Carbon-Transition Risk and Net-Zero Portfolios*

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Abstract

Net-zero portfolios (NZP), which aim to reduce carbon footprint exposure to zero by a target date, are becoming a popular vehicle to align investors' incentives with climate scenarios and to exert pressure on carbon emitters. We characterize the decision and timing to divest individual 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* have higher valuation ratios and lower expected returns, consistent with the hypothesis that *DTE* captures uncertain institutional pressure to decarbonize and thus can be a useful tool to quantify carbon-transition risk.

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1 Introduction

The growing concerns about climate change motivate the need for a transition away from fossil fuels to renewable energy. The uncertainty about the process generates risk for companies and investors in the economy. How to measure such transition risk is one of the key questions tackled by the literature on climate finance, largely because transition risk is often regarded as a market-based incentive mechanism facilitating decarbonization efforts (e.g., Pedersen, 2024). Among various channels driving such risk, an increasing and uncertain pressure from institutional investors on the corporate sector is one of the most debated. In this paper, we propose a novel framework to assess the scope and magnitude of such pressure based on the scientific social objective to decarbonize the economy. This approach allows us to conceptualize a forward-looking firm-level measure of institutional pressure, distance-to-exit (DTE), which we further relate to the the cross-section of global stock returns.

The starting point to quantify DTE is the concept of net-zero portfolios (e.g., Bolton et al., 2022). Net-zero portfolios (NZP) aim to reduce carbon footprint over time 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. The popularity of broadly defined NZP among institutional investors has been rapidly growing, with more than $130 trillion of assets under management currently covered by various initiatives[1] and some institutions formally tracking the net-zero objective in their investment.[2] The NZP initiative has also shaped some discussions surrounding sustainable finance, as is the case for the EU Climate Transition Benchmark Regulation, which establishes uniform rules for low-carbon investment benchmark indexes and sets their required decarbonization trajectories.[3]

Important in the NZP framework are decarbonization paths reported by climate scientists

[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]For example, in January 2024, PenSam, one of Denmark's largest labor market pension providers, licensed S&P's NZP-focused index for its exclusive use, tracking roughly $6 billion.

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

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 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 immediate pressure. We measure such exposures using the distance in years until the expected exclusion from the NZP takes place, and define them as DTE. We argue that DTE are forward-looking measures of carbon-transition risk implied by investor preferences, and test how much compensation investors require for bearing such risk.

We begin our empirical analyses by discussing a step-by-step process to construct DTE. The advantage of our approach is its flexibility to incorporate variants of decarbonization effort and the speed of implementing it. In the first step, we assume that climate-oriented investors, at each point in time, decarbonize their portfolios' carbon exposures to near zero by 2050. Further, informed by the last available level of portfolio carbon footprint, their subsequent carbon budget gets reduced at a constant rate, the assumption we later relax, subject to not exceeding the total cumulative budget for the entire period. This process generates a path of individual budget constraints over time. In the second step, investors select stocks for their portfolios given their per-period budget. Our selection rule is based on a novel, composite *Misalignment Score* measure of decarbonization efforts integrating three industry-adjusted 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. To fill up the portfolio carbon budget, we set emissions of companies either as constant over time, or we predict their levels until 2050 using past firm-level emission growth rates and their future commitments. In the final step, depending on our model of future emissions, we obtain two variants of firm-level measures of DTE calculated as the number of years a given stock is kept in an investor's net-zero portfolio.

Next, we study the determinants of DTE using a large panel of over $13,000$ global firms with emissions and other firm characteristics, sampled over the 2005-2022 period. We document a number of results. Both *DTE* measures are negatively related to levels of total emissions. They are also negatively related to market-to-book ratios, past stock returns, and firm investments. In turn, they are positively related to firm assets size and market capitalization, though the coefficients are statistically significant only for the latter measure. They are also positively related to measures of property, plant, and equipment and firm age.

We further test whether by excluding companies in a non-random fashion, NZP drifts away from the unconstrained benchmark. Testing such property can be useful if the social planner implementing NZP aims to reach inclusive, broad-based decarbonization, rather than the outcome in which some economic sectors are excluded 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 constrained portfolios relative to the benchmark are not very different. We also do not find a strong evidence that NZP underweight large companies and thus they are unlikely to endure significant transaction costs. Finally, they do not penalize companies that could be instrumental in driving the transition to green equilibrium.

In the second part of the paper, we examine how much the variation in *DTE* can explain the cross-section of stock returns. There are at least three direct channels through which the pricing effect could operate. First, divestment by a significant fraction of investors can reduce risk sharing, and thus affect equilibrium prices and returns (e.g., Merton, 1987). The cross-sectional variation in equilibrium expected returns would become even larger if companies differ in their levels of idiosyncratic risk, as is the case for companies with different *DTE*. 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 because asset prices discount both current and future divestment.[4] Finally, through net-zero portfolios, investors could communicate expectations of future divestment, and thus put pressure on corporates to adjust their decarbonization efforts to avoid potential penalties. To the extent that companies facing investor pressure would face uncertain paths

[4]Using a calibrated model a concurrent theoretical paper by Cheng et al. (2023) also presents significant pricing effects of such future-divestment channel.

of adjustment, holding everything else the same, companies for which divestment horizon is shorter would be more risky, similar to the duration-based mechanism (e.g., Lettau and Wachter, 2007). More broadly, this last communication channel generates a new insight, namely, *DTE* can be tools of *both* divestment and engagement. Notably, in contrast to standard economic frameworks, in which price effects largely depend on individual firms' actions, in our setting, the strength of the three forces depends not only 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 portfolio holdings.

Our baseline model relates *DTE* to next month's stock returns. Our empirical specification is based on a pooled cross-sectional regression framework of Bolton and Kacperczyk (2021b), and includes a host of firm-level characteristics, as well as country and industry-year-month fixed effects. We find a statistically strong negative association between *DTE* and future stock returns, both in the univariate and multivariate setting. The results are economically sizable: Depending on the empirical specification, a one-standard-deviation increase in *DTE* for a given cross-section of firms is associated with an approximate 1.2–2.3 percentage-point reduction in next month's annualized stock returns.

Given that the variation in *DTE* depends jointly on stock selection mechanism and carbon budget, a natural question to ask is how much each of the elements contributes to the explanatory power of stock returns. To answer this question, we expand our baseline model to include both *DTE* and *Misalignment Score* as separate control variables. We find two results. First, in the regression without *DTE*, the *Score* is positively related to future stock returns. This is consistent with the view that investors require higher compensation for holding companies with lower decarbonization efforts. Second, when we include both the *Score* and *DTE* in the same regression, we find that *DTE* is negative and statistically significant, while statistical significance of the *Score* becomes weaker. These results imply that the significance of *DTE* to explain the cross-sectional variation of stock returns does not simply stem from the selection of companies; carbon budget also plays a crucial role.

Another dimension of interest concerns the dynamics of the annual portfolio carbon budget. Even though the aggregate budget every year is pinned down by the scientific evidence, how investors distribute it over time is at their discretion and directly informs the dynamics of institutional pressure. To assess the importance of this margin, we consider a number of possibilities: (a) investors decarbonize their portfolios at a slower rate for the first half of the remaining period and then at a faster rate for the second half; (b) investors decarbonize their portfolios at a faster rate for the first half and then at a slower rate for the second half; (c) investors follow a more sophisticated science-based decarbonization path, of Andrew (2020). Each of the three scenarios implies different measures of DTE because aggregate annual constraints vary in each case. Using the different DTE in our baseline specification, we find that the qualitative results across different options are similar. Quantitatively, however, we find that the return premium is economically larger for the case in which the pressure applied by investors is weaker in the first period and stronger in the second period, relative to the case in which the pressure is first stronger and then weaker.

A crucial element of our DTE setting is the measurement of firm-level decarbonization efforts. Our *Misalignment Score* in the baseline tests assigns an equal weight to three elements of predicted decarbonization success. However, in the absence of the specific knowledge, the specific weighting of the three elements we apply is somewhat arbitrary. We assess the robustness of our results to different weighting schemes and find that the qualitative results of our regression models remain similar. Nonetheless, the economic power of the different DTE to explain stock returns varies. Notably, our baseline equal-weight scheme produces the mid-of-the range magnitudes.

A broader interpretation of DTE is that of transition risk. In this regard, we can think of DTE as one of several competing transition risk measures. While this view clearly has some merits, it is important to note that DTE is based on a very specific friction driving transition risk, which is investor pressure. As such, other alternatives are not exactly like-to-like comparisons. How much common variation in transition risk such measures cover, relative to DTE, is an empirical question. We answer this question by including additional popular measures of transition risk, such as emission levels, their intensities, ESG scores provided by LSEG and MSCI, and text-based measures of Sautner et al. (2023). As expected, we find that some of the variation in returns due to DTE can be explained by the other measures. Nonetheless, the coefficients of DTE retain their sign and statistical significance. These results suggest that DTE carry independent variation to explain stock returns.

A common challenge with the interpretation of any asset pricing model is the distinction between expected and realized returns. In line with studies on large global equity data, we provide additional supportive evidence using valuation regressions. The benefit of using this approach is that valuation ratios are less noisy than stock returns and we can control for future growth opportunities; thus the interpretation of our results is more aligned with the pure discount rate effect. In our tests, we consider two measures of firm value: price-to-earnings and price-to-book. We find a strong positive correlation between DTE and these multiples.

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 that even though the directions of the relationships are the same, their economic and statistical significance are weaker. Thus, the pressure from institutional investors matters more at an intensive than extensive margin. This result is quite intuitive in that beyond certain point whether company gets excluded or not from NZP is less relevant.

In principle, our tests aim to capture economic significance of investor pressure. Whether such interpretation is consistent with empirical evidence can be assessed in our data. To this end, we consider two tests. In the first one, we relate the size of the DTE premium to a shift in investors pressure due to Paris Agreement. Anecdotally, the pressure on corporates to decarbonize has increased significantly in the post-Paris period. Using our regression framework, we find that the cross-sectional premium in stock returns doubles when we measure risk premia using stock returns, and increases by about 60% when we use price-to-earnings ratios; these results are statistically more precisely estimated for measures based on forecasted emissions. In the second test, we test whether the strength of our effects gets larger over time, consistent with the view that the increasing investor pressure is a more continuous process. To this end, we study the variation of the DTE coefficients over time. We find that the coefficient of DTE in our regressions becomes progressively stronger over time. Interestingly, the effect becomes slightly smaller in 2022, supporting the view that investors' willingness to pay for green preference has subsided in that year (Baker et al., 2022).

In the last part of the paper, we provide additional robustness to our findings. First, our baseline model measures contribution of each company's emissions using both direct (scope 1) and indirect emissions (scope 2 and scope 3). This consideration is supported by the view that the source of emissions should not dictate whether companies are responsible for them or not. At the same time, scope 3 emissions are generally more difficult to assign to firms within their production function and thus they can be more noisy. We show that our results hold when we exclude scope 3 emissions. Second, our results hold when we restrict our sample to companies that have emissions data in any period prior to 2016 (legacy sample). Finally, the effect of DTE on stock returns interacts with the firm-level decision to disclose their climate data directly, consistent with the economic rationale of disclosure (e.g., Bolton and Kacperczyk (2021a)), but the reduction in our effect is less than 40% of the total effect. Overall, our results indicate a strong and robust relation between firms' DTE and their equity values, consistent with the view that NZP are a source of transition risk for companies with different degrees of institutional pressure.

Our paper is related to various strands of literature on climate finance. First, we extend the literature on firm-level transition risk (e.g., Bolton and Kacperczyk, 2021b, 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., 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., 2023; Berk and van Binsbergen, 2022; Ceccarelli et al., 2024; 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 that divestment may intensify in the future. Second, we argue that the threat of future divestment can be a form of engagement with firms to decarbonize their operations.

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 DTE. 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 to construct DTE measures. Our starting point is the concept of net-zero portfolios (NZP) following the work of Bolton et al. (2022) and adapted to our framework. Important in this concept are two elements: (a) the 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 of how to calculate DTE. Finally, we provide summary statistics related to the main variables. Our data set covers a large sample of global firms with historical and forward-looking carbon emissions metrics and other firm characteristics over the 2005-2022 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, investors reward companies that undertake emissions reduction, by including such companies in NZP, and penalize companies that are behind the decarbonization curve, by excluding them from NZP.

2.1.1 Dynamic Carbon Budget

The starting point for constructing a 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;[5] 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 from all such firms in a given year (e.g., 25.8 GtCO2e in 2020).[6] 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 170.3 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) investors decarbonize their portfolios at a slower rate for the first half of the remaining period and then at a faster rate for the second half, (c) investors decarbonize their portfolios at a faster rate for the first half and then at a slower rate for the second half, (d) investors follow a more sophisticated science-based decarbonization path. Pathways (b) and (d) allow for some inertia in the early years of mitigation ("an oil

[5] See https://globalcarbonbudget.org/.

[6] 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.

tanker cannot turn on a dime"), which can be thought of as more realistic forms of putting pressure on the corporates.

Figure 1 shows how these different decarbonization paths evolve over time, when choosing starting dates between 2006 and 2022. 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 GtCO2.[7] The light blue pathways, *SF*, assume that investors' carbon budget switches from a slower reduction rate of 1% to a faster reduction rate that is not larger than 30% (determined based on feasibility) after several years. The yellow pathways, *FS*, switch from a faster reduction rate to a slower reduction rate of 1%. Here, the faster rate is applied to the maximum number of years possible to make the 2050 emission budget as low as possible while making sure that the total cumulative budget is fully used. As an example, for the cohort starting in 2006, the terminal 2050 emission budget can be as high as 12 GtCO2. The dark blue pathways, *RAEM*, follow the emission mitigation pathway of Andrew (2020).[8] Here, emissions can increase initially and then decrease. Historical emissions are reported by black lines.

To provide a visual illustration of the portfolio budget's construction, Figure 2 zooms in on a snapshot of decarbonization pathways using a constant reduction rate as of the beginning of 2021. Specifically, historical global emissions in 2020 amount to 39.3 GtCO2 (indicated by the brown bar in the upper panel), and the corresponding annual carbon footprint of the investable universe is 25.8 GtCO2 (the brown bar in the lower panel). Using the proportionality rule, the remaining *global* emissions budget of 260.3 GtCO2 translates into a cumulative *portfolio* budget of 170.3 GtCO2 from 2021 onward. This proportionality rule applies not only to total emissions but also to all individual yearly carbon budgets. This procedure gives rise to the entire portfolio decarbonization pathways with a 30-year horizon from 2021 to 2050, as is shown by the green bars in the lower panel of Figure 2. For example, for the first year of decarbonization, global emissions would need to drop to 32.2 GtCO2 (first green bar on the upper panel), and, correspondingly, our net-zero portfolio would allow for a carbon footprint of 21.2 GtCO2 (first green bar on the lower panel) in 2021.

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

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

2.1.2 NZP Selection Rule

As a final step to obtaining NZP, we select companies, such that their total emissions jointly do not exceed the yearly emission budget. In this section, we describe the selection rule. Our broad principle is that companies with greater decarbonization prospects should be given preference. Specifically, we select companies according to their combined efforts to decarbonize their activities, measured by our novel composite, the *Misalignment Score*. Each individual firm-level component of our measure is neutral with respect to a 4-digit Global Industry Classification Standard industry group (GICS-4). Our 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: LSEG ESG, CDP, and Orbis Intellectual Property. Trucost reports firm-level absolute greenhouse gas emissions in tons of carbon dioxide equivalent (tCO2e) for scope 1, 2, and 3 upstream emissions.[9]

In our analysis, we distinguish between carbon budgets based on current emissions and those based on forecasted emissions. For the latter, 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.[10] In the Appendix, we describe the details of our data and methods to source commitments data, and then present our method to incorporate trend data. The final forecasted emissions pathway is a weighted average of the decarbonization target-based path and the emissions trend path. Following the target credibility framework set out by the Glasgow Financial Alliance for Net Zero (GFANZ, 2023), we assign a 75% weight to a target-based path if a firm meets two criteria: (1) its targets are approved by the Science Based Targets initiative (SBTi), and (2) has targets for both short-term and medium-to-long-term horizon. In the case in which a firm only

[9] 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.

[10] This experiment is akin to that utilized in equity valuation research in which future cash flows are determined by subjective analyst expectations of cash flows and their growth and past growth rates.

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.

Selection Rule: Misalignment Score. 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 *Misalignment Score*, defined as a weighted average of the three categories of variables: (1) historical emissions levels and their growth rates, (2) historical emissions intensities and their growth rates, and (3) forward-looking climate-related activity metrics. In our baseline analysis, we apply equal weights to each of the categories but our results are robust to other weighting schemes. Within each category, we assign equal weights to individual characteristics.[11] 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 companies' carbon intensities, measured as tons of CO2 equivalent divided by the company's revenue in millions of dollars.[12] 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,

[11] 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.

[12] We winsorize the year-on-year growth rate of the company's absolute carbon emissions and carbon intensities at the 2.5% level.

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 two variants of DTE depending on whether we sum up constant (DTE-CE) or forecasted emissions (DTE-FE) to fill up the carbon budget. To illustrate the construction and basic properties of the two 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 Apple's stock remains in the net-zero portfolio. We repeat this process for every year from 2006 until 2022. The table below provides numerical results for the DTE.

Estimation Year		2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
DTE-CE	Exit Year	2014	2018	2019	2018	2018	2014	2014	2015	2016	2017	2018	2018	2019	2020	2021	2022	2023
	Distance-to Exit	7	10	10	8	7	2	1	1	1	1	1	0	0	0	0	0	0
DTE-FE	Exit Year	2012	2014	2017	2017	2017	2014	2013	2015	2016	2017	2018	2018	2019	2020	2021	2022	2023
	Distance-to Exit	5	6	8	7	6	2	0	1	1	1	1	0	0	0	0	0	0

In the first panel, we present results from sorting companies on DTE-CE. Apple's DTE is generally decreasing from 2006 to 2022. This could reflect both a tightening of the portfolio budget or a worsening of the company's decarbonization efforts. However, given that the decline is not monotonic, this suggests that at least part of the effect is driven by the changing performance of Apple relative to its peers. The second panel shows the results based on DTE-FE. Compared to the previous case, we observe values which are significantly lower. This result suggests that Apple is likely performing worse when you take into consideration the projection of its emissions into the future. In both cases, we can see that Apple would hit an immediate divestment outcome no later than 2018. For the rest of the paper, we apply the same procedure for all other companies in our data, thereby generating a panel of firm-level 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.[13] 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 the natural logarithm of price-to-earnings, $LOGPE_{i,t}$.

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

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

property, plant, and equipment; the firm's earnings performance, $ROE_{i,t}$, which is given by the ratio of firm i's net yearly income divided by the value of its equity; the firm's total risk, $AGE_{i,t}$, which is the firm age in number of years, $VOLAT_{i,t}$, which is the standard deviation of returns based on the past 12 monthly returns; $SALESGR_{i,t}$, which is the annual growth rate in firm sales. To mitigate the impact of outliers, we winsorize *LEVERAGE*, *INVEST/ASSETS*, *ROE*, *MOM*, *VOLAT*, and *SALESGR* at the 2.5% level.

2.3 Summary Statistics

In this section, we summarize the variables we use in our analysis based on the pooled sample of all companies observed in any period during the period 2005–2022. 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 218,000. We also find that emissions are highly dispersed across firms, as indicated by a high value of standard deviation, which is over 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 *Misalignment Score* and its subcomponents. Summary statistics for the components are presented on an industry-adjusted basis and after being standardized. We note that different components exhibit a 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 DTE. Since one of the DTE measures is based on the budget based on forecasted emissions we also report summary statistics of the emission forecasts one year and five years ahead. We observe a similar variation in the distribution of the two DTE. The metric based on constant emissions has greater values, with an average of about 11.4. In turn, DTE based on forecasted emissions is slightly smaller with the average value of about 10.9.

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 with different DTE 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 DTE to each other, to firm emissions, and to *Misalignment Score*, which is its main building block. Next, we show the time-series distributions of DTE. Both are reported in Table 2 below.

In Panel A, we report the correlation matrix across DTE and measures on which they are based.[14] We find that DTE are strongly positively correlated with each other, which suggests that the role of forecast emissions in the budget calculation may not be that critical. We also find that DTE are negatively correlated both with emission measures and with *Misalignment Score* but the correlations are fairly modest, which suggests that DTE do not capture exactly same information as the raw metric from which they are derived. The likely driver of the

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

difference is the dynamic carbon budget constraint that induces additional variation in *DTE*.

In Panel B, we study the time-series variation of *DTE*. As expected, average values of both *DTE* decrease slightly over time, consistent with the shrinking carbon budget and greater decarbonization pressure. At the same time, given that the marginal decline in *DTE* is less than a unit of time corresponding to it, this pattern suggests that companies undertake additional measures beyond their emission adjustments to reduce the institutional pressure. An additional interacting factor potentially affecting our interpretation of the average is the changing universe of firms in our data. For this reason, we resort to a more detailed regression analysis of the determinants of *DTE*.

3.2 Determinants of *DTE*

We relate the variation in *DTE* to various corporate characteristics by estimating the following regression model:

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

where $DTE_{i,t}$ is a generic term standing for two measures of distance-to-exit for firm i at time t. The vector of firm-level controls includes the firm-specific variables *LOGCO2*, *LOGMKT-CAP*, *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 industry-year-month fixed effects. We double cluster standard errors at the firm and time dimensions. We present the results in Table 3. We document a number of regularities. First, both *DTE* measures are negatively related to levels of total emissions. Second, we find that both *DTE* are positively related to firm assets size and market capitalization, though the coefficients are statistically significant only for the latter measure. Third, *DTE* are positively related to firms' measures of property, plant, and equipment and firm age. Fourth, *DTE* is negatively related to firm *LOGMB*, *MOM*, and *INVEST/ASSETS*. Finally, the results for other variables, such as *LEVERAGE*, *VOLAT*, and *ROE* indicate no strong relationship.

3.3 Industry and Style Exposures of *DTE* Portfolios

In this section, we provide additional insights regarding 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. Each figure presents results for *DTE-CE* in the left panel, and for *DTE-FE* in the right panel. 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 $DTE = 30$, the maximum value of *DTE* for this cohort.

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-CE* portfolios. We note that most of the sector weights are not significantly different from those of the benchmark. Nonetheless, certain sectors are underweighted (Pharmaceuticals, Consumer Discretionary, and Technology Hardware) and others are overweighted (Materials, Food, Utilities, and Insurance). These results conform to the general patterns of carbon footprints of these industries. When we consider the composition of industries for *DTE-FE*, 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 Banks, Technology, Energy, and Transportation (in the left panel) and Banks and Transportation (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 under-diversified. 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 $DTE\text{-}CE \geq 5$ 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 in terms of their factor/style exposure. In Figure 7, we look at the percentage deviations of median values in style exposures for each of the above-defined three portfolios from those of Trucost. Our style characteristics include *LOGASSETS*, *LEVERAGE*, *LOGMB*, *MOM*, and *ROE*. As a reference, we also show the deviations in terms of current and forecasted emissions. Our

DTE portfolios are not significantly tilted away from the benchmark in almost all the characteristics. The small deviation in size exposure for the portfolio of $DTE > 5$ is particularly comforting in light of potential concerns regarding transaction costs or exclusion of salient companies due to holding small stocks. What is particularly impressive, however, is that our DTE portfolios exhibit a significant reduction in carbon footprint.

4 DTE and Stock Returns

In this section, we present our main findings on the pricing effects of our DTE measures. We begin by reporting results for the measures constructed with constant decarbonization paths. 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 (2021b, 2023), we take a characteristic-based approach along the lines of Daniel and Titman (1997). This approach is particularly well suited given the rich cross-sectional variation in firm characteristics in our sample.[15] 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); and a measure of, respectively, stock return momentum and volatility. This characteristics-based approach also allows us to take full advantage of fixed effects along time, country, and industry-year-month 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

[15] 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.

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:

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

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*, and *AGE*.

We estimate this cross-sectional regression model using pooled OLS. We also include country fixed effects, as well as industry-year-month fixed effects. Including industry-year-month fixed effects is important in transition risk regressions due to significant cross-industry differences in emissions, as indicated by Bolton and Kacperczyk (2023). The added benefit of firm-level data is that the absorbed industry effects can be time varying. We double cluster standard errors at the industry and year levels, which allows us to account for any cross-industry correlation in the residuals as well as capture the fact that some control variables, including *DTE*, are measured at an annual frequency.[16] Our coefficient of interest in equation (2) is b_1, which measures the association between *DTE* and returns.

We report the results in Table 4, separately for *DTE-CE* and *DTE-FE*. We first consider models without firm controls but with fixed effects (columns 1 and 2) and then models with all time-varying controls (columns 3 and 4). Throughout all four 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 four coefficients of *DTE* are statistically significant at the 1% level of statistical significance. The effects are also econom-

[16] As a robustness, we have also considered specifications with clustering at firm and year dimensions and found very similar results.

ically significant. To illustrate, a coefficient in column (3) equals -0.017 and the standard deviation of *DTE-CE* in this specification is 6.6. This means that a one-standard-deviation increase in *DTE-CE* is associated with 0.12% lower stock returns per month, or 1.5% annualized. The equivalent result for *DTE-FE* is a slightly larger 1.7%. Among other controls, *LOGPPE*, *MOM*, and *ROE* are positively related to future stock returns, and *LOGMB* and *LOGMKTCAP* are negatively related. All other characteristics are statistically insignificant.

4.2 Additional Analyses

In this section, we report a number of results from various analyses that provide further evidence on the economic mechanism driving our results as well as offer additional robustness of the main results.

4.2.1 The Relative Importance of Misalignment Score and Carbon Budget

The basic principle to construct any *DTE* measure involves two elements: (1) the carbon budget that limits the exposure of the portfolio to carbon emissions, and (2) the sorting rule that decides the rank of companies for the net-zero portfolio. A natural question to ask is how much of the variation in stock returns we observe due to *DTE* is driven by each of the elements. We provide some evidence on this issue by conducting an additional analysis in which we directly include the measure of *Misalignment Score* in our regression model. In such a specification, the coefficient of *DTE* captures the residual variation, mostly due to carbon budget. We report the results from estimating the model in equation (2) in Table 5.

As a starting point, in column 1, we show the results in which *Misalignment Score* is the main control variable, along with other time-varying firm characteristics and fixed effects. We find that the *Score* is strongly positively related to future stock returns. This result is comforting for two reasons. First, it suggests that the measure is not a noisy proxy for firm decarbonization efforts. Second, the positive sign of the coefficient is consistent with the view that companies that are more misaligned with the decarbonization objective, and likely having higher exposure to transition risk, should be associated with higher expected returns.

Next, in columns 2 and 3, we report the results in which *Misalignment Score* is jointly included in the same regression model with DTE measures. Three notable results emerge from the analysis. First, in the joint regression both DTE and *Misalignment Score* have expected signs of the coefficients with respect to returns. Second, relatively speaking, DTE is a stronger predictor of returns than is the *Score*. In fact, compared to our baseline results, the coefficient of DTE gets reduced by only a small fraction, which suggests that most of the variation in DTE is due to tightening budget rather than the *Score* itself. This is not totally surprising given that DTE and *Misalignment Score* are not highly correlated with each other. Finally, given the results, one cannot argue that DTE is simply a more complicated transformation of ingredients of *Misalignment Score*; rather, the carbon budget is an integral part of the signal.

4.2.2 Alternative Decarbonization Pathways

In our analysis so far, we have assumed that investors follow the decarbonization path, and the resulting carbon budget, 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. Which of the paths each investor follows is hard to determine and our paper does not aim to answer this question directly. What is more important to us is that the annual portfolio constraint becomes tighter over time as more carbon emissions are produced in the economy and the carbon budget gets depleted. In fact, the use of different paths allows us to capture quantitatively different scenarios through which the pressure of investors holding NZP can be imposed on companies.

With this insight in mind, we analyze three alternative paths. First, we consider the case 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 an *SF* path. This path reflects an argument that is often made in climate discussions that rapid decarbonization may not be easy and companies need some time to adjust to the new paradigm. Second, we consider the opposite situation in which investors decarbonize first at a faster rate and then at a slower rate, an *FS* path. This idea is consistent with the alternative view expressed by people such Mark Carney, the former Governor of the Bank of Canada and Bank of England, that the climate problem is the tragedy of the horizon and the society cannot afford to wait. Finally, we consider a theory-motivated path from Andrew (2020), who 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. Further, 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. This choice is dictated by policy that often dictates that portfolio decarbonization should strictly adhere to a scientific objective.

We report the results for the above decarbonization paths in Table 6. As before, we look at the impact on next-month stock returns following specification (2). The results indicate a strong empirical robustness to the choice of different decarbonization paths. For all three decarbonization paths and two variants of DTE, we find a strong negative coefficient that is also statistically highly significant at the 1% level. This result confirms our hypothesis that a large class of paths implying growing institutional pressure results in an economically significant spread in returns. As an additional insight, we find some variation in the strength of the relationship with the different paths. For example, the results for SF path are economically stronger than those for FS path, which may suggest that investors consider the former to be a more realistic form of putting a stronger pressure on the corporates whose shares they hold in their portfolios.

4.2.3 Alternative Weighting of the Misalignment Score

Another relevant aspect of our analysis relates to the construction of our *Misalignment Score*. In doing that, we have arbitrarily assumed an equal exposure to three different elements of decarbonization efforts. In the absence of any economic prior such assumption seems least controversial. Of course, it could still be that this choice made us focus on a very specific solution that could be different from any other choices. To allay a potential concern of such non-robustness, we consider two alternative weighting schemes. One in which we put a 25% weight on absolute emissions category and equal weights on the remaining two, and another one in which the first weight is set at 50%. Each of the two variants has an additional number attached to the variable of *DTE*. With these alternative measures we repeat our estimation of the baseline return regression. We report the results in Table 7.

Our tests uncover two findings. First, our baseline results are not specific to our choice of the equal weighting in the *Misalignment Score* as the other two weighting schemes generate a very similar pattern of effects with the coefficients being negative and highly statistically significant. Second, and more interesting, we find that the economic magnitude of our results, if anything, gets stronger for some of the alternatives. In particular, when we assign the weight of 50% to absolute emissions, the implied annualized return spread is as high as 2.3%. We conclude that our baseline choice does not produce any specific upward bias in the observed effect and our results extend to other reasonable choices of *DTE* measurement.

4.2.4 Controlling for Other Climate Change Measures

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, forward-looking announcements, and broader ESG policies. In addition, one may argue that *DTE* do not capture any additional information beyond what the typical signals of transition risk that have been previously studied in the literature capture. To this end, in Table 8, 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 natural logarithm of the cumulative forecasted total emissions,*Log Cumulative Forecasted Emissions*, the *Misalignment Score*, and emission intensity, in columns 3 and 4, the text-based measure of aggregate climate change exposure (*CCExposure*) of Sautner et al. (2023), in columns 5 and 6, the sub-components of the text-based measure capturing opportunities ($CCExposure^{Opp}$), policy ($CCExposure^{Reg}$), and physical aspects ($CCExposure^{Phy}$) of climate risk, and in columns 7-10, broadly defined ESG scores across environment, social, and governance factors. These scores are provided by LSEG (formerly Refinitiv) sourced via Workspace and are reported in percentile ranks (columns 7 and 8) and by MSCI (columns

9 and 10). They are designed to measure a company's relative ESG performance, commitment, and effectiveness, based on company-reported data. Notably, both text-based and ESG measures are available only for a subset of companies, so the results across different specifications are not fully comparable.

We find that controlling for all the past information we still find a negative and statistically significant relationship between DTE and future stock returns. The results are statistically stronger for the larger sample of firms in columns 1-2, but still significant even if we reduce our sample size, as is evident in columns 3-8. Obviously, since DTE is partly based on the measures we control for the economic magnitudes get smaller but the reduction in the magnitudes of both DTE measures is merely 40%. 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 simply mimicking other previously used 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) and Sautner et al. (2023)).[17] When it comes to the effects from ESG scores the results from the literature on those are less conclusive.

4.2.5 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 DTE measures to two different valuation ratios, $LOGMB$ and $LOGPE$, 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

[17] In our tests, the text-based measures of transition risk are largely insignificant, which is in line with the results in Sautner et al. (2023) who report similar null results in their own specifications.

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 price-to-earnings ratio, *LOGPE*, and market-to-book ratio, *LOGMB*.[18] Our control variables include *MOM*, *VOLAT*, *AGE*, *ROE*, and *SALESGR*. In addition, we use one and two year-ahead measures of *ROE* and *SALESGR* to proxy for future investment opportunities. Finally, in all specifications, we include country and industry-year-month fixed effects. As before we double-cluster standard errors at the industry and year level. The main independent variables of interest are *DTE-CE* and *DTE-FE*. Our coefficient of interest is c_1. We present the results in Table 9.

In columns 1-2, we show the results for *LOGMB*. Consistent with our hypothesis of the presence of carbon-transition risk, we find that companies with high values of *DTE* have higher *LOGMB*. The effects are statistically significant at the 1% level of significance for both measures of *DTE*. In columns 3-4, we show the results for *LOGPE*. We again find a positive and statistically highly significant relation between *DTE* and *LOGPE*. Overall, the results indicate strong pricing effects for both *DTE* measures. Given that we control for future growth opportunities, these results are more consistent with the risk-based explanations of returns rather than the cash-flow-based unexpected return story.

4.2.6 Extensive Margin

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 (*EXTDTE-CE* and *EXTDTE-FE*) 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 use

[18] As a third alternative we have also considered log of price-to-sales ratio. The results for this measure are even stronger.

such indicator variables as predictors of future stock returns in specification (2), columns 1 and 2, *LOGPE*, columns 3 and 4. We report the results from estimating these alternative models in Table 10. The results show a consistent negative coefficient of each individual indicator variable for *RET*, suggesting that companies that never exit have lower expected returns than those that do, and the positive coefficient for *LOGPE*. Of the four estimates, however, only one coefficient, in column 1, is marginally statistically significant. Hence, we conclude that the *DTE* effect is a better predictor of values on the intensive rather than extensive margin. This result is useful as it suggests that the relative rankings of companies in terms of their exit times are an important consideration in valuation effects.

4.2.7 Time-Series Effects

One of the advantages of our framework is that *DTE* aim to capture economic significance of investor pressure. Whether such interpretation is consistent with empirical evidence can be assessed in our data. Anecdotally, it seems that the pressure to align with net-zero objectives has been growing up, as has been evident from the formation of new investor alliances. In this section, we aim to formally identify some of the pressure in the data.

As a first test, we test whether the *DTE* effects become larger in the post-2015 period, that is, following the Paris agreement of 2015 (e.g., Bolton and Kacperczyk, 2021b). To this end, we define an indicator variable, *Paris*, that is equal to one for the years starting from 2016 and equal to zero up to and including 2015. To measure the incremental pricing effect of the structural shift, we modify our baseline regression model by adding the interaction term between *DTE* and *Paris* as the main control variable:

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

Our coefficient of interest is d_2. We report the results from this model in Table 11. Our dependent variables are *RET*, in columns 1 and 2, and *LOGPE*, in columns 3 and 4. On average, we find that the valuation effects get larger following the Paris agreement. The absolute value of the coefficient of *DTE*, in either specification, increases by a substantial fraction relative to the pre-Paris period. However, most of the effects are not precisely estimated as is evident from the relatively weaker statistical significance.

In another test, we examine the time-series properties of the DTE premium, consistent with the view that the increasing investor pressure is a more continuous process. To this end, we estimate our baseline regression model of returns for each year-month in our sample. The only modification is that we do not include time fixed effects in the regression model. Next, to estimate the average cross-sectional effect, we average the coefficients across time and calculate standard errors using Newey-West method allowing for 12 lags of autocorrelation. We report the results in Table 12. We find that the results largely conform to the estimates obtained from the pooling regression in Table 4. The magnitudes are slightly smaller but this could be explained by the effect that our aggregate sample is weighted more towards the later periods of the sample during which the effect is likely more pronounced. We formally test this conjecture by estimating a univariate regression model with the estimated coefficients as a dependent variable and the monthly time trend as a control. These results are presented in the bottom panel of the table. We consider two specifications, a full sample one and another excluding observations from 2022. The latter approach accounts for the possible slow-down in the intensity of sustainable investment following the onset of the war in Ukraine and the polarization of green preferences in the United States due to energy price increase. For both tests, we find a negative coefficient of the time trend, which is consistent with the hypothesis that the pressure to conform to net-zero alignment has been growing larger over time and does not only result from a discrete shift in transition risk following Paris.

A potential confounding factor of our time-series effects results from the change in the sample of firms covered by Trucost. In particular, Trucost has expanded the scope of its coverage of emissions in the post-Paris period. As a result, it is possible that the apparent acceleration of the net-zero effects could simply reflect the changing sample composition. To test this conjecture formally, we restrict our sample to companies which had any emission coverage in any period up to and including 2015, that is, before the structural break in our data. With this restricted sample, we estimate our baseline model for returns, with and without other firm controls. We report the results from this estimation in Table IA.3 of the Internet Appendix.

The results indicate that our basic results are not a simple artifact of the changing coverage of firms by Trucost. The coefficients of *DTE* in the restricted sample, though slightly smaller, are still statistically significant, as seen from columns 1 and 2, and they cannot be explained by inclusion of *Misalignment Score* in the model, as seen from columns 3 and 4. Notably, both *DTE* and *Misalignment Score* remain statistically significant in the latter specification.

4.2.8 The Role of Carbon Disclosure

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 (e.g., Bolton and Kacperczyk, 2021a). 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 (Trucost). 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 with the main effect being captured by the interaction term between *DTE* and *Disclosure*:

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

The main coefficient of our interest is e_2. We report the results from estimating this model in Table IA.4. We find that the marginal effect of disclosure on stock returns is positive and statistically significant. Companies with disclosed emissions face a lower degree of transition risk, which is consistent with the results in Bolton and Kacperczyk (2021a) using emissions data. What is important here is that both the effect for the estimated and disclosed data is negative and statistically different from zero. Hence, our *DTE* findings are not simply restricted to a specific subset of companies for which Trucost estimates emissions.

4.2.9 Excluding Scope 3 Emissions

our baseline model measures contribution of each company's emissions using both direct (scope 1) and indirect emissions (scope 2 and scope 3). One concern is that scope 3 are generally more difficult to assign to firms within their production networks and thus they can be more noisy. Another issue could be that of double counting emissions. The former issue is probably not first order since measurement error tends to bias the coefficient of the regression towards zero. The latter consideration is supported by the view that the source of emissions should not dictate whether companies are responsible for them or not. However, since the hypothesis can be formally tested, 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 13. The results of the model are qualitatively identical and quantitatively very similar to those in our baseline model. Again, we find a strong negative association between DTE and future stock returns. The economic magnitudes of the results are also similar. Thus, it is unlikely that our results are spurious or not robust to alternative specifications.

5 Conclusions

In the coming years and decades investors will be exposed to substantial risk resulting from the transition to a greener economy. What has emerged as a formidable driving factor of this process is the social pressure manifested through investment decisions of shareholders globally. With the intensifying climate events, one can expect this pressure to become even stronger over time. Quantifying this pressure both in terms of investors' risks and companies' cost of capital has become of first-order economic importance, largely because market-based carbon pricing could be part of the solution to the climate problem. In this paper, we provide a formal framework of net-zero portfolios that allows one to capture this economic force. Net-zero portfolios generate a shock to asset ownership structure and possibly can influence asset prices.

We operationalize this empirical mechanism using a novel measure of distance-to-exit

(*DTE*) that blends climate forecasts into portfolio decisions. In a large sample of global stocks, we show that companies that are more exposed to an exit from net-zero portfolios, and thus face greater investors' pressure to be excluded from their portfolios, have lower price multiples and higher returns. This result is economically large and is consistent with the view that *DTE* offer 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 or subjective corporate beliefs. 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 empirical attempt to highlight the role of *expected divestment* and its role for asset prices. Earlier studies on portfolio holdings 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 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 *DTE* setting does not involve a formal optimization problem, our framework is closely representative of the decision of a large passive investor. Indirectly, this insight is supported by two observations: our NZP are well diversified across sectors and the tracking error of our portfolio is minimal for fairly large amounts of capital. Similarly, even though our empirical results are reported for a subset of listed global equities, the *DTE* idea is quite flexible and can be applied to unlisted companies, as well as it can be extended beyond equity markets. The reason why we restricted our universe was to present pricing effects associated with the cross-sectional variation in *DTE*.

While 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, our current approach involves dynamic carbon budget with investors making decisions conditional on a given point they enter the market. In this regard, our framework is static with different investors entering the market at different points in time. This type of cohort effect is representative of the world in which entry into NZP investments is staggered over time. Solving a fully dynamic model could shed additional insights into this decision process. Another promising avenue 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. Notably, the choice of the signals is unified by the same objective function of maximizing decarbonization. All in, much more remains to be done, and we hope this study opens up the burgeoning literature on climate finance to new avenues of research.

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Appendices

This Appendix provides the details related to the construction of the variables we use to select stocks into NZP. We discuss the data on commitments, forecasted emissions, and individual components of the *Misalignment Score*.

A Commitments Data

We obtain all firm commitments tracked by the annual CDP survey from 2011 to 2022. 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*, *target year* defining how far the commitment extends into the future, as well as *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 magnitude 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.[19] Within a given emissions scope, we define *CECOVER* as the reported percentage of carbon emissions covered by the target; as an 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* equals 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*:

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

[19] For example, Table IA.2 shows that 953 companies reported 1645 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 emission 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 emissions) 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 3, 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 *Targeted Emissions 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 median of the emissions growth rate to proxy for the short-term growth rate from t to $t+3$.[20] We proxy for the long-term industry-level emissions growth rates using annual growth rates from 2006 to 2022 across all firms. We apply the above long-term growth rate to data from $t+16$ and hold it constant until 2050. Between years $t+4$ and $t+16$, 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.[21] 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 Misalignment Score

Corporate Social Responsibility Indicators

We focus on six firm characteristics that are directly linked to a firm's potential decarbonization actions, all of them obtained from LSEG. The primary underlying source for

[20]To proxy for the short-term growth rate from t to $t+3$, we use a two-year moving median of the emissions growth rate when there are only two years of growth rate data available. Alternatively, we use the industry median year-on-year growth rate if there is only one year of data available. The year-on-year growth rate of the company's absolute carbon emissions is winsorized at the 5% level for forecasting emissions.

[21]If the 90th percentile of the cross-sectional scope $1+2$ growth rate is larger than 40%, we flag the growth rates that are larger than the 90th percentile. Otherwise, we flag the growth rates that are larger than 40%. For the flagged growth rates, we replace them with the smaller number between the applied cutoff or scope $1+2+3$ growth rate to alleviate the effect of outliers.

LSEG 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 *Misalignment 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 2022. 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 misalignment 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[22], the reduction left is 75% − 34.64% = 40.36% and that indicates a *Dynamic Abatement Rate* of 4.04% per year from 2020 to 2030, leading to a target impracticability measure of 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 *Misalignment 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.[23] Third, we aggregate variables within each sub-category using equal weights and then construct the final composite score using appropriate weights.

Category	Category Weight	Data Source	Variables	Reported Value	Score Input	Standardized Value
Historical hard data	33.33%	Trucost	Carbon emission	39,453,087.42	39,453,087.42	165.24
			Emission growth	0.14	0.14	0.68
Historical soft data	33.33%	Trucost	Carbon Intensity	143.72	143.72	-0.56
			Intensity growth	0.06	0.06	1.61
Forward-looking soft data	33.33%	CSR Report	Decarbonization target existence	Yes	0.00	-2.63
			Decarbonization policy existence	Yes	0.00	-1.75
			Emission disclosure	Reported	0.00	-1.91
			Sustainability committee existence	Yes	0.00	-2.05
			UNPRI signatory	No	1.00	NA
			SDG13 climate action	Yes	0.00	-2.62
		Orbis Patent	Green patent number	23	-23.00	-2.10
			Brown efficiency patent number	0	0.00	0.10
			Green patent citation number	264	-264.00	-16.47
			Brown efficiency patent citation number	0	0.00	0.11
			Green patent ratio	0.04	-0.04	-0.03
			Brown efficiency patent ratio	0	0.00	0.08
		CDP Survey	SBTi participation	Submitted	1.00	-2.76
			Greenwashing indicator	0	0.00	-0.04
			Abatement rate	5	-5.00	-6.36
			Target underperformance	18.96	18.96	-3.08
			Target impracticability	18.00	18.00	-3.13
					Final Score	28.28

The Table above presents an example of the *Misalignment Score* breakdown for Apple Inc., as of the end of 2020. This illustrative case is further extended into all companies and

[22] 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 ($\frac{25,100,000-38,400,000}{38,400,000\times(2020-2015)}$) or 34.64% in total from 2015 to 2020.

[23] In the early sample period, the standardized z-scores for Boolean variables are undefined if there is no variability within an industry group for a particular year. In such cases, we assign NA to the standardized value of the variable, and firms are not scored on this particular variable for that year.

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.[24] In general, higher values of the score are associated with a greater misalignment of a company.

We observe that Apple's *Misalignment Score* is equal to 28.28. The main individual factors contributing negatively to the score are carbon emissions levels. On the other hand, Apple's score is reduced by the impact of its green patents, abatement rate, and CDP target performance-related variables.

[24]The standardized value for the UNPRI signatory variable is set to NA due to a lack of variability within industry groups, as none of the firms were reported to be signatories in 2020. Therefore, no firm in the technology industry is scored based on this variable for 2020.

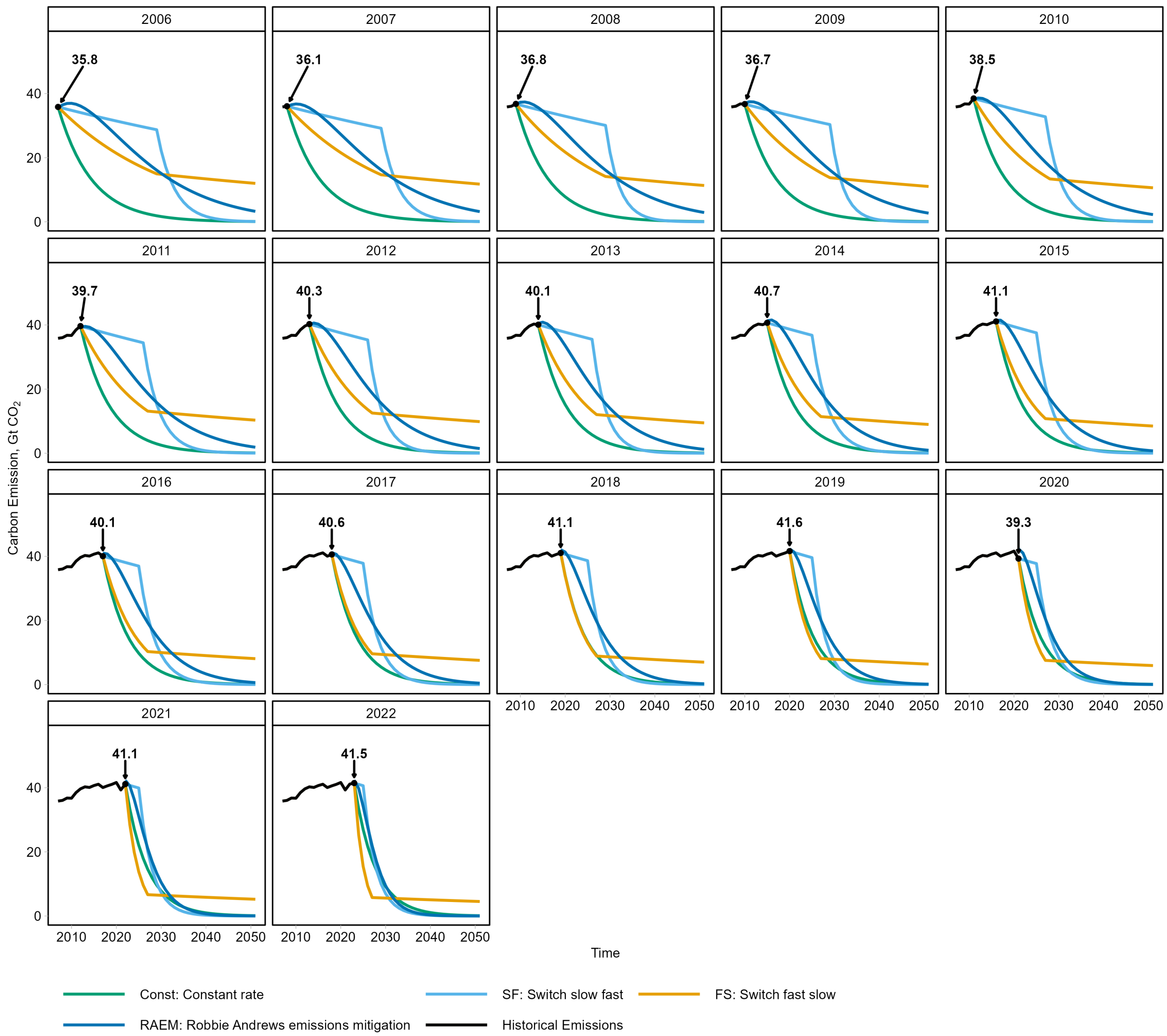

Figure 1: Global carbon budget

This figure shows the evolution of decarbonization paths from 2006 to 2022. The green pathways, *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 GtCO2. The light blue pathways, *SF*, switch decarbonization rate from a slower reduction rate of 1% to a faster reduction rate that is not larger than 30% (selected based on feasibility) after several years. The yellow pathways, *FS*, switch from a faster reduction rate to a slower 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 dark blue pathways, *RAEM*, follow the emissions mitigation pathway of Andrew (2020). The mitigation curves were adapted from Raupach et al. (2014) by Andrew (2020). Historical emissions are depicted by the black lines.

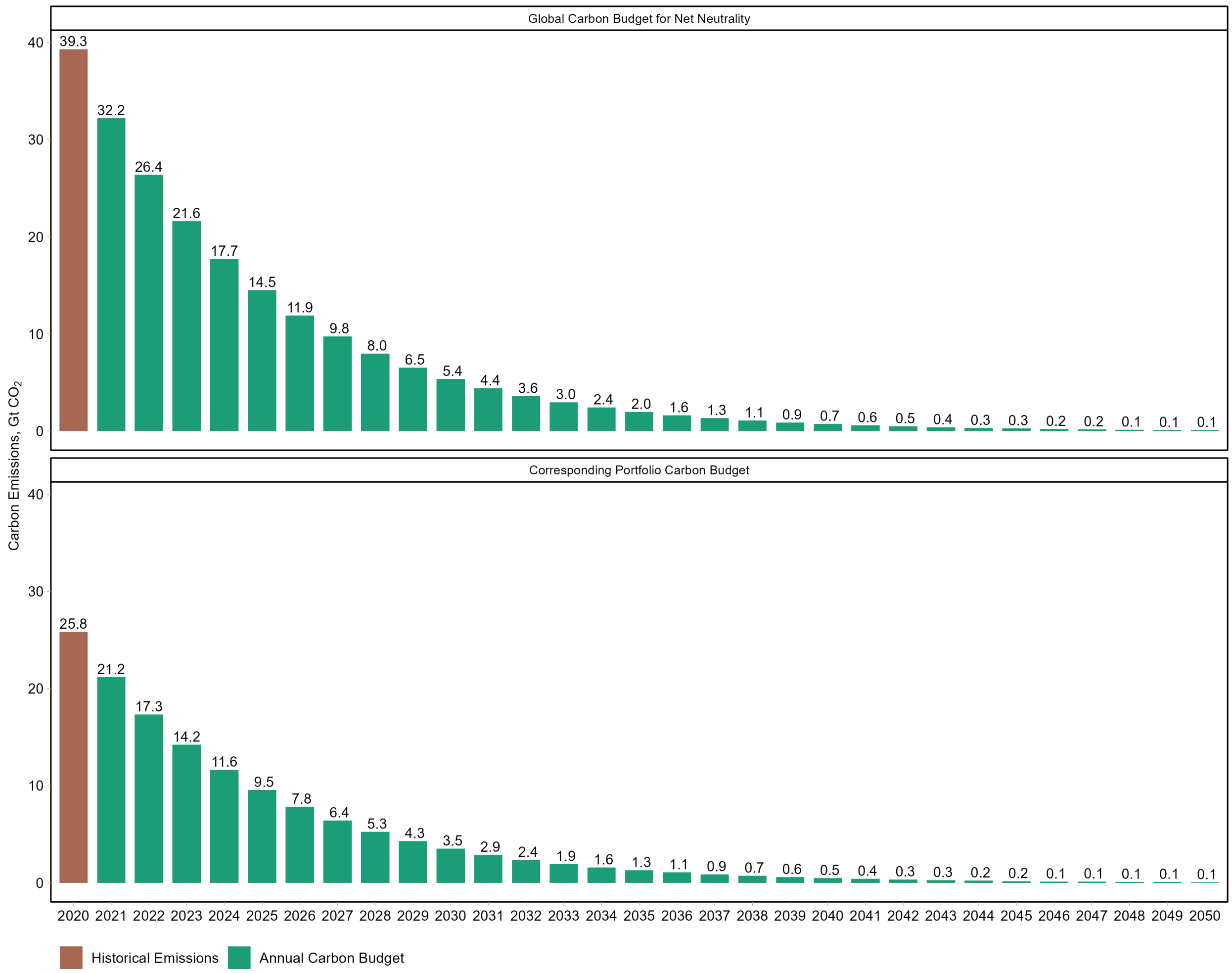

Figure 2: Net-zero portfolio carbon budget

This figure illustrates the correspondence between the global decarbonization pathway and one applied at the portfolio level as of the beginning of 2021. The coefficient of proportionality between the two pathways is equal to the ratio of the historical portfolio emissions (25.8 GtCO2) over the world emissions (39.3 GtCO2) measured at the end of 2020. The first carbon constraint for 2021 is illustrated by the first green bar (second bar in each figure).

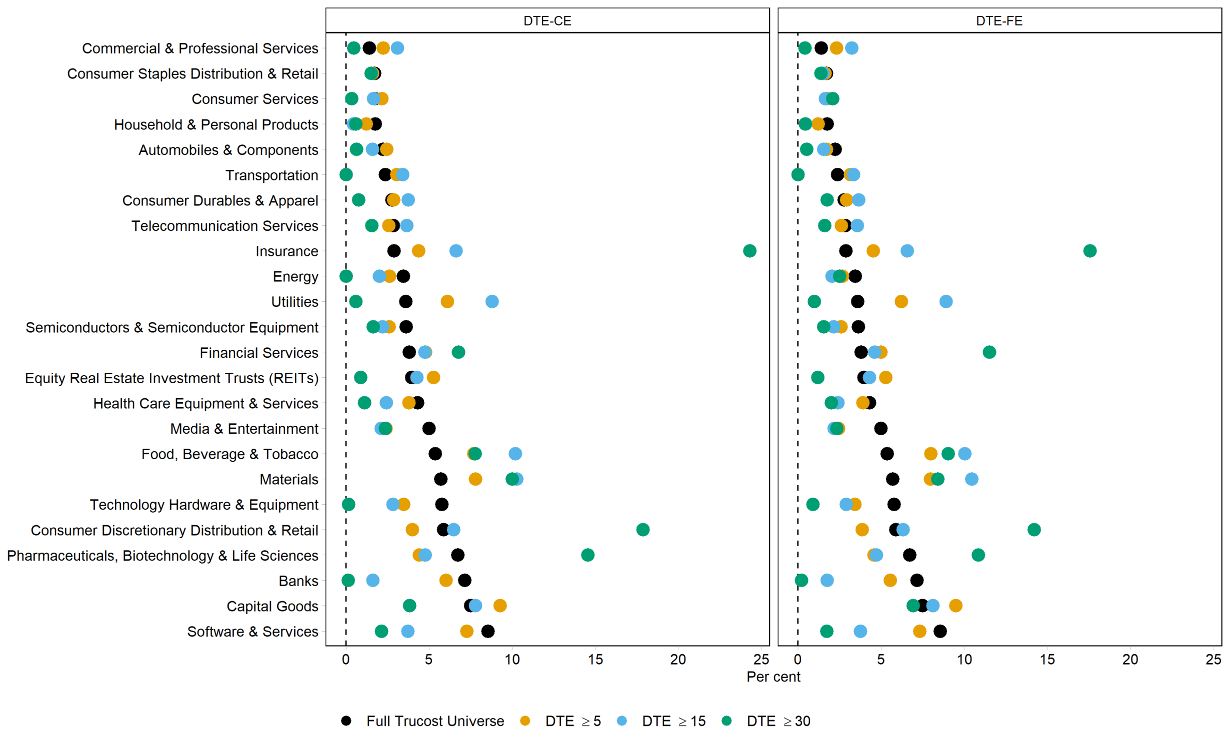

Figure 3: Industry exposures (in %) of the *DTE*-investable portfolios relative to the Trucost universe in 2020

This figure shows industry exposures of *DTE* value-weighted portfolios compared with those displayed by the (value-weighted) universe of all stocks in the Trucost database as of 2020. We show results for portfolios based on two variants of *DTE*. In the left panel, we use *DTE-CE*, and in the right panel, *DTE-FE*. We consider three investable sets: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

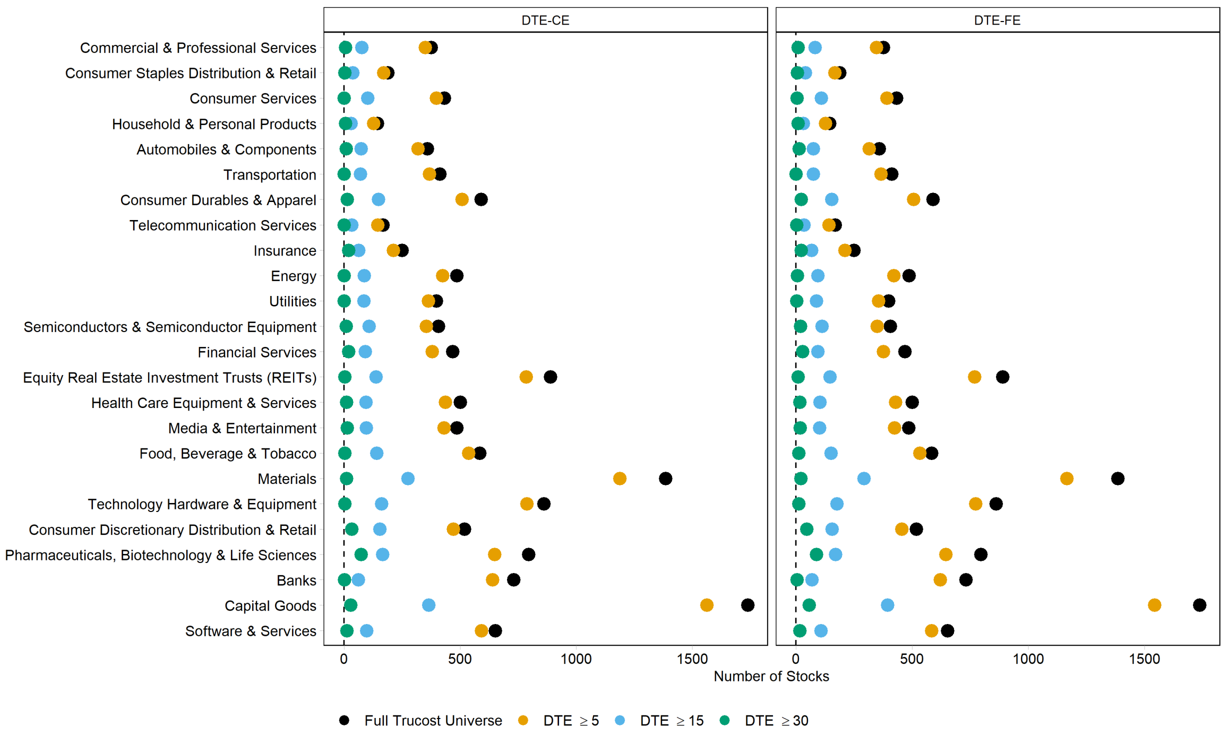

Figure 4: The number of *DTE*-investable stocks by industry in 2020

This figure shows the number of stocks held in *DTE* industry portfolios compared with that in the universe of all stocks in the Trucost database as of 2020. We consider portfolios based on two variants of *DTE*. In the left panel, we use *DTE-CE*, and in the right panel, *DTE-FE*. We consider three investable sets: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

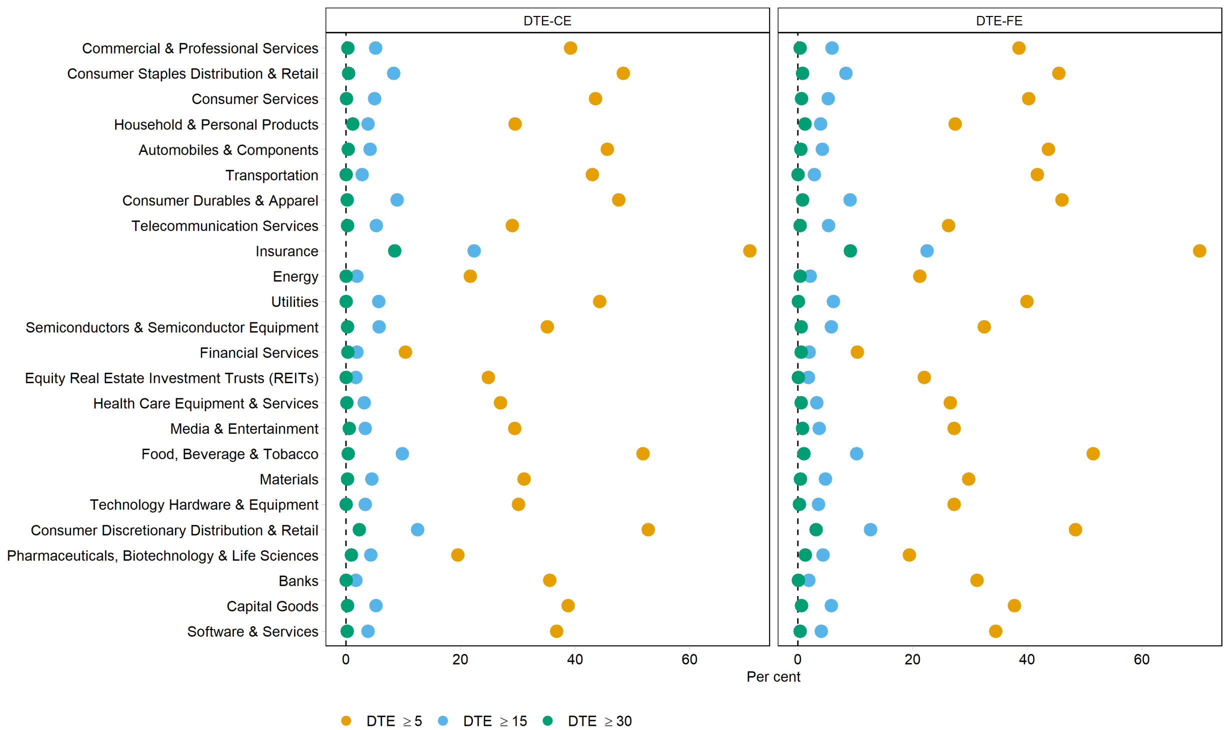

Figure 5: Carbon emissions of *DTE*-investable industry portfolios relative to the Trucost universe in 2020: Constant-emission model

This figure shows the percentage reductions in carbon footprint of *DTE* value-weighted industry portfolios compared with that in the universe of all stocks in the Trucost database as of 2020. We show results for portfolios based on two variants of *DTE*. In the left panel, we use *DTE-CE*, and in the right panel we use *DTE-FE*. Carbon footprint is based on the observed annual total emissions in 2020. We consider three investable sets: stocks with $DTE \geq 5$, stocks with $DTE \geq 15$, and stocks with $DTE \geq 30$.

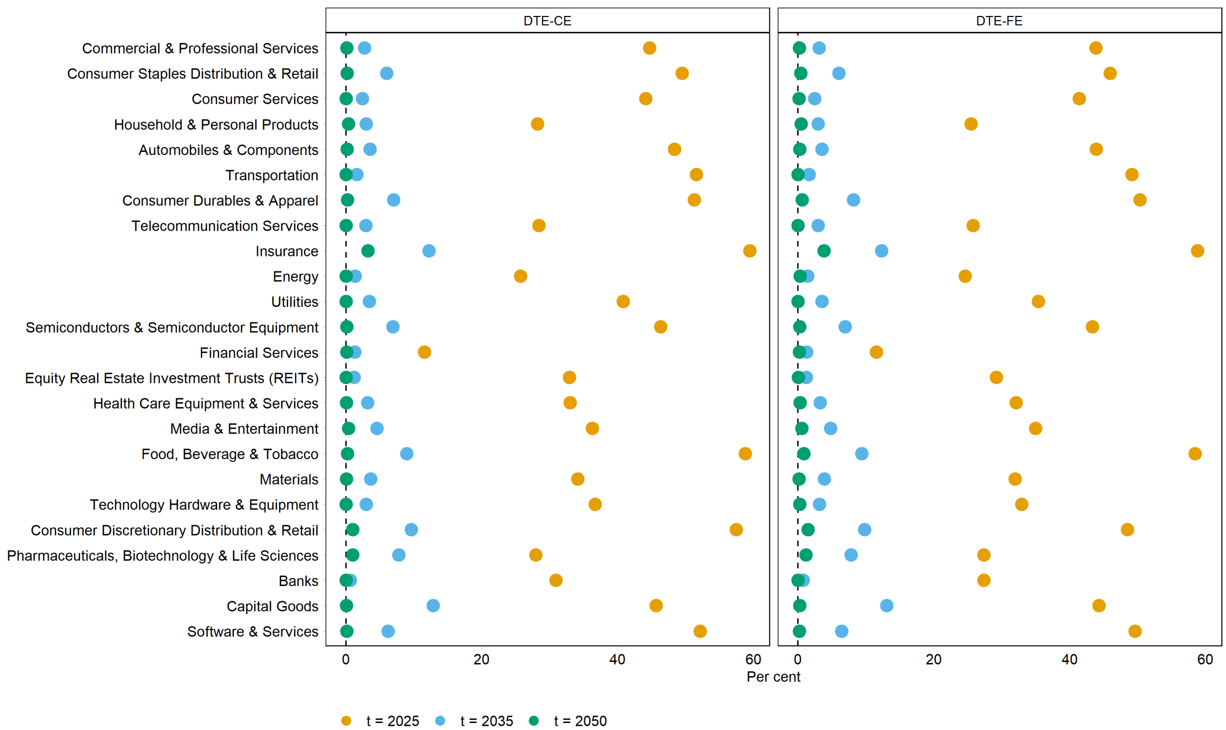

Figure 6: Carbon emissions of *DTE*-investable industry portfolios relative to the Trucost universe as of 2020: Forecasted-emission model

This figure shows the percentage reduction in total carbon footprint of *DTE*-investable portfolios compared with that in the universe of all stocks in the Trucost database as of 2020. We characterize *DTE*-investable value-weighted portfolios in three years: 2025, 2035, and 2050. We analyze the investable sets based on two variants of *DTE*. In the left panel, we use *DTE-CE*, and in the right panel, we use *DTE-FE*. The carbon footprint is based on the 2020 emissions forecasts over the horizon from 2020 to 2050.

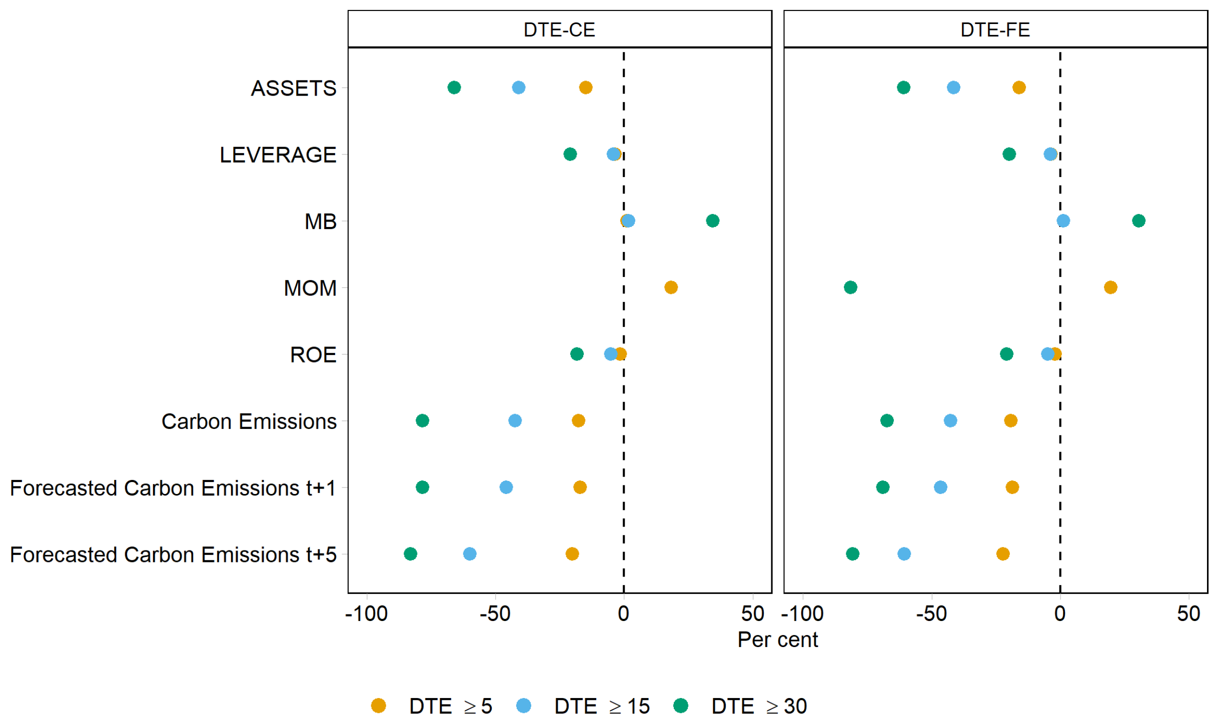

Figure 7: Percentage deviations in characteristics of DTE-investable portfolios from those of the Trucost universe in 2020

This figure shows the the percentage deviations in style characteristics of *DTE* portfolios compared with those in the universe of all stocks in the Trucost database as of 2020. We consider portfolio median values based on two variants of *DTE*. In the left panel, we use *DTE-CE*, and in the right panel, *DTE-FE*. The characteristics we consider include *ASSETS*, *LEVERAGE*, *MB*, *MOM*, and *ROE*. Carbon footprint is based on both 2020 emissions and emission forecasts. We consider three investable sets: 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 2005–2022. Panel A reports the emissions variables. Panel B shows the *Misalignment 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 show two variants of *DTE*: *Misalignment Score* plus constant emissions (*DTE-CE*); *Misalignment Score* plus forecasted emissions (*DTE-FE*). 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; *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; *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)	2956648	15472626	45403	217431	1063323
Growth Rate in Carbon Emissions (Scope 1, 2, 3 upstream)	0.098	0.234	-0.029	0.051	0.168
Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	548.713	2911.106	85.174	190.412	419.693
Growth Rate in Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	-0.009	0.087	-0.053	-0.016	0.025
Panel B: Misalignment Score Components (Industry-Group Standardized)					
Misalignment Score	0.457	9.720	-0.050	0.142	0.400
Carbon Emissions (Scope 1, 2, 3 upstream)	1.659	15.291	-0.205	0.020	0.826
Growth Rate in Carbon Emissions (Scope 1, 2, 3 upstream)	0.222	1.143	-0.392	0.001	0.580
Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	1.286	41.945	-0.292	0.000	0.613
Growth Rate in Carbon Emissions Intensity (Scope 1, 2, 3 upstream)	0.522	62.318	-0.442	0.000	0.503
Decarbonization Target	-0.016	1.010	0.284	0.429	0.561
Decarbonization Policy	-0.017	1.003	-1.098	0.556	0.757
Reported Emissions	-0.015	1.004	-1.141	0.547	0.716
CSR Committee	-0.013	1.003	-1.095	0.513	0.708
UNPRI Signatory	0.000	1.017	0.039	0.050	0.120
SDG 13 Climate Action	-0.010	1.013	0.039	0.381	0.552
# Patent (Green)	-0.007	1.026	0.084	0.114	0.169
# Patent (Brown)	-0.005	1.022	0.072	0.100	0.140
# Patent Citation (Green)	-0.007	1.024	0.074	0.114	0.177
# Patent Citation (Brown)	-0.005	1.018	0.066	0.103	0.136
Ratio of # Green Patent over # Patent	-0.008	1.013	0.089	0.180	0.289
Ratio of # Brown Patent over # Patent	-0.004	1.011	0.063	0.097	0.175
SBTi Status	-0.007	1.019	0.135	0.177	0.221
Greenwash Indicator	0.002	1.014	-0.067	-0.028	0.015
Abatement rate	-0.005	1.003	0.150	0.186	0.240
Underperformance	-0.009	1.015	0.202	0.249	0.306
Infeasible Indicator	-0.009	1.017	0.195	0.233	0.300
Panel C: DTE-Related Variables					
Forecasted Emissions $t+1$	3068398	16162804	46627	224722	1101036
Forecasted Emissions $t+5$	4031219	25607157	49911	259456	1329257
DTE-CE	11.399	6.826	7.000	11.000	14.000
DTE-FE	10.914	7.300	6.000	10.000	14.000
Panel D: Additional Regression Variables					
RET	0.893	12.151	-5.238	0.347	6.167
LOGPE	3.075	0.933	2.520	2.980	3.498
LOGMB	0.748	0.983	0.112	0.690	1.333
LOGSIZE	9.628	2.461	7.990	9.417	11.141
LOGASSETS	9.665	2.606	7.904	9.411	11.305
LEVERAGE (winsorized at 2.5%)	0.218	0.172	0.067	0.198	0.334
MOM (winsorized at 2.5%)	0.131	0.427	-0.152	0.059	0.319
INVEST/ASSETS (winsorized at 2.5%)	0.045	0.044	0.014	0.032	0.061
LOGPPE PPE	7.919	3.094	5.861	7.798	9.908
VOLAT (winsorized at 2.5%)	0.102	0.052	0.065	0.090	0.125
ROE (winsorized at 2.5%)	0.113	0.174	0.044	0.107	0.188
Age	-0.029	0.029	-0.038	-0.022	-0.013

Table 2: *DTE*: Basic Properties

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

	Emissions	Misalignment Score	DTE-CE
Panel A: Correlations			
Misalignment Score	0.056	1.000	
DTE-CE	-0.170	-0.104	1.000
DTE-FE	-0.159	-0.097	0.982

Year	No. Firms	DTE-CE	DTE-FE
Panel B: Stock universe and average DTEs by year			
2006	3117	12.762	10.255
2007	3381	11.878	8.488
2008	3351	11.640	9.483
2009	3435	11.180	10.893
2010	3605	11.457	11.802
2011	3859	11.940	11.775
2012	3994	11.330	10.261
2013	4014	11.315	11.247
2014	4715	11.594	11.434
2015	5020	11.441	12.684
2016	5158	10.897	12.060
2017	11697	11.843	10.726
2018	12494	12.113	11.674
2019	12985	11.341	10.696
2020	13698	10.886	11.210
2021	14991	10.541	10.412
2022	14484	11.427	10.336

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

The dependent variables are *DTE-CE* and *DTE-FE*, 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*, and *AGE*. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the firm and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable:	DTE-CE (1)	DTE-FE (2)
Log Emissions	-1.669***	-1.719***
	(0.111)	(0.121)
LOGMKTCAP	0.395***	0.432***
	(0.130)	(0.142)
LOGASSETS	0.150	0.161
	(0.134)	(0.143)
LOGMB	-0.394***	-0.439***
	(0.102)	(0.111)
LEVERAGE	0.104	0.078
	(0.364)	(0.386)
MOM	-0.315*	-0.351*
	(0.158)	(0.169)
INVEST/ASSETS	-8.200***	-8.493***
	(1.423)	(1.426)
LOGPPE	0.300***	0.313***
	(0.063)	(0.066)
VOLAT	-0.780	-0.697
	(0.754)	(0.842)
ROE	0.023	-0.002
	(0.308)	(0.327)
AGE	9.798***	10.701***
	(1.988)	(2.164)
Constant	25.742***	25.394***
	(1.061)	(1.157)
Country fixed effects	Yes	Yes
Industry-year-month fixed effects	Yes	Yes
Observations	1,009,299	1,009,299
R-squared	0.293	0.290

Table 4: Returns and *DTE*

The dependent variable is firm-level return, $RET_{i,t+1}$, measured monthly. The main independent variables are *DTE-CE* and *DTE-FE*, as defined in Table 1. Control variables include *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, and *AGE*, as defined in Table 1. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	(1)	(2)	(3)	(4)
DTE-CE	-0.013***		-0.017***	
	(0.004)		(0.004)	
DTE-FE		-0.013***		-0.016***
		(0.003)		(0.004)
LOGMKTCAP			-0.210***	-0.209***
			(0.049)	(0.049)
LOGMB			-0.242***	-0.243***
			(0.069)	(0.069)
LEVERAGE			-0.064	-0.063
			(0.243)	(0.243)
MOM			0.465**	0.465**
			(0.160)	(0.160)
INVEST/ASSETS			-0.447	-0.444
			(0.846)	(0.845)
LOGPPE			0.076**	0.076**
			(0.028)	(0.028)
VOLAT			1.961	1.963
			(3.150)	(3.150)
ROE			0.811***	0.812***
			(0.262)	(0.262)
AGE			0.972	0.977
			(0.981)	(0.979)
Constant	1.033***	1.019***	2.394***	2.363***
	(0.040)	(0.037)	(0.414)	(0.415)
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes
Observations	995,505	995,505	995,505	995,505
R-squared	0.230	0.230	0.231	0.231

Table 5: Controlling for Misalignment Score

The dependent variable is firm-level return, $RET_{i,t+1}$, measured monthly. The main independent variables are *Misalignment Score* and *DTE-CE* and *DTE-FE*, as defined in Table 1. Control variables include *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, and *AGE*, as defined in Table 1. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	(1)	(2)	(3)
Misalignment Score	0.119***	0.032	0.039
	(0.037)	(0.034)	(0.030)
DTE-CE		-0.014***	
		(0.003)	
DTE-FE			-0.013***
			(0.003)
Controls	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes
Observations	995,505	995,505	995,505
R-squared	0.231	0.231	0.231

Table 6: Returns and *DTE*: Alternative Decarbonization Pathways

We consider alternative portfolio decarbonization pathways. Pathway *RAEM* follows the emission mitigation pathway of Andrew (2020). 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%. The main independent variables are *DTE-CE* and *DTE-FE*, defined as in Table 1, but assuming alternative pathways. The dependent variable is *RET*, measured monthly. Control variables mimic those from respective tables. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: returns	(1)	(2)	(3)	(4)	(5)	(6)
Pathway RAEM: DTE-CE	-0.016***					
	(0.004)					
Pathway RAEM: DTE-FE		-0.013***				
		(0.004)				
Pathway FS: DTE-CE			-0.010***			
			(0.003)			
Pathway FS: DTE-FE				-0.009***		
				(0.002)		
Pathway SF: DTE-CE					-0.026***	
					(0.007)	
Pathway SF: DTE-FE						-0.019***
						(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	995,505	995,505	995,505	995,505	995,505	995,505
R-squared	0.231	0.231	0.231	0.231	0.231	0.231

Table 7: Returns and *DTE*: Different Misalignment Score Weights

The dependent variable is firm-level return, $RET_{i,t+1}$, measured monthly. The main independent variables are *DTE-CE* and *DTE-FE*, as defined in Table 1, but with different weights applied to the *Misalignment Score* categories. The "25" in the variable indicates a 25% weight in the absolute emissions category; the "50" in the variable indicates a 50% weight in the absolute emissions category. Control variables include *LOGMKTCAP*, *LOGMB*, *LEVERAGE*, *MOM*, *INVEST/ASSETS*, *LOGPPE*, *VOLAT*, *ROE*, and *AGE*, as defined in Table 1. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	(1)	(2)	(3)	(4)
DTE-CE 25	-0.014***			
	(0.004)			
DTE-FE 25		-0.013***		
		(0.003)		
DTE-CE 50			-0.026***	
			(0.006)	
DTE-FE 50				-0.023***
				(0.006)
Controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes
Observations	995,505	995,505	995,505	995,505
R-squared	0.231	0.231	0.231	0.231

Table 8: Returns and *DTE*: Controlling for Other Environmental Variables

The dependent variable is *RET*, measured monthly. The main independent variables are *DTE-CE* and *DTE-FE*, 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 natural logarithm of cumulative forecasted emissions until 2050 (*Log Cumulative Forecasted Emissions*) in columns (1) and (2); the following text-based climate change exposure variables from Sautner et al. (2023): climate change exposure (*CCExposure*) in columns (3) and (4), and opportunity climate change exposure ($CCExposure^{Opp}$), regulatory climate change exposure ($CCExposure^{Reg}$), physical climate change exposure ($CCExposure^{Phy}$), in columns (5) and (6); and LSEG's and MSCI's Environmental, Social, and Governance Pillar Scores in columns (7) to (10). The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DTE-CE	-0.009**		-0.009*		-0.009*		-0.010**		-0.008**	
	(0.003)		(0.005)		(0.005)		(0.004)		(0.003)	
DTE-FE		-0.009***		-0.009*		-0.009*		-0.009**		-0.007**
		(0.003)		(0.004)		(0.004)		(0.004)		(0.003)
Misalignment Score	-0.011	-0.008								
	(0.032)	(0.028)								
Log Emissions	0.257***	0.258***								
	(0.052)	(0.052)								
Log Cumulative Forecasted Emissions	0.056	0.055								
	(0.044)	(0.043)								
CCExposure			7.957	7.967						
			(19.490)	(19.494)						
$\text{CCExposure}^{\text{Opp}}$					9.492	9.517				
					(26.539)	(26.539)				
$\text{CCExposure}^{\text{Reg}}$					-11.007	-11.073				
					(46.399)	(46.424)				
$\text{CCExposure}^{\text{Phy}}$					142.913	143.044				
					(83.408)	(83.392)				
Environmental Pillar Score (LSEG)							0.002*	0.002*		
							(0.001)	(0.001)		
Social Pillar Score (LSEG)							0.004***	0.004***		
							(0.001)	(0.001)		
Governance Pillar Score (LSEG)							0.000	0.000		
							(0.001)	(0.001)		
Environmental Pillar Score (MSCI)									0.037***	0.037***
									(0.011)	(0.011)
Social Pillar Score (MSCI)									0.002	0.002
									(0.012)	(0.012)
Governance Pillar Score (MSCI)									0.022*	0.022*
									(0.012)	(0.012)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year-month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	995,505	995,505	325,757	325,757	325,757	325,757	562,645	562,645	477,681	477,681
R-squared	0.231	0.231	0.383	0.383	0.383	0.383	0.313	0.313	0.320	0.320

Table 9: Valuation Ratios and *DTE*

The dependent variables are *LOGPE* and *LOGMB*, measured monthly. The main independent variables are *DTE-CE* and *DTE-FE*, as defined in Table 1. Control variables mimic those in Table 4. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include a vector of controls, industry-year-month fixed effects, and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable:	LOGMB		LOGPE	
	(1)	(2)	(3)	(4)
DTE-CE	0.004***		0.005***	
	(0.001)		(0.001)	
DTE-FE		0.003***		0.004***
		(0.001)		(0.001)
Controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes
Observations	712,023	712,023	633,015	633,015
R-squared	0.577	0.577	0.429	0.429

Table 10: Returns and *DTE*: Extensive Margin

The dependent variables are *RET* and *LOGPE*, measured monthly. The independent variables (*EXT*) are transformations of *DTE-CE* and *DTE-FE*, 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 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable:	RET		LOGPE	
	(1)	(2)	(3)	(4)
EXT DTE-CE	-0.146*		0.028	
	(0.076)		(0.039)	
EXT DTE-FE		-0.106		0.015
		(0.075)		(0.034)
Controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes
Observations	995,505	995,505	633,015	633,015
R-squared	0.231	0.231	0.428	0.428

Table 11: Valuations and *DTE*: The Role of Paris Agreement

The dependent variables are *RET* and *LOGPE*, measured monthly. We define an indicator variable, *Paris*, that is equal to one for all observations from year 2016 onwards, and equal to zero for the period of up to and including 2015. The main independent variables are *DTE-CE* and *DTE-FE*, as defined in Table 1, and the interaction terms between *DTE* and *Paris*. All regressions include the same set of control variables as in Table 4. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable:	RET		LOGPE	
	(1)	(2)	(3)	(4)
DTE-CE	-0.009*		0.003***	
	(0.005)		(0.001)	
DTE-FE		-0.008**		0.003***
		(0.004)		(0.001)
DTE-CE × Paris	-0.014		0.002*	
	(0.009)		(0.001)	
DTE-FE × Paris		-0.015*		0.002*
		(0.008)		(0.001)
Controls	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes
Observations	995,505	995,505	633,015	633,015
R-squared	0.231	0.231	0.429	0.429

Table 12: Returns and *DTE*: Time-Series Effects

The top panel presents the results in which the coefficients are obtained each period from the cross-sectional regressions and then averaged over time. The dependent variable is *RET*, measured monthly. The main independent variables are *DTE-CE* and *DTE-FE*, as defined in Table 1. We include the same set of control variables as in Table 4. The bottom panel reports estimates from a regression of cross-sectional coefficients of the *DTE* (from step 1 of the cross-sectional regression) on time trend. *Trend* is a variable that is equal to 1 to 203 indicating each month from 2006.02 to 2022.12, *Trend (ex 2022)* excludes observations in 2022. The Newey-West standard errors (in parentheses) allow for 12 lags in autocorrelation structure. All regressions include industry fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: RET	(1)	(2)
DTE-CE	-0.012***	
	(0.003)	
DTE-FE		-0.011***
		(0.003)
Controls	Yes	Yes
Country fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Trend	-0.006	-0.005
	(0.004)	(0.003)
Observations	203	203
Trend (ex 2022)	-0.009**	-0.008**
	(0.004)	(0.004)
Observations	191	191

Table 13: Returns and *DTE*: Excluding Scope 3 Emissions

The dependent variable is *RET*, measured monthly. The main independent variables are *DTE-CE* and *DTE-FE*, as defined in Table 1, but excluding scope 3 emissions. Control variables mimic those in Table 4. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: returns	(1)	(2)	(3)	(4)
DTE-CE	-0.007**		-0.007**	
	(0.003)		(0.003)	
DTE-FE		-0.007**		-0.008***
		(0.003)		(0.003)
Controls	No	No	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month-fixed effects	Yes	Yes	Yes	Yes
Observations	995,505	995,505	995,505	995,505
R-squared	0.230	0.230	0.231	0.231

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, Misalignment Score, and DTE.

This table presents the correlation matrix between carbon emissions, *Misalignment Score*, and DTE. DTE are constructed using different ranking measures and portfolio decarbonization pathways. We show two variants of DTE: *Misalignment Score* plus constant emissions (*DTE-CE*); *Misalignment Score* plus forecasted emissions (*DTE-FE*). Pathway *RA* assumes that investors follow the emission mitigation pathway of Andrew (2020). Pathway *FS* assumes that investors switch from a faster reduction rate to a slow reduction rate of 1%. 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 RA		Pathway FS		Pathway SF
	Carbon Emissions	Misalignment Score	DTE-CE	DTE-FE	DTE-CE	DTE-FE	DTE-CE
Misalignment Score	0.06	1.00					
Robbie Andrews (RA) Reduction Pathway							
DTE-CE	-0.11	-0.09	1.00				
DTE-FE	-0.13	-0.09	0.97	1.00			
Switch Fast-Slow (FS) Reduction Pathway							
DTE-CE	-0.17	-0.09	0.78	0.80	1.00		
DTE-FE	-0.17	-0.09	0.76	0.81	0.96	1.00	
Switch Slow-Fast (SF) Reduction Pathway							
DTE-CE	-0.07	-0.10	0.94	0.87	0.69	0.65	1.00
DTE-FE	-0.12	-0.10	0.96	0.94	0.76	0.74	0.94

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

This table presents further details on the forward-looking sub-components of the *Misalignment 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 considered targets.

Year	# Firms	Decarbonization Target	Decarbonization Policy	Reported Emissions	CSR Committee	UNPRI Signatory	SDG 13 Climate Action
Panel A: Refinitiv ESG							
2007	3381	19.91	26.56	23.93	15.76	0.47	
2008	3351	25.28	36.35	27.84	24.44	0.60	
2009	3435	28.70	40.52	35.02	35.23	0.70	
2010	3605	29.68	45.16	40.25	41.75	0.83	
2011	3859	30.19	45.24	41.10	43.64	0.96	
2012	3994	30.05	47.20	42.89	45.62	1.05	
2013	4014	29.35	47.73	43.85	46.06	1.17	
2014	4715	24.86	43.39	39.75	40.45	1.17	
2015	5020	24.58	43.94	40.56	38.65	1.22	
2016	5158	24.58	46.18	43.41	39.74	1.84	0.02
2017	11697	12.81	25.25	23.51	20.89	1.00	0.01
2018	12494	14.32	28.04	26.25	22.52	0.95	0.14
2019	12985	17.34	33.48	30.44	26.69	1.05	11.90
2020	13698	20.02	37.23	33.14	30.77	1.47	19.88
2021	14991	24.24	39.91	34.79	35.14	1.58	24.43
2022	14484	27.73	42.18	36.67	39.06	1.28	27.19
Overall	17632	21.88	36.90	33.28	31.88	1.15	13.13

		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	3117	15.72	6.92	269.86	0.22	7.83	7.36	108.91	0.19 [t]
2007	3381	15.47	6.96	256.20	0.22	7.48	6.75	140.92	0.17
2008	3351	16.50	6.70	492.65	0.23	8.06	7.26	1567.29	0.20
2009	3435	16.48	7.45	484.68	0.23	6.96	7.72	228.07	0.17
2010	3605	17.00	8.00	286.37	0.25	7.71	7.73	102.63	0.17
2011	3859	17.05	8.42	301.26	0.24	7.20	7.11	79.91	0.19
2012	3994	17.63	9.68	285.13	0.25	7.54	8.03	103.04	0.16
2013	4014	17.96	10.84	311.18	0.26	7.90	8.43	79.27	0.16
2014	4715	16.69	11.00	312.37	0.28	7.53	7.67	79.31	0.19
2015	5020	16.57	11.97	166.91	0.28	7.33	8.72	67.09	0.18
2016	5158	16.71	12.59	247.10	0.28	7.74	8.96	55.24	0.16
2017	11697	9.66	10.39	146.40	0.33	3.93	8.65	40.73	0.20
2018	12494	8.86	9.81	84.03	0.33	3.87	8.57	30.80	0.20
2019	12985	9.09	10.15	69.16	0.33	3.63	10.73	28.76	0.22
2020	13698	8.73	9.96	267.39	0.35	3.20	8.53	20.85	0.20
2021	14991	7.97	10.16	43.78	0.35	2.69	8.01	16.53	0.21
2022	14484	8.07	9.89	42.89	0.36	2.20	7.92	13.46	0.21
Overall	17632	11.52	9.78	211.87	0.30	4.74	8.29	134.28	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								
2012	3994	465	324	299	283	92		
2013	4014	553	386	353	339	118		
2014	4715	655	453	410	400	129		
2015	5020	582	410	356	356	112		
2016	5158	869	551	491	490	134		126
2017	11697	1196	688	614	614	183	56	133
2018	12494	1286	743	675	675	200	100	206
2019	12985	1523	869	807	802	253	171	231
2020	13698	1645	953	900	888	318	262	303
2021	14991	2471	1354	1307	1287	529	386	474
2022	14484	3465	1974	1934	1915	900	551	518
Overall	17632	15162	2379	2299	2298	1146	635	1023

Table IA.3: Returns and *DTE*: Restricted Universe of Firms

The dependent variable is *RET*, measured monthly. The main independent variables are *Misalignment Score* and *DTE-CE* and *DTE-FE*, as defined in Table 1. The sample universe uses firms for which any emission data is available prior to 2016. Control variables mimic those in Table 4. The sample period is 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: returns	(1)	(2)	(3)	(4)
DTE-CE	-0.011***		-0.006**	
	(0.002)		(0.003)	
DTE-FE		-0.010***		-0.005*
		(0.002)		(0.003)
Misalignment Score			0.057*	0.062**
			(0.033)	(0.030)
Controls	No	No	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Industry-year-month fixed effects	Yes	Yes	Yes	Yes
Observations	578,647	578,647	578,647	578,647
R-squared	0.315	0.315	0.315	0.315

Table IA.4: 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-CE* and *DTE-FE*, 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 2005–2022. Standard errors (in parentheses) are double clustered at the industry and year levels. All regressions include industry-year-month fixed effects and country fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent variable: returns	(1)	(2)
DTE-CE	-0.041***	
	(0.007)	
DTE-FE		-0.036***
		(0.006)
Disclosure	-0.211*	-0.142
	(0.114)	(0.109)
DTE-CE × Disclosure	0.024***	
	(0.007)	
DTE-FE × Disclosure		0.019**
		(0.007)
Controls	Yes	Yes
Country fixed effects	Yes	Yes
Industry-year-month fixed effects	Yes	Yes
Observations	995,453	995,453
R-squared	0.256	0.256