFE						-0.018***
						(0.005)
Observations	937,400	937,400	937,400	937,400	937,400	937,400
R-squared	0.121	0.121	0.121	0.121	0.121	0.121
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 IA.5: Returns and DTE: GICS-4 Industry-Groups-Fixed Effects

The dependent variable is RET, measured monthly. The main independent variables are DTE constructed with different ranking variables, as defined in Table 1. Control variables include *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, *DOLVOL*, and *AGE*, as defined in Table 1. The sample period is 2005–2021. 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 GICS-4 industry-group-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	Constant Emissions		Forecasted Emissions		Ambition Score	
	(1)	(2)	(3)	(4)	(5)	(6)
DTE-CE	-0.034***					
	(0.009)					
DTE-SCE		-0.032***				
		(0.009)				
DTE-FE			-0.028***			
			(0.008)			
DTE-SFE				-0.028***		
				(0.008)		
DTE-ACE					-0.026***	
					(0.006)	
DTE-AFE						-0.023***
						(0.006)
LOGMKTCAP	-0.293***	-0.309***	-0.282***	-0.295***	-0.224***	-0.224***
	(0.064)	(0.069)	(0.062)	(0.065)	(0.054)	(0.054)
LOGMB	-0.103	-0.092	-0.127*	-0.122*	-0.155**	-0.156**
	(0.059)	(0.055)	(0.062)	(0.060)	(0.066)	(0.066)
LEVERAGE	-0.310	-0.346*	-0.299	-0.319	-0.197	-0.199
	(0.197)	(0.188)	(0.201)	(0.197)	(0.203)	(0.202)
MOM	0.597***	0.594***	0.586***	0.585**	0.568**	0.567**
	(0.199)	(0.201)	(0.198)	(0.199)	(0.200)	(0.200)
INVEST/ASSETS	-0.019	-0.014	-0.408	-0.393	-0.614	-0.631
	(1.054)	(1.044)	(1.010)	(1.009)	(0.999)	(0.997)
LOGPPE	0.026	0.016	0.040	0.033	0.051	0.052
	(0.036)	(0.036)	(0.036)	(0.036)	(0.035)	(0.035)
VOLAT	3.064	3.109	3.049	3.047	3.116	3.104
	(4.036)	(4.044)	(4.032)	(4.035)	(4.052)	(4.050)
DOLVOL	-0.010	-0.009	-0.010	-0.009	-0.008	-0.008
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
AGE	-0.237	-0.248	0.078	0.097	0.228	0.242
	(1.163)	(1.154)	(1.115)	(1.116)	(1.100)	(1.099)
Constant	4.253***	4.351***	3.939***	4.038***	3.043***	3.011***
	(0.462)	(0.532)	(0.403)	(0.443)	(0.324)	(0.330)
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	922,365	922,365	922,365	922,365	922,365	922,365
R-squared	0.120	0.120	0.120	0.120	0.120	0.120

Table IA.6: Valuation Ratios and DTE: GICS-4 Industry-Groups-Fixed Effects

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 DTE constructed with different ranking variables, defined in Table 1. Control variables include MOM, $VOLAT$, AGE, and $SALESGR$, defined in 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 2005–2021. 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 GICS-4 industry-group-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-CE	0.009***					
	(0.001)					
DTE-SCE		0.008***				
		(0.001)				
DTE-FE			0.007***			
			(0.001)			
DTE-SFE				0.006***		
				(0.001)		
DTE-ACE					0.006***	
					(0.001)	
DTE-AFE						0.005***
						(0.001)
Observations	579,357	579,357	579,357	579,357	579,357	579,357
R-squared	0.217	0.216	0.214	0.214	0.212	0.212
Panel B. Dependent Variable: LOGMB						
DTE-CE	0.008***					
	(0.001)					
DTE-SCE		0.007***				
		(0.001)				
DTE-FE			0.004***			
			(0.001)			
DTE-SFE				0.004***		
				(0.001)		
DTE-ACE					0.006***	
					(0.001)	
DTE-AFE						0.005***
						(0.001)
Observations	651,621	651,621	651,621	651,621	651,621	651,621
R-squared	0.358	0.359	0.355	0.356	0.356	0.355
Panel C. Dependent Variable: LOGPS						
DTE-CE	0.039***					
	(0.002)					
DTE-SCE		0.032***				
		(0.002)				
DTE-FE			0.028***			
			(0.002)			
DTE-SFE				0.025***		
				(0.002)		
DTE-ACE					0.017***	
					(0.002)	
DTE-AFE						0.014***
						(0.002)
Observations	658,913	658,913	658,913	658,913	658,913	658,913
R-squared	0.438	0.437	0.418	0.418	0.385	0.384
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