Carbone, Sante et al.

Working Paper

The low-carbon transition, climate commitments and firm credit risk

SAFE Working Paper, No. 442

Provided in Cooperation with:
Leibniz Institute for Financial Research SAFE

Suggested Citation: Carbone, Sante et al. (2025) : The low-carbon transition, climate commitments and firm credit risk, SAFE Working Paper, No. 442, Leibniz Institute for Financial Research SAFE, Frankfurt a. M.,
https://doi.org/10.2139/ssrn.5125405

Sante Carbone | Margherita Giuzio | Sujit Kapadia | Johannes Sebastian Krämer | Ken Nyholm | Katia Vozian

The Low-Carbon Transition, Climate Commitments and Firm Credit Risk

SAFE Working Paper No. 442 | February 2025

The low-carbon transition, climate commitments and firm credit risk*

Sante Carbone[3] Margherita Giuzio[1] Sujit Kapadia[1]

Johannes Sebastian Krämer[5] Ken Nyholm[1] Katia Vozian[2]

[1]*European Central Bank*
[2]*Leibniz Institute for Financial Research SAFE*
[3]*Stockholm Business School, Center for Monetary Policy and Financial Stability, Stockholm University*
[4]*International Monetary Fund*

Abstract: This paper explores how the low-carbon transition affects firms' credit ratings and market-implied distance-to-default. We develop a novel dataset covering firms' greenhouse gas emissions alongside climate disclosure and forward-looking emission reduction targets. Panel regression analysis indicates that high emissions are associated with higher credit risk, but that this relationship can be mitigated by disclosing emissions and committing to reduce emissions. After the Paris agreement, firms most exposed to transition risk saw their ratings deteriorate relative to their peers, with the effect larger for European than US firms, probably reflecting differential climate policy expectations. A dynamic difference-in-differences approach also shows that European firms who make a climate commitment subsequently experience an improvement in their credit rating relative to comparable firms who do not set a target. These results have policy implications for corporate disclosure and pricing of transition risk.

JEL classification: C58, E58, G11, G32, Q51, Q56
Keywords: climate change; transition risk; climate disclosure; net zero targets; green finance; credit risk

*Authors' information: sante.carbone(at)sbs.su.se; margherita.giuzio(at)ecb.europa.eu; sujit.kapadia(at)ecb.europa.eu; JKramer(at)imf.org; ken.nyholm(at)ecb.europa.eu; vozian(at)safe-frankfurt.de. S. Carbone, K. Vozian, and J. Krämer were affiliated with the European Central Bank when conducting this work. We would like to thank Spyros Alogoskoufis, Miriam Breitenstein, Olimpia Carradori, Stephan Fahr, Irene Heemskerk, Ari Hyytinen, Marcin Kacperczyk, Markku Kaustia, Katri Mikkonen, Fernando Monar, Rasmus Pank Roulund, Loriana Pelizzon, Anamaria Piloiu, Peter Sarlin, Torsti Silvonen, Thomas Werner, Ivo Vehviläien, and two anonymous referees for their helpful comments, as well as seminar and conference participants at the European Central Bank, Bank of England, Sveriges Riksbank, International Monetary Fund, the Helsinki Graduate School of Economics, the Helsinki Graduate School of Finance, the Leibniz Institute for Financial Research SAFE, the MIT Golub Center for Finance and Policy 8th Annual Conference, the OCC Symposium on Climate Risk in Banking and Finance, the 2022 CEBRA Annual Meeting, the 2022 Annual Symposium of the Yale Initiative on Sustainable Finance, and the 2024 IMF Banca d'Italia conference on Embedding Sustainability in Credit Risk Assessment. K. Vozian acknowledges gratefully funding by the OP Group Research Foundation.

Disclaimer: The views expressed in this paper are those of the authors only and do not necessarily reflect the views of the European Central Bank, the Eurosystem, or the IMF, the IMF Executive Board or its management.

1 Introduction

Climate change is one of the biggest challenges of our time. Urgent action is needed to rapidly reduce greenhouse gas (GHG) emissions to avert the catastrophic consequences of significant global warming (IPCC, 2021). Meeting the goals of the 2015 Paris Agreement to limit global warming to well below 2 degrees Celsius compared to pre-industrial levels, and preferably to 1.5 degrees Celsius, is crucial. To achieve these objectives, European countries have pledged to reduce GHG emissions to zero in net terms by 2050. But doing so requires much sharper annual reductions in emissions than those observed since 1990.

It is therefore essential for the planet that firms substantially reduce their GHG emissions in the coming years. Firms which fail to adapt sufficiently may also endanger their own medium-term survival. This is because they may be left with stranded assets such as unusable coal mines, or remain exposed to heavily carbon-intensive technologies that may eventually attract punitive taxation. Such firms may also see an increase in their financing costs if they face changing market sentiment and growing investor pressure. Early signs of this can be seen both in the rapid growth of green finance and in several initiatives of investor groups that aim to foster the low-carbon transition.[1]

All of these factors present significant transition risk for firms that have to reduce their GHG emissions. And if they reduce a firm's ability to service and repay its debt, the credit risk associated with this firm will increase (BCBS, 2021). As such, a firm with a higher carbon footprint today is more exposed to transition risk and may have higher credit risk either now or in the future, especially if it has no credible plan to transition towards the low-carbon economy or if it fails to adapt in a timely fashion. Partly linked to these considerations, S&P and Moody's signed the "Statement on ESG in Credit Ratings" (an initiative launched by the Principles for Responsible Investment) in 2016, committing to systematically and transparently integrate climate change related aspects into credit ratings and analysis.[2]

[1]Notably, Climate Action 100+ is a global investor-engagement group that calls upon companies with highest greenhouse gas (GHG) emissions to set decarbonisation targets, disclose their climate-related risks, and improve governance around those risks. More recently, the Glasgow Financial Alliance for Net Zero (GFANZ) encompassing large parts of the financial system has been created to mobilise the necessary capital to build a global net zero emissions economy and deliver on the goals of the Paris Agreement.

[2]https://www.unpri.org/download?ac=256

This paper assesses whether and how firm credit risk – as measured by credit ratings and market-implied distance-to-default – is influenced by firm climate-related transition risk. Importantly, we go beyond considerations of firms' actual current emissions and emission intensities, which are the focus of most existing research, to assess how climate-related disclosure practices, forward-looking emission reduction targets and realised performance in reducing emissions may all influence credit risk. This recognises that while actual emissions and intensities proxy a firm's *current* exposure to climate-related transition risk, disclosure practices, forward-looking targets and realised emission reductions may all reflect a firm's commitment and strategy to reduce emissions and, therefore, *future* transition risk. And future transition risk should inform firms' current credit risk.

We first develop a novel firm-level dataset covering the non-financial corporations included in the S&P 500 and STOXX Europe 600 indices over the period 2010-2019, with the end date chosen to avoid subsequent complications linked to the Covid-19 pandemic. The dataset provides a rich picture of firms' climate-related transition risk and their strategies to manage such risk, alongside standard financial variables that influence credit risk. We then conduct panel regressions and apply two complementary difference-in-differences approaches to assess how climate-related metrics, such as current emissions, disclosure and forward-looking commitments, influence firm credit risk.

In relation to emissions, we consider both absolute emissions and emissions intensities when gauging firms' current exposure to transition risk. As discussed further in Section 2.2, this recognises the debate between Bolton and Kacperczyk (2021a), who emphasize that cutting the level of emissions is what matters from a societal perspective to transition to a low-carbon economy, and Aswani, Raghunandan, and Rajgopal (2023a), who argue that absolute emissions may be confounded by firm size effects and that emissions intensity better captures the carbon efficiency of an individual firm which, in our context, could also be relevant for firm's credit risk. Throughout our analysis, we also consider how our results differ for European and US-domiciled firms. This is motivated by the consistency of climate-related regulatory policies over time in Europe, such as the EU Emissions Trading Scheme, while Donald Trump's 2016 election and the announcement of the withdrawal from the Paris Agreement cast uncertainty over the long term commitment of the US to reduce emissions.

In line with the existing literature (Stellner, Klein, and Zwergel, 2015; Seltzer, Starks, and Zhu, 2022), panel regressions confirm that higher GHG emission levels and intensities tend to be associated with higher credit risk as assessed by credit rating agencies. But when we split the results geographically, we find that the relationship is only present for European firms. This result is also confirmed for the market-implied credit risk of European firms, in line with Capasso, Gianfrate, and Spinelli (2020). Turning to firms' mitigation strategies, the panel regressions indicate that choosing to disclose emissions is associated with a better credit rating and lower market-implied credit risk for European firms, with the relationship on credit ratings also holding for US-domiciled firms. In addition, European firms who have adopted a forward-looking target to cut emissions have lower credit risk under both our metrics, with some evidence that this effect tends to be stronger for more ambitious commitments in terms of the percentage reduction in emissions targeted. But these relationships do not seem to hold for the credit ratings of US-domiciled firms. Finally, there is also some evidence that achieving reductions in emissions is associated with better credit ratings for European firms.

While our panel regressions attempt to confront potential endogeneity issues, including by controlling for other variables, using fixed effects and implementing lag structures, our two complementary difference-in-differences approaches establish clearer causality for some of our findings. The first analysis focuses on the causal role of emissions levels and intensities by exploiting the 2015 Paris Agreement. We find that firms most exposed to transition risk saw their credit ratings deteriorate after the event, whereas other comparable firms did not. We also find that the impact of transition risk on credit ratings was larger for firms domiciled in Europe than in the US after the Paris agreement. This probably reflects different (expectations around) government climate policies and commitment both after the Paris agreement and across countries. This result is consistent with the finding of Ilhan, Sautner, and Vilkov (2021), who use the Paris Agreement and Trump election as shocks in the option market to show that climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation.

We then conduct a dynamic difference-in-differences estimation to examine the causal effect of emission targets and disclosure on credit ratings. For European firms, we find that firms who make a climate commitment subsequently experience a statistically significant improvement in their credit rating relative to comparable firms who do not set a target. The magnitude of the effect is economically meaningful, with firms who set a target experiencing about a half of a credit notch increase in their ratings, which is similar to the implied effect from the panel regressions and almost as much as the effect from a one standard deviation reduction in leverage. Consistent with this, we also present descriptive evidence on the correlation between firms' commitments to reduce emissions and observed changes in emissions. Firms with a target cut their emissions by more than peers without a target. This suggests that such commitments are meaningful in indicating likely tangible progress towards meeting the Paris goals, and should therefore be priced. However, since we do not find a similar effect of targets for US firms in either the panel regressions or the dynamic difference-in-differences estimation, we deem it likely that national climate policies also affect the pricing of forward-looking indicators of transition risk, in line with the results from the analysis on emissions around the Paris Agreement.

By contrast, we find no evidence of a causal impact on credit ratings from firms' first disclosure of their emissions in either Europe or the US. Taken together with the panel regression results, this points to more mixed conclusions overall on the links between emission disclosure and credit risk. In principle, effective management of transition risk begins with measurement of the risk, and by disclosing emissions, firms demonstrate awareness and transparency of their risk. Such disclosure could also have signaling value, in line with the findings of Bolton and Kacperczyk (2021c), who suggest that carbon disclosure enhances perceptions of corporate responsibility in managing transition risks. But the relatively weaker evidence we find for climate disclosures in affecting credit risk for European firms compared to both current emissions and forward-looking commitments suggest that actual transition risk and the clear ambition to reduce emissions are more important for credit risk assessment than awareness of transition risk.

Taken together, and acknowledging some limitations related to the reliability and comparability of climate-related metrics, our results suggest that high emitters have a higher risk of failure in countries committed to reducing carbon emissions, but that active strategies to manage transition risk are also crucial. Firms in countries that have a clear plan to reduce their emissions – as indicated primarily by their forward-looking commitments but to some extent also by their disclosure practices – have better credit ratings and receive a more favourable market-based credit risk assessment, relative to similar firms that show less preparedness. At the same time, while our results indicate that climate-related transition risk and strategies are somewhat reflected in credit risk metrics, the true extent of such risks could still be materially underestimated by rating agencies and the market, especially given uncertainties over future climate policies and wider evidence of climate risks not being very well priced in financial markets (Schnabel, 2021).

Our results have several policy implications. First, they show the importance of firms' adopting credible strategies to monitor and reduce their GHG emissions for their own long-term viability. This highlights the value of policies to strengthen corporate disclosure of emissions and promoted credible emissions reduction plans. Such action would also have the added benefit of helping investors and credit rating agencies to measure climate-related risks more accurately, which is crucial given the wider role that financial markets will need to play in financing the transition to a low-carbon economy (see also Lagarde (2021) and Schnabel (2021)). Second, they have potential implications for the way that central banks approach climate-related transition risk in their monetary and non-monetary policy operations. Finally, they call for an assessment of whether the climate-related transition risk faced by firms is adequately and consistently reflected in the prudential and supervisory framework for banks and insurance companies given their extensive exposures to the corporate sector. At the same time, it is important to note that government action, especially in relation to carbon-tax related climate policies, must remain the prime focus in the fight against climate change.

Our paper is related to a wide literature which investigates the relationship between corporate sustainability, including environmental performance, and financial performance (Edmans, 2021a,b; Nguyen, Kecskés, and Mansi, 2020; Misani and Pogutz, 2015; Ghisetti and Rennings, 2014; Rexhäuser and Rammer, 2014) as well as cost of capital (Sharfman and Fernando, 2008; Chava, 2014; El Ghoul, Guedhami, Kim, and Park, 2018). Much recent work has focused on the specific link between climate-related transition risk and stock returns (Bolton and Kacperczyk, 2021a,b,c; Aswani, Raghunandan, and Rajgopal, 2023a). This line of research finds that equity market investors tend to require higher stock returns for their exposure to those firms with higher levels of GHG emissions. But Aswani, Raghunandan, and Rajgopal (2023a) find that emissions intensity − which they argue is just as important a measure – is not correlated with stock returns.

There is also growing empirical research on the relationship between climate-related transition risk and credit risk, but most of it has only considered either environmental scores provided by rating agencies and/or backward-looking environmental metrics.[3] This line of literature tends to find that firms with higher GHG emissions and/or worse environmental scores exhibit greater credit risk, as measured by bond yield spreads, bond credit ratings, and CDS spreads (Stellner, Klein, and Zwergel, 2015; Höck, Klein, Landau, and Zwergel, 2020; Barth, Hübel, and Scholz, 2020). In particular, in a similar vein to the part of our analysis relating current emissions to credit risk, Seltzer, Starks, and Zhu (2022) exploit the Paris agreement to document empirically that US firms with a poorer environmental profile (as measured by their environmental score, emissions, or emissions intensity) saw a subsequent deterioration in their credit ratings and higher yield spreads. The relationship was particularly evident for firms with facilities located in US States with stricter regulatory enforcement, with this result also speaking to our comparison of climate policies at the international level. Safiullah, Kabir, and Miah (2021) also find a negative, economically meaningful impact of carbon emissions on credit ratings in the US. Attig, El Ghoul, Guedhami, and Suh (2013) analyse the relationship between firm credit ratings and ESG scores, including environmental scores, and find that a better environmental score is associated with a better rating. Notably, in line with the part of our analysis considering climate policy uncertainty, Ilhan, Sautner, and Vilkov (2021) show that the Paris Agreement initially raised the market-implied protection cost for carbon-intensive firms, followed by a decline after Trump's election, highlighting the sensitivity of hedging costs to political shifts. This underscores how investor sentiment and market reactions respond dynamically to a change in the climate-related policy stance. Finally, other empirical studies covering different geographies suggest that firms with higher GHG emissions levels and/or intensities are associated with a lower distance-to-default (Nguyen, Diaz-Rainey, and Kuruppuarachchi, 2021; Kabir, Rahman, Rahman, and Anwar, 2021; Capasso, Gianfrate, and Spinelli, 2020).

[3]There is also a brief literature which directly attempts to assess whether credit rating agency methodologies reflect environmental considerations. For example, Kiesel and Lücke (2019) run a textual analysis on the credit rating reports of Moody's published between 2004 and 2015 and suggest that the credit rating agency does account for the environmental performance of a firm in its rating decisions, albeit to a small extent.

Although some of these studies suggest that credit rating agencies and financial market participants account to some extent for environmental performance as proxied by environmental scores, important caveats exist regarding the use of scores. Such metrics are often inconsistent over time, incomparable across firms and sectors, and display a very low correlation when compared across different providers (Berg, Koelbel, and Rigobon, 2022; OECD, 2022; Billio, Costola, Hristova, Latino, and Pelizzon, 2020; Schnabel, 2020a). The divergence across ESG score providers reflects not only a large discretion in the methodology, due to differences in measurements, scope and weight of environmental indicators, but also a rater-specific view (Berg, Koelbel, and Rigobon, 2022). By contrast, GHG emissions are likely to be a better proxy for transition risk and can be effectively exploited under informed methodological choices that acknowledge and address caveats on the availability, reliability, and comparability of such data (see for instance Busch, Johnson, and Pioch (2020) and Kalesnik, Wilkens, and Zink (2020)), noting also the importance of leveraging available data sources despite such caveats (NGFS, 2021; Elderson, 2021). In addition, while acknowledging some reliability and comparability challenges, hard information on firms' climate disclosure practices and forward-looking commitments provides a more direct and consistent read on their forward-looking strategies to manage transition risk than opaquely computed environmental scores.

In this regard, the literature on the links between climate disclosures, forward-looking emission reduction commitments, and firm-level financial performance remains limited. Notably, Bolton and Kacperczyk (2021a) examine the relationship between climate disclosures and stock returns, finding that disclosed emissions in the U.S. are correlated with stock performance. Aswani, Raghunandan, and Rajgopal (2023a) highlight that these findings are highly sensitive to how the disclosure measure is constructed. Additionally, Bolton and Kacperczyk (2021c) show that disclosing emissions carries a signaling effect, enhancing perceptions of corporate responsibility in managing transition risks. Some research has also explored the impact of emission reduction commitments. Bolton and Kacperczyk (2023b) find that companies making such commitments subsequently reduce their emissions, but no study has examined whether these commitments influence firms' credit risk. Jiang, Kim, and Lu (2025) show that initial announcements of emission targets are positively reflected in environmental scores and media coverage, yet failure to achieve these targets does not generate comparable reactions. However, their analysis does not extend to the link between such commitments and firms' financial performance.

We contribute to the existing literature in three ways. First, we move beyond measures of current GHG emissions and opaque environmental scores to develop a rich, novel firm-level dataset covering firms' climate disclosure practices and information on their forward-looking commitments to reduce emissions. This allows to examine how firms' climate mitigation strategies might influence their credit risk. Second, we provide evidence of a causal relationship between firms' climate variables and credit ratings via two complementary difference-in-difference analyses. While previous literature has exploited the Paris agreement to analyse credit rating variation in relation to contemporaneous metrics of transition risk, we also employ a dynamic difference-in-differences estimator on forward-looking metrics which compares the group of firms which switch to disclosing emissions and/or committing to an emissions reduction target against other firms. Third, with our data set spanning firms in both Europe and the United States, we are able to characterize the effect of transition risk in both our panel and difference-in-difference analyses conditional on the different climate policymaking enacted in the two geographies.

The rest of the paper is organized as follows. Section 2 describes the dataset, with a particular focus on the forward-looking climate-related metrics that we employ. Section 3 presents the hypotheses and our empirical strategy. Section 4 discusses the results of the panel regressions. Section 5 presents the results of difference-in-differences analysis on high emitters and low-carbon transition policy. Section 6 shows the results on firms' climate disclosure and commitments and discusses the credibility of emission reduction targets. Section 7 focuses on additional results when using market-implied distance to default as indicator of credit risk. Section 8 discusses policy implications and concludes.

2 Dataset and variable selection

For constructing our dataset, we consider all non-financial firms listed in the S&P 500 and STOXX Europe 600 indices at any point during the 2010–2019 period. This approach ensures the inclusion of firms that may have entered or exited the indices over time. The set amounts to 728 firms operating in Europe (322) and in the US (406) that have a credit rating issued by S&P. [4] For these firms, we further collect data on environmental and financial performance, as well as macroeconomic indicators. In relation to some metrics of financial performance, we apply winsorization to remove the effect of outliers, following Baghai, Servaes, and Tamayo (2014): leverage, debt service, and profitability are winsorized at 99th percentile; debt service and profitability are also winsorized at the 1st percentile; when leverage is negative, we set it equal to zero. The time period spans from 2010 to 2019 and includes the time before and after the signature of the Paris Agreement in 2015 and the signature of the PRI statement by S&P and Moody's in 2016. This allows us to analyse potential changes in the awareness of climate change and related transition risk, as may be reflected in credit ratings and market prices. As the availability of credit ratings changes over time, the resulting dataset is an unbalanced panel. The frequency of the firm-level environmental and firm-financial variables is yearly and the frequency of macroeconomic variables is monthly, with the latter variables being used in additional regressions with monthly distance to default as dependent variable. Table 1 presents the sample composition by year, country and sector. Given our data covers both US and European firms, we ensured that no significant differences are present in the distribution of sectors across the two jurisdictions.

Table 1: Sample composition by year, country, and sector.

Notes: The table shows the sample composition for observations with an available S&P. The definition of the variables year, country, and sector is given in Appendix.

Year	**Obs.**	**Country**	**Obs.**	**Sector**	**Obs.**
2010	417	Austria	33	B-Mining and quarrying	388
2011	555	Belgium	63	C-Manufacturing other than C19	2648
2012	571	Switzerland	160	C19-Manufacture of coke and refined petroleum products	98
2013	584	Germany	352	D-Electricity, gas, steam and air conditioning supply	557
2014	611	Denmark	40	E-Water supply; sewerage, waste management and remediation	66
2015	631	Spain	108	F-Construction	82
2016	653	Finland	62	G-Wholesale and retail trade; repair of motor vehicles	556
2017	667	France	439	H-Transportation and storage	269
2018	695	United Kingdom	610	I-Accommodation and food service activities	154
2019	715	Ireland	91	J-Information and communication	649
		Italy	134	M-Professional, scientific and technical activities	239
		Luxembourg	33	N-Administrative and support service activities	281
		Netherlands	145	O-Public administration and defence; compulsory social security	10
		Norway	52	Q-Human health and social work activities	48
		Poland	9	R-Arts, entertainment and recreation	52
		Portugal	10	S-Other services activities	2
		Sweden	167		
		US	3551		
		Czechia	9		
Obs.	6099	Obs.	6099	Obs.	6099
Firms (Europe)	322	Firms	322	Firms	322
Firms (US)	406	Firms	406	Firms	406

[4] Out of these 728 firms, a credit rating is observed continuously for 416 firms throughout the time of the sample 2010-2019.

In the following we describe the variables employed for the measurement of credit risk and transition risk as well as the set of controls that we employ in the empirical analysis.

2.1 Measures of firm credit risk

Two complementary measures of credit risk are analysed. In our baseline tests, we rely on credit ratings issued by Standard and Poors (S&P). Additionally, we investigate whether our results hold true when using as dependent variable the distance-to-default measure calculated using the approach of Merton (1974) and Bharath and Shumway (2008). This latter exercise using the distance-to-default is conducted only for European firms.

Credit ratings constitute a publicly available source of firm credit risk information that is based on specialised analysis of default risk performed by the issuing credit rating agency. Firms that need a credit rating procure one from the issuing credit rating agency and the rating is subsequently made public. Fundamental balance sheet analysis, market surveys, as well as quantitative models are used, together with expert judgement, to form and update these rating assessments. Credit rating agencies indicate that they account for environmental and climate factors where such factors materially affect the creditworthiness of the firm (see S&P Global Ratings (2015), S&P Global Ratings (2017b), S&P Global Ratings (2017a)). Moody's Investors Service (2016) describes four primary categories of risk related to the low-carbon transition used in the rating assessment of corporate and infrastructure sectors: 1) policy and regulatory uncertainty regarding the pace and detail of emissions policies; 2) direct financial effects such as declining profitability and cash flows, due to higher research and development costs, capital expenditure and operating costs; 3) demand substitution and changes in consumer preferences; and 4) technology developments and disruptions that cause a more rapid adoption of low-carbon technologies. S&P Global Ratings (2017a) explains that "over the past two years (between July 16, 2015, and Aug. 29, 2017), environmental and climate (E&C) concerns affected corporate ratings in 717 cases, or approximately 10% of corporate ratings assessments". Also, the frequency with which environmental and climate factors have affected corporate ratings has increased over time. The final ratings are issued on a discrete letter scale, as shown in Table 2, with a rating grade equivalent to S&P's AAA reflecting the lowest credit risk.

Table 2: Credit rating scale

Notes: The table shows the rating scale typically expressed as a letter combination {AAA} being the best, i.e. corresponding to an assessment of a very low probability of default, and {CCC} being the worst, i.e. corresponding to a high probability of default. A firm with a rating grade equivalent to S&P's AAA, AA, or A reflects a minimal-to-low credit risk, while a rating grade equivalent to S&P's BBB, BB, or B reflects a moderate-to-high credit risk. The last column shows the ordinal value for each rating grade that we use in the analysis.

Summary scale	**Rating scale**	**Ordinal value**
IG: minimal credit risk	AAA	21
IG: very low credit risk	AA+, AA, AA-	18-20
IG: low credit risk	A+, A, A-	15-17
IG: moderate credit risk	BBB+, BBB, BBB-	12-14
HY: substantial credit risk	BB+, BB, BB-	9-11
HY: high credit risk	B+, B, B-	6-8
HY: very high credit risk	CCC+, CCC, CCC-	3-5

Credit rating agencies regularly reassess firms' credit risk and, where needed, update the rating assigned to a firm upon consideration of new information. The re-rating is done on a regular basis (e.g. when annual financial and non-financial statements are released) as well as upon specific events. When we use credit ratings as the dependent variable in the empirical specification, we lead the dependent variable by three months to ensure that the information disclosed in the financial and non-financial statements are available to the rating agency when assessing the firm's credit risk as part of the rating process. In addition, leading the dependent variable allows us to mitigate eventual reverse causality concerns. We retrieve credit ratings issued by S&P from the proprietary ECB Ratings Database. For our baseline specifications, we use the long-term issuer credit ratings provided by S&P. This metric is operationalised by converting its string coding into 21 ordinal values such that the higher the value, the better the rating, as shown in Table 2. This is in line with the wider approach in the literature (see for instance Doumpos, Niklis, Zopounidis, and Andriosopoulos (2015)).

Ratings are the go-to credit risk assessment for investors and official organisation, and often constitute a pivotal role in investment and official policy decisions[5]. As an alternative to ratings issued by rating agencies, we also consider market-based ratings. Even if it is elusive, a direct mapping can be established between agency-issued ratings and the probability of default. At the same time, market prices also contain information

[5]For example, the collateral and investment frameworks of public institutions, such as many central banks, depend heavily on ratings for eligibility assessments.

about credit risk (and thus probabilities of default)[6]. In this way there are two sources of available credit risk information: rating agencies and that implied by market prices.

Whereas agency-issued ratings are mapped to a discrete scale and are updated at regular frequencies, or when firm specific events require it, the market implied default probabilities are typically measured on a continuous scale and are updated every time market prices are recorded, as the output of an assumed pricing model. Different models can be used to extract credit risk information from market prices. For example, a simple and easily implementable approach assumes that the yield spread over the reference pricing curve for firm j can be decomposed into the firm's probability of default (PD) and it's loss-given-default (LGD): $S_j = PD_j \cdot LGD$, where S_j is observed in the financial markets and LGD can be approximated using historical default events, allowing the probability of default for firm j to be inferred. However, there are naturally other factors affecting the yield spread of a firm apart from its probability of default, for example idiosyncratic market perturbations, the liquidity and subordination of the bond issue in question. Merton (1974) represents an approach that relies on balance sheet fundamentals and the equity prices to gauge a firms credit risk. The intuition of the approach is that default occurs when the value of a firm's assets falls below the value of its liabilities. In this case the value of the firm's equity is negative, and the firm is hence in a state of default. To implement this idea, Merton applies contingent claims analysis on the summary positions of the firms balance sheet. Using the put-call parity from option pricing theory (Stoll, 1969), and following the Black-Scholes-Merton option-pricing approach (Merton, 1973 and Black and Scholes, 1973), Merton (1974) treats the firm's equity as a call option on the firm's assets with the exercise value equal to the present value of the firm's debt, if it was risk free. The put-option (from the parity) thus has an economic interpretation as the credit risk taken by the firm. The put-call parity is written as:

$$\mathit{Underlying\ Asset} + \mathit{Put} = \mathit{Call} + \mathit{PV(X)}, \tag{1}$$

[6]For example, the spread between yields of different companies is typically (among other things) associated to credit risk. We even talk about yield curves predicated by rating scales, e.g. the AAA-yield curve and the CCC-yield curve.

which can be applied to the firm's balance sheet as:

$$
\begin{aligned}
&\textit{Firm Asset} + \textit{Credit risk} = \textit{Equity} + \textit{Risk-free debt} \\
&\Updownarrow \\
&\textit{Equity} = \textit{Firm Asset} + \textit{Credit risk} - \textit{Risk-free debt}. \qquad (2)
\end{aligned}
$$

With this set-up, it is possible to use the option pricing formula for an American call option to extract market based estimates of the firm's credit risk expressed as a statistical measure of the distance the assets are from falling below the value of the firm's debt at a given point in time, using only information available in capital markets and from the firm's accounts.

The sample used for the DtD analysis is build based on similar principles as the sample used for the credit ratings analysis, but includes only firms domiciled in Europe. For this reason, we present results on DtD as further tests of the main evidence on credit ratings of European firms. The model is populated with the most recent accounting data obtained from Bloomberg. For each included company in the sample, the value of the firms' equity, the historical 1-year equity volatility, and the debt is collected. To estimate the DtD measure for each firm we use the accounting value of the firms' debt as a proxy for the market value of debt, and the risk-free rate is set at 0%. Appendix D shows more details on how we implement this approach.

2.2 Measures of firms' climate-related transition risk

We focus on GHG emissions-related variables as our key measures of transition risk, covering both backward-looking and forward-looking metrics (see appendix Tables 15 and 16, respectively). The backward-looking variables exploit GHG emissions data from Urgentem.[7] We distinguish between Scope 1, 2 and 3 GHG emissions in line with the GHG protocol for accounting and reporting purposes. Scope 1 corresponds to the direct emissions of the firm from owned or controlled sources. Scope 2 relates to the emissions associated with the consumption of purchased energy. Scope 3 includes all emissions

[7] We also collect data on emissions from Refinitiv and Eurostat for further robustness analysis as well as the EU ETS carbon price from ICE.

that occur in the value chain of the firm, excluding Scope 2; this generally represents the highest emissions category as it includes, among others, the emissions stemming from the usage of products sold by the firm.

We consider GHG emissions both in absolute terms, i.e. in levels, and in relative terms scaled by revenues, i.e. emissions intensity (see also Bolton and Kacperczyk (2021b) for a discussion on this). Cutting the level of emissions is clearly what matters from a societal perspective to transition to a low-carbon economy and so it is evident that firms with high levels of current emissions are likely to be more vulnerable. GHG emissions in levels are also more straightforward in distinguishing high-carbon firms and sectors and arguably less prone than emission intensities to window-dressing or being conflated with cost-efficiency issues. However, emissions intensity, as emphasized in recent debates (Aswani, Raghunandan, and Rajgopal, 2023a; Bolton and Kacperczyk, 2023a; Aswani, Raghunandan, and Rajgopal, 2023b), may offer insights into firm-level carbon efficiency and competitiveness under transitioning policy regimes. To balance these perspectives, we analyze both measures throughout our study, acknowledging their respective strengths and limitations.

Since past GHG emissions may be either disclosed or inferred by third-party data providers, we also compile a dedicated dummy variable indicating whether Scope 1, 2, and/or 3 GHG emissions, whether in absolute or relative terms, are self-disclosed (see also Busch, Johnson, and Pioch (2020) and Kalesnik, Wilkens, and Zink (2020) regarding consistency of disclosed and inferred emissions). We classify a firm as disclosing if any of the three Scope emissions are self-reported, though in the most recent data the vast majority, i.e. over 80%, of disclosing firms disclose all three Scopes. Finally, we construct a variable capturing realised year-on-year changes in direct, Scope 1 emissions in both absolute and relative terms.[8] This provides a gauge on whether the emissions trajectory of a firm has been moving in the right direction in the past and may also give a signal of the firm's commitment and ability to continue reducing emissions in the future.

The forward-looking transition metrics focus on firms' commitments to reduce emissions.

[8] This variable is most meaningful for firms that consistently disclose emissions in consecutive years and is subject to greater measurement challenges for firms for which it can only be computed by relying on inferred emissions (see Busch, Johnson, and Pioch (2020) and Kalesnik, Wilkens, and Zink (2020)).

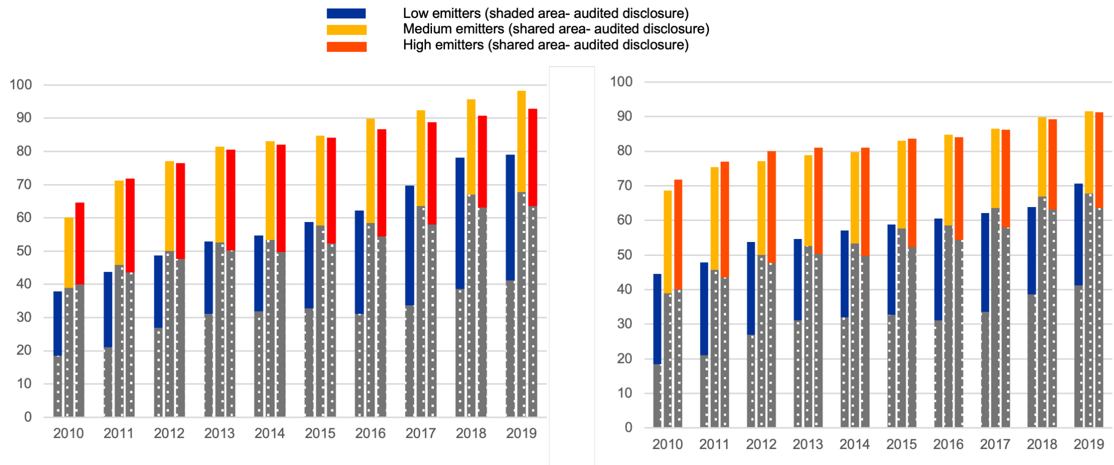
A dedicated dummy variable indicates whether the firm reports an emission reduction target or not. Two further variables consider the ambitiousness of commitments in quantitative terms: the percentage by which the firm commits to reduce GHG emissions and the number of years by which the firm commits to reduce emissions. Given the emerging state of forward-looking information, the latter two variables are available only for the time period starting 2015. Finally, given the limitations regarding the quality and availability of such data, we collect this type of data from two alternative data sources: Refinitiv and the Carbon Disclosure Project (CDP) data retrieved from Bloomberg. By comparison with Refinitiv data, the CDP data provides additionally the base year to which the emission reduction target refers and the absolute level of emissions in the base year against which the target is set, allowing us to construct the targeted absolute emission reduction and the implied targeted average annual absolute emission reduction.

We also employ two dummy variables proxying the validation of the reliability of emissions reduction targets and of emissions figures: SBTi and audit. A science-based target indicates whether the self-disclosed target is aligned with the Paris Agreement 2050-temperature goal. Where firms disclose emissions and emission reduction targets, this disclosure is typically included in the non-financial statement. While the auditing of non-financial statements is not mandatory, firms may ask an auditor to assure their quality, including the climate-related information. Auditing increases the likelihood that emissions reported in non-financial statements are verified, but does not necessarily imply that this is the case.

Figure 1 shows that the share of firms disclosing data on GHG emissions and committing to emission reduction targets has increased over time. But despite having similar trends, the firm-level correlation between the two variables is only 47% , clearly making them of independent interest. The chart also shows that a large fraction of disclosures are audited and that high emitters consistently disclose the most. The latter is in line with the observation of Marquis, Toffel, and Zhou (2016) that more environmentally-damaging firms who are exposed to greater scrutiny choose to disclose more climate-related information.

Figure 1: Disclosure of GHG emissions and commitment

Notes: Left panel: Disclosure of GHG emissions by emitters class. Y-axis: Percentage of firms in each emitters class disclosing GHG emissions out of a sample of 728 non-financial firms. X-axis: Time in years. Right panel: Disclosure of GHG emission reduction targets by emitters class. Y-axis: Percentage of firms in each emitters class disclosing emission reduction commitment out of a sample of 728 non-financial firms. X-axis: Time in years. Firms are classified as high, medium, or low emitters based on the terciles of the distribution of firm-level aggregate Scope 1, 2 and 3 in 2010. Sources: Urgentem, Refinitiv, and authors' calculations.

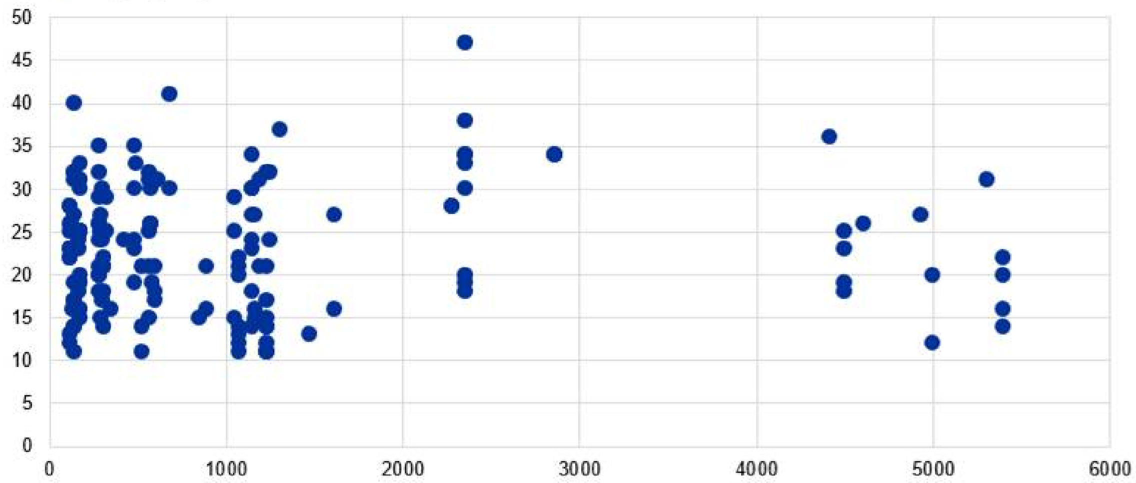


In addition to the assumption establishing the link between GHG emissions/intensities and firms' backward-looking exposure to transition risk, we use the forward-looking variables as proxies of firms' management of such risk. The disclosure variable, albeit being backward-looking, plays a dual role. On one hand, it provides evidence of firms' commitment on being transparent concerning their transition risk exposure. It also serves a signalling role, when considered vis-a-vis non-disclosing peers, whereby firms engaging in this practice convey the image of being more aware of the risks inherent with the transition to a greener economy. As discussed in the introduction, the existing caveats on environmental scores lead us to not include these variables in our baseline analysis.

Climate-related risks include transition risk and physical risk. These two types of risks are different in nature and are likely to affect a firm's credit risk through very different transmission channels. At the same time, if a firm's physical risk is correlated with its transition risk, it would be important to control for physical risk in an empirical analysis of transition risk. Figure 2 shows that this is not the case for European firms. A similar finding is documented by S&P Global, Trucost ESG analysis (2019) for US firms, who additionally note that variation in climate risk exposures for physical versus transition risk does not show any clear sectoral patterns. For example, the majority of S&P500 utility sector firms have high transition risk but significantly variable physical risk dependent on the location of their operations. In view of this, we focus only on climate-related transition risks in this paper, while recognising that the link between physical risk and credit risk is an important topic for future research.

Figure 2: Relation of firm-level physical risk to transition risk for European firms

Notes: Y-axis: Firm-level physical risk score provided by 427 for the year 2018. X-axis: Firm-level transition risk metric proxied by scope 1, 2, and 3 GHG emissions in tons of eCO2 relative to revenues provided by Urgentem for the year 2018. Data source: 427 and Urgentem from Alogoskoufis, Dunz, Emambakhsh, Hennig, Kaijser, Kouratzoglou, Muñoz, Parisi, and Salleo (2021)



2.3 Controls

Firm-level financial variables and macroeconomic variables are included as controls for credit risk, with the latter group being implemented only for specifications run on distance-to-default (see Table 17 in the Appendix). We select the firm financial variables considering prior literature on credit ratings (Baghai, Servaes, and Tamayo, 2014; Doumpos, Niklis, Zopounidis, and Andriosopoulos, 2015; Jones, Johnstone, and Wilson, 2015) and market practices of credit rating agencies. These variables include: profitability proxied by return on equity; firm size proxied by book total assets; leverage proxied by the ratio between the sum of short-term and long-term debt and EBITDA; debt service capacity proxied by the ratio between EBIT and interest expenses; solvency proxied by the ratio between PPE and total assets, and governance score. As profitability should reduce default risk, we expect a negative sign between profitability and credit risk. The larger the firm, the better its ability to ensure debt repayment in normal as well as adverse economic circumstances. More leveraged firms are typically associated with higher credit risk, whereas higher debt service capacity is associated with lower credit risk. The more solvent the firm, the lower should be its credit risk. A firm's governance score, which is provided by Refinitiv on a 0 to 100 scale at sectoral level, yields a relative ranking of firms operating in the same economic sector where an higher score corresponds to better managed firms. This variable is particularly relevant for our analysis, as better management may well be correlated with better environmental practices and higher awareness towards transition risk. We also collect data on the economic sector and the country of main activity of the firm, considering the country of registration and the country of incorporation. Moreover, we include a control variable that captures whether a firm was a constituent of the S&P 500 or STOXX Europe 600 indices during a given year. Finally, several control variables that proxy for the state of the economy on the macroeconomic level are included in the setup of the analysis on the market-implied distance-to-default. These variables are market return, return on oil spot price, inflation change, industrial production, return on gold, rates of treasury bills and implied market volatility. Summary statistics on ratings, GHG emissions-related variables and firm-level financial variables are provided in Table 18.

3 Hypotheses and empirical specifications

We test three hypotheses to explore how the climate-related metrics discussed in Section 2 influence our measures of firm credit risk. First, we note that uncertainties surrounding the timing and speed of the transition to a low-carbon economy, government policy, technological change and market sentiment can represent a source of transition risk for firms with high current GHG emissions. If these drivers significantly increase the costs of a firm with high emissions and reduce its ability to repay and service its debt, they may increase its probability of default. We also hypothesize distinct effects for European and US firms, given Europe's steadier course on climate-related regulatory policies over time relative to the US. For this reason, we investigate whether:

H1. There is a positive relationship between a firm's exposure to transition risk, as proxied by GHG emissions, and its credit risk.

Data on GHG emissions are either disclosed by firms or inferred by data providers using proprietary methods. Listed firms are often required to disclose on environmental matters, but they can choose which standards to adopt and which information to disclose, thus potentially engaging in selective disclosure. Where firms do not disclose, GHG emissions are inferred by special-purpose data providers, although these data may be significantly less effective than firm self-reported data (Kalesnik, Wilkens, and Zink, 2020).

Against this background, we investigate the effect of disclosure on credit risk. Reporting environmental information can be perceived by rating agencies and market participants as a positive effort of the firm to convey its exposure to transition risk (see e.g. Eliwa, Aboud, and Saleh (2019) for firms' ESG practices). Furthermore, higher level of disclosure is linked to lower information asymmetry between markets, rating agencies and firms, and hence lowers credit risk. In this context, we test the following hypothesis:

H2. The interaction between firms' GHG emissions and its decision to disclose GHG emissions has a significant impact on credit risk estimates.

Reporting a forward-looking emissions reduction target can convey not only that a firm is aware of the transition risk to which it is exposed, but also that it has an active plan to manage this risk. As climate policies and their tightness are time-varying, setting a clear target to reduce the environmental footprint of a firm, can have a strong effect in minimizing the variance of the expected costs the firm will incur and thereby its riskiness. We therefore set-out to test whether:

H3. There is a negative relationship between firm's management of transition risk, as proxied by GHG emission reduction targets and actual GHG emission reduction, and credit risk estimates.

Finally, for each of the three hypotheses, we add an additional dimension in our tests by addressing the role played by country-level heterogeneity in climate policies. As this dimensions is ultimately driving whether firm level transition risk will have material consequences, we test our hypotheses separately for the European and US subsamples.

Our empirical strategy consists of two approaches: difference-in-differences and panel regressions. First, a difference-in-differences analysis identifies potential causal relationship between a firm's exposure to transition risk and credit ratings by employing the 2015 Paris agreement as a shock and further exploring potential differences between European and US firms. A dynamic difference-in-differences investigates the causal impact of the self-reporting of an emissions reduction target and disclosing emissions on ratings. Then, a panel regression examines how the relationship between firm transition and credit risks is affected by firms' disclosure of environmental variables and adoption of targets. The latter analysis is applied to the two different credit risk measures: credit ratings and distance-to-default. The next subsections describe in detail the empirical specifications.

3.1 Panel regressions

Depending on the hypothesis, we employ three specifications for each measure of firm credit risk, with the same set of controls, but with different metrics of transition risk: (i) current GHG intensities and GHG emissions, (ii) as (i) but including the disclosure dummy and its interactions with emissions metrics, (iii) as (ii) but also including year-on-year change in GHG emissions, a dummy indicating the existence of a forward-looking commitment, and the ambitiousness of this commitment.

In the first hypothesis, we analyse the direction and significance of the relationship between the firm credit risk measures, and Scope 1, 2 and 3 GHG intensities or emissions, which proxy its current exposure to transition risk. The model is summarised in Equation 3. The dependent variable is the measure of firm credit risk, either the rating or the distance-to-default. $Scope1_{i,t}$, $Scope2_{i,t}$ and $Scope3_{i,t}$ are the corresponding GHG intensities/emissions. The $Controls_{j,i,t}$ vector includes the variables described in the section 2.3 and is common throughout the different specifications. Finally, we account for unobserved variation at sectoral, time and country level through fixed-effects.

$$\begin{aligned} CreditRisk_{i,t} =& \alpha + \beta_1 Scope1_{i,t} + \beta_2 Scope2_{i,t} + \beta_3 Scope3_{i,t} + \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \\ & \rho SectorFE_i + \tau TimeFE_t + \sigma CountryFE_i + \epsilon_{i,t} \end{aligned} \tag{3}$$

To test the second hypothesis, we introduce a dummy variable $DiscloseGHG_{i,t}$ for disclosure of GHG emissions, as described in 2.2. The model is summarised in Equation 4. The coefficient of interest is the interaction term of the dummy and the level of GHG intensities/emissions. The coefficient on the disclosure dummy itself is also relevant, as it shows how the act of disclosing GHG emissions affects the relationship between transition risk and credit risk.

$$\begin{aligned} CreditRisk_{i,t} = &\alpha + \beta_0 DiscloseGHG_{i,t} + \beta_1 Scope1 + \beta_2 Scope2_{i,t} + \beta_3 Scope3_{i,t} + \\ &\beta_4 DiscloseGHG_{i,t} \times Scope1_{i,t} + \beta_5 DiscloseGHG_{i,t} \times Scope2_{i,t} + \\ &\beta_6 DiscloseGHG_{i,t} \times Scope3_{i,t} + \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \rho SectorFE_i + \\ &\tau TimeFE_t + \sigma CountryFE_i + \epsilon_{i,t} \end{aligned} \tag{4}$$

Finally, for the third hypothesis, we augment the model specification by adding the past year-on-year change in Scope 1 intensities/emissions, $DisclosedLevelChange_{i,t} = (Scope1_{i,t} - Scope1_{i,t-1})$, and any information on the forward-looking emission reduction target of a firm, as described in Equation 5. The vector of variables $Target$ has two different specifications, that we test separately: (i) a dummy variable for disclosure of a target $DiscloseCommit_{i,t}$ and (ii) quantitative information reflecting its ambitiousness, i.e. the targeted percentage of emission reduction $TargetPerc_{i,t}$ and the targeted year $TargetYear_{i,t}$. While the dummy variable is well-populated in our dataset, the quantitative information is available only starting 2015.

$$\begin{aligned} CreditRisk_{i,t} = &\alpha + \beta_0 DiscloseGHG_{i,t} + \beta_1 Scope1 + \beta_2 Scope2_{i,t} + \beta_3 Scope3_{i,t} + \\ &\beta_4 DiscloseGHG_{i,t} \times Scope1_{i,t} + \beta_5 DiscloseGHG_{i,t} \times Scope2_{i,t} + \\ &\beta_6 DiscloseGHG_{i,t} \times Scope3_{i,t} + \beta_7 DisclosedLevelChange_{i,t} + \\ &\Sigma_{k=1}^{N} \psi_k Target_{k,i,t} + \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \\ &\rho SectorFE_i + \tau TimeFE_t + \sigma CountryFE_i + \epsilon_{i,t} \end{aligned} \tag{5}$$

Within this empirical setup, we attempt to tackle potential endogeneity concerns. In particular, alongside standard firm-level controls for credit risk, the design of our panel regressions considers governance as a control variable as this may clearly be a common factor which explains both credit risk and climate-related disclosures and commitments. The inclusion of country fixed-effects allows us to control for country-level differences concerning climate disclosure policies. Finally, when ratings are the dependent variable, we lead the variable by three months to capture rating adjustments performed following the publication of firms' annual reports, while for the market-based distance-to-default credit metrics, we assume that the markets are efficiently reflecting the relevant disclosures at the time of their publication. Hence, we are deferring the information contained in the annual reports to the end of the month following the publication date, while for the climate information and forward-looking commitments collated by external climate data providers, we lag the data by 6 months, which in our view conservatively approximates the publication lag of this relevant data group, too. In various robustness exercises, which are discussed in Appendix C we also repeat the analysis on a sample excluding high-emitters and use firm fixed-effects as opposed to sector and country ones.

3.2 Static difference-in-differences approach

A firm's exposure to climate-related transition risk depends on the environmental performance of the firm, but also on government policy as an acknowledged risk driver for the climate-related transition (BCBS, 2021). Employing a quasi-experimental research design, we exploit the Paris Agreement as a shock that increases the climate-related regulatory risk faced by firms without changing their environmental profiles - drawing inspiration from a broader literature that has leveraged the Paris Agreement as an exogenous shock in other context (Ginglinger and Moreau, 2019; Ilhan, Sautner, and Vilkov, 2021; Seltzer, Starks, and Zhu, 2022). The Paris Agreement represents an exogenous event that likely influenced the assessment frameworks of credit rating agencies, contributing to the more systematic integration of environmental and climate risks into their evaluations. In May 2016 both Moody's and S&P signed the PRI "Statement on ESG in Credit Risk and Ratings" committing to a systematic and transparent consideration of climate change and ESG factors more broadly in the assessment of creditworthiness[9]. In June 2016, Moody's announced its intention to analyse carbon transition risk based on emissions reduction scenarios that are consistent with the Paris Agreement. This commitment was outlined in the report "Moody's To Analyse Carbon Transition Risk Based On Emissions Reduction Scenario Consistent with Paris Agreement" (Moody's Investors Service, 2016), reflecting the increasing emphasis on climate risks within credit analysis. While S&P Global Ratings released in October 2015 the report "How Environmental And Climate Risks Factor Into Global Corporate Ratings" showing ex-post on whether and how in past ratings decisions these risks have been factored in, it was following the Paris Agreement (December 2015) and the PRI statement signature (May 2016) that a shift towards incorporating climate risks and opportunities in a more systematic and transparent way into credit rating methodologies - as can be seen in the S&P's reports from 2017 ("How Does S&P Global Ratings Incorporate Environmental, Social, And Governance Risks Into Its Ratings Analysis" and "How Environmental And Climate Risks And Opportunities Factor Into Global Corporate Ratings – An Update").

After this event, some political developments in the period 2016-2019 may have altered the perceived credibility of the US government commitment to the Paris Agreement: the election of Donald Trump in November 2016, his administration's announcement in June 2017 of the intention to withdraw from the agreement, and the formal withdrawal filing in November 2019 cast uncertainty over the long-term enforcement of US climate policies. In contrast, European countries maintained consistent regulatory efforts, such as the EU Emissions Trading System, providing a stable policy framework for emissions reduction. These contrasting trajectories may have influenced how the transition risks of firms in the two regions were perceived by credit rating agencies. Recognising these differences, we run a difference-in-differences regression to test the relationship between credit ratings and measures of GHG emissions or intensities, around the date of the Paris Agreement, for European countries and for the US separately. Finally, the Paris Agreement has been widely used as shock for identification purposes in the literature on the pricing of climate risk (Bolton and Kacperczyk, 2021a; Ilhan, Sautner, and Vilkov, 2021; Capasso, Gianfrate, and Spinelli, 2020; Seltzer, Starks, and Zhu, 2022).

[9] The PRI publication "Shifting Perceptions: ESG, Credit Risk and Ratings - Part 1: The State of Play" (2017) gives a complete overview of the timeline of the PRI-launched initiative on credit ratings : https://www.unpri.org/download?ac=256

We start by comparing changes in credit ratings for high polluting firms operating in Europe versus other European firms, both before and after the Paris Agreement, as described in Equation 6. Second, we compare changes in credit ratings for high polluting firms operating in Europe versus other European firms and versus US firms, as described in Equation 7.

$$
\begin{aligned}
CreditRating_{i,t} = & \alpha + \beta_0 Treatment_i \times postParis_t + \\
& \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \rho FirmFE_i + \tau TimeFE_t + \epsilon_{i,t}
\end{aligned}
\tag{6}
$$

The indicator variable *Treatment* is defined for each firm i and has three different specifications: (i) top GHG NACE; (ii) top GHG intensity; (iii) top GHG level. The treatment top GHG NACE (corresponding to dummy variable *TopGHGNACE*) refers to firms in the top polluting economic activities in terms of carbon dioxide and methane emissions, based on data we collect from Eurostat for the period 2010-2019 (dummy variables *TopCO2NACE* and *TopCH4NACE*). The treatment top GHG intensity (corresponding to dummy variable *TopGHGintensity*) refers to firms with values of GHG emissions intensity (Scope 1[10]) in the top quartile of the distribution of GHG emissions intensity. The treatment top GHG level (corresponding to dummy variable *TopGHGlevel* refers to firms with values of GHG emissions levels (Scope 1) in the top quartile of the distribution of GHG emissions levels. The 75th percentile for determining the quartile is set based on the values as of end-2014. We include the set of controls, described in the section 2.3, firm and time fixed-effects and, for European firms, the EU ETS carbon price to account for the EU carbon market.

In addition, we separately investigate whether credit rating agencies assess firms in European countries differently by comparison with firms in the US. European countries have a low-carbon transition policy including the EU ETS carbon market since 2005, whereas the US do not have a low-carbon transition policy. We do this by employing a triple difference-in-differences specification, which includes the dummy *TransitionPolicy*, equal

[10]By comparison with Scope 2 and Scope 3 GHG emissions, Scope 1 GHG emissions are the ones with the highest degree of data availability and credibility to market participants. The quality of data for firm-level Scope 1 GHG emissions benefits from the data that firms have to mandatory report since 2009 to the Environmental Protection Agency (EPA) for selected facilities in the US and to the EU Transaction Log under the EU ETS for selected installations since 2005. We consider Scope 1 in line with the panel regression results where we test the relationship between credit risk and GHG-emissions-variables.

to 1 for European countries, as described in Equation 7.

$$
\begin{aligned}
CreditRating_{i,t} = &\alpha + \beta_0 Treatment_i \times TransitionPolicy_i \times postParis_t + \\
&\beta_1 Treatment_i \times postParis_t + \\
&\beta_2 TransitionPolicy_i \times postParis_t + \\
&\Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \rho FirmFE_i + \tau TimeFE_t + \epsilon_{i,t}
\end{aligned}
\tag{7}
$$

3.3 Dynamic difference-in-differences approach

While the Paris agreement represents an exogenous variation in governments' preferences concerning climate risks that affects all firms in the same period, the act of reporting forward-looking climate commitments and disclosing emissions is, by nature, staggered in time across firms. Testing for a causal effect of these metrics on credit ratings via the standard two-way fixed effects estimator could yield biased results if heterogeneity in outcomes conditional on treatment status occurs across firms or time. As it is conceivable that a firm reporting an emissions reduction target or disclosing its emissions prior to the Paris agreement might have been assessed differently to a firm committing in times of heightened societal attention to climate risks, we opt to rely on the heterogeneity robust estimator of De Chaisemartin and d'Haultfoeuille (2020). The estimator is unbiased under a setting where dynamic effects can be ruled out, which is the case in our dataset as we solely consider the impact of the two binary variables indicating whether

- A firm has reported an emissions reduction target in a given year.
- A firm discloses any of the three scopes of GHG emissions in a given year.

The two variables also have the feature of being absorbing treatments in the difference-in-differences setting, meaning that firms do not backtrack once they engage in either of the behaviours. Given the above, the dynamic estimator can be interpreted as the change in credit ratings that firms experience in the year when they switch from not disclosing emissions or setting an emissions reduction target to doing so, relative to the set of firms that keep their non-reporting status in the same adjacent years.

In order to interpret our estimates as causal we address the canonical difference-in-differences assumptions. In our setup, a clear concern is the endogeneity between firms' decisions along the two dimensions that we consider and credit rating agencies' assessments, which would imply that non anticipation of treatment does not hold. Given we are imposing a strict lag structure between the disclosure of environmental metrics and the subsequent rating action, we view non-anticipation as holding. Parallel trends, albeit fundamentally untestable, can be inspected by computing placebo estimators of the difference in credit ratings for our treatment and control group of firms in years prior to emissions disclosure and commitments. As the estimator of De Chaisemartin and d'Haultfoeuille (2020) compares outcomes only for firms that switch their treatment status in a given time period, this restricts the number of observations we are able to use in the regressions. However, it is precisely this fundamental theoretical insight that guarantees the unbiasedness of the estimator. The first definition of treatment we consider is the dummy variable of reporting of an emission reduction target, as it is well populated both before and post Paris agreement. On the disclosure treatment, we employ the constructed disclosure dummy described in section 2. The effects are estimated at individual firm level, and hence groups are defined accordingly. We thus estimate

$$DiD_M = \sum_{t=2}^{T} \frac{N_{1,0,t}}{N_s} DiD_{+,t} \tag{8}$$

which corresponds to a weighted average of the time t average change in rating for the firms that move from not reporting to reporting an emissions reduction target and from not disclosing emissions to disclosing emissions. Individual $DiD_{+,t}$ are estimated through standard OLS, where the first-difference in credit ratings is regressed on the first-difference of either of the treatments and firm, time fixed-effects. For robustness, we follow De Chaisemartin and d'Haultfoeuille (2024) and conduct estimations where the dependent variable is replaced with the residuals of regressing the first-difference of ratings on the first-difference of the same firm-level controls we use in our panel regressions and time fixed-effects. This approach allows to deal with potential heterogeneity in firm-level credit ratings' dynamics provided that the determinants of credit risk we employ as controls are significant, which is confirmed in our sample and follows the literature described in section 2.3.

4 Results of regression analysis

Given the categorical nature of credit ratings, we employ both standard ordinary least square and ordered logit estimators, in line with Baghai, Servaes, and Tamayo (2014)[11], controlling for time, sector and country fixed-effects. To assess the overall impact of both backward- and forward-looking metrics on ratings we also compute the average marginal effects stemming from the logistic regression.

Table 3: Panel regression for credit ratings and emissions, Testing H1 from 2010-2019, for European- and US-domiciled firms

Notes: The table presents the results of the panel regression relevant for H1, where the relationship between GHG emissions (expressed in intensity and levels) and credit ratings is tested from 2010 to 2019. The full sample of European and US firms is used here. We use both OLS (Models 1 and 3) and ordered logit estimators (Models 2 and 4). Firm-level clustered standard errors are in parentheses. Statistical significance is indicated by *** for p<0.01, ** for p<0.05, and * for p<0.10.

Variable	**(1 - int., OLS)**	**(2 - int., logit)**	**(3 - levels, OLS)**	**(4 - levels, logit)**
Scope 1 GHG intensity	-270***	-228***		
	(81.6)	(75.3)		
Scope 2 GHG intensity	87.1**	71.0**		
	(34.5)	(31.7)		
Scope 3 GHG intensity	16.4	21.8		
	(48.7)	(55.6)		
Scope 1 GHG level			-0.017***	-0.016***
			(0.0044)	(0.0044)
Scope 2 GHG level			-0.00080	0.0013
			(0.019)	(0.017)
Scope 3 GHG level			0.0027**	0.0024*
			(0.0013)	(0.0013)
Governance	0.0065**	0.0046	0.0064**	0.0045
	(0.0033)	(0.0030)	(0.0032)	(0.0030)
Constant	11.5***		11.4***	
	(0.29)		(0.29)	
Controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	5,058	5,058	5,058	5,058
R-squared	0.431	0.1697	0.432	0.1698

First, we test the relationship between firms' exposure to transition risk and their credit rating using Equation 3. We present the results in Table 3 for the full sample of US and European firms. Results suggest an overall negative relationship between GHG emissions, intensities and credit ratings, with more carbon intensive firms having on average lower ratings. Specifically, higher Scope 1 and 3 emissions, and Scope 1 and 2 intensity are

[11]The ordered logit estimator is more suitable for categorical variables, as it does not assume that moving, for example, from BB to BBB is equivalent to moving from AA to AAA. We also report the results obtained using OLS estimators since some of our specifications employ firm fixed-effects, which could lead to biased and inconsistent point estimates with ordered response models.

associated with worse ratings. We also find an higher governance score to be associated with better credit ratings. Controlling for this effect is particularly relevant, as the quality of the management structure of a firm can influence its environmental practices and therefore its credit risk.

We test the second and third hypotheses separately for European and US firms. To facilitate readability, we defer the regression tables for US firms in Appendix B, whilst discussing main differences in the two samples throughout this section. On our second hypothesis, we present results for the specification in Equation 4 in Table 4. We find strong evidence of the relevance of the act of self-disclosing GHG intensities, which is confirmed also for US firms. Firms disclosing such information report better credit ratings than their non-disclosing peers, as reflected in the coefficients on the dummy variable in the first row of the table. In addition to the standalone effect of being a disclosing firm, we find a significant difference in how GHG emissions/intensities are associated with ratings, depending on whether emissions are self-reported or inferred by third-party data providers. In particular, for European firms, Scope 1 levels and intensities are found to be significantly associated with lower ratings irrespective of interaction with disclosure. For Scope 1 intensities, we find a similar result when employing OLS estimation but not logit. For US firms, as visible in table 19, only disclosed Scope 1 metrics are reflected in ratings. This difference might be indicative of the greater access to environmental data within European countries, limiting the needed to rely on third party inferred data.

As discussed later in this section, there is a trade-off between the benefit coming from the act of disclosing emissions and the negative impact that the level of disclosed emissions and intensities has on credit ratings. The net effect of these two factors depends crucially on the scale of carbon emissions/intensities. Still, it is clear that disclosure has a significant bearing on credit ratings and our results appear to confirm the effect of this variable similarly to what has been documented by Bolton and Kacperczyk (2021c).

Table 4: Panel regression for credit ratings and emissions for European firms, Testing H2 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H2, see Equation 4, where the relationship between disclosure, its interaction with GHG emissions and credit ratings is tested for the full data sample covering the period from 2010 to 2019. Model 1 shows the OLS results considering GHG emission intensity, while model 2 shows the corresponding ordered logit results. Model 3 shows the OLS results considering GHG emission level, while model 4 shows the ordered logit results. Non-interacted terms form intensities and levels are included in the estimation but not reported. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	(1 - int., OLS)	(2 - int., logit)	(3 - levels, OLS)	(4 - levels, logit)
DiscloseGHG dummy	0.54***	0.67***	0.60***	0.66***
	(0.20)	(0.21)	(0.22)	(0.21)
DiscloseGHG x Scope 1 GHG intensity	-235*	-316**		
	(126)	(132)		
DiscloseGHG x Scope 2 GHG intensity	1,032	1,034		
	(696)	(740)		
DiscloseGHG x Scope 3 GHG intensity	75.5	8.31		
	(166)	(163)		
DiscloseGHG x Scope 1 GHG level			-0.0050	-0.0045
			(0.0050)	(0.0055)
DiscloseGHG x Scope 2 GHG level			0.089	0.060
			(0.054)	(0.057)
DiscloseGHG x Scope 3 GHG level			-0.0031	-0.0030
			(0.0020)	(0.0025)
Scope 1 GHG intensity	-283**	-203		
	(140)	(144)		
Scope 2 GHG intensity	-835	-836		
	(689)	(737)		
Scope 3 GHG intensity	-81.9	-7.59		
	(161)	(154)		
Scope 1 level			-0.015***	-0.018***
			(0.0048)	(0.0062)
Scope 2 level			-0.081	-0.062
			(0.056)	(0.061)
Scope 3 level			0.0062**	0.0070**
			(0.0024)	(0.0035)
Governance	0.0053	0.0044	0.0060	0.0053
	(0.0050)	(0.0051)	(0.0050)	(0.0052)
Constant	10.9***		10.7***	
	(0.49)		(0.50)	
Firm-level controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	2,106	2,106	2,106	2,106
R-squared	0.518	0.18	0.517	0.18

The third hypothesis, which we test via the specifications in Equation 5, relates to the potentially moderating impact of transition risk management on the negative relationship between carbon emissions/intensities and credit risk. Table 5 presents the results for past year-on-year changes in (disclosed) emission levels/intensities and the forward-looking commitment dummy. Table 6 presents the results for variables speaking to the ambitiousness of commitments in quantitative terms in place of the forward-looking commitment dummy, on the more restricted sample for which we have the necessary data. Corresponding tables for US firms are in tables 20 and 21.

Table 5: Panel regression for credit ratings and emissions for European firms, Testing H3 (binary reduction target measure) from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see Equation 5, where the relationship between quantitative backward and qualitative forward-looking metrics (commitment to reduce emissions) and credit ratings is tested for the full data sample covering the period from 2010 to 2019. Model 1 shows the OLS results considering GHG emissions intensity, while model 2 shows the corresponding ordered logit results. Model 3 shows the OLS results considering GHG emissions level, while model 4 shows the ordered logit results. Non-interacted terms form intensities and levels are included in the estimation but not reported. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int., OLS)**	**(2 - int., logit)**	**(3 - levels, OLS)**	**(4 - levels, logit)**
DiscloseGHG dummy	0.42*	0.57**	0.49**	0.57**
	(0.22)	(0.24)	(0.23)	(0.23)
DiscloseGHG x Scope 1 GHG intensity	-208	-290*		
	(135)	(150)		
DiscloseGHG x Scope 2 GHG intensity	1,329	1,326		
	(1,041)	(1,105)		
DiscloseGHG x Scope 3 GHG intensity	95.6	34.0		
	(173)	(187)		
Disclosed intensity change	-0.076*	-0.084*		
	(0.045)	(0.047)		
DiscloseCommit dummy	0.71***	0.63***	0.73***	0.64***
	(0.22)	(0.22)	(0.22)	(0.21)
DiscloseGHG x Scope 1 GHG level -0.0043	-0.0046			
			(0.0049)	(0.0058)
DiscloseGHG x Scope 2 GHG level			0.013	-0.016
			(0.080)	(0.100)
DiscloseGHG x Scope 3 GHG level			0.00039	0.00083
			(0.0016)	(0.0017)
Disclosed level change			-0.00079	-0.019
			(0.035)	(0.038)
Governance	0.0053	0.0046	0.0061	0.0057
	(0.0051)	(0.0054)	(0.0052)	(0.0055)
Constant	11.3***		11.2***	
	(0.31)		(0.31)	
Firm-level controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	1,842	1,842	1,842	1,842
R-squared	0.449	0.1273	0.446	0.1272

In all specifications, the results indicate that committing to a forward-looking emission reduction target is clearly associated with better credit ratings in Europe, but not in the US, confirming the results of the dynamic DiD estimations.[12] The magnitude of this effect is comparable to that for the act of disclosure. In addition, although there appears to be no meaningful relationship between changes in emission levels and credit ratings, realized reductions in emission intensities are associated with better ratings in

[12]We also run an additional specification to account for a possible moderating effect of making a commitment on the adverse effect associated with high emissions. The main results are confirmed. Setting a forward-looking target remains associated with better credit ratings and the interacted terms (DiscloseCommit X Scope 1 GHG level and DiscloseCommit X Scope 1 GHG intensity, respectively) remain both negatively associated with credit ratings. The results suggest that disclosing a commitment may mitigate the exposure to transition risk that is proxied through emissions.

some specifications. For US firms, neither metric has a significant effect. Taken together, these results highlight how a range of transition risk management strategies enacted by European firms can help to offset the negative effect on credit ratings coming from exposure to high emissions levels and intensities.

Table 6: Panel regression for credit ratings and emissions for European firms, Testing H3 (quantitative reduction target measures) from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see (5), where the relationship between quantitative backward and, where available, quantitative forward-looking transition metrics and credit ratings. Model 1 and 2 show the OLS estimates considering GHG emissions intensity and quantitative forward-looking metrics from Refinitiv and from CDP, respectively. Model 3 and 4 show the OLS estimates considering GHG emissions level and quantitative forward-looking metrics from Refinitiv and from CDP, respectively. Ordered logit estimators lead to similar conclusions and are not reported here for brevity. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int., OLS)**	**(2 - int., OLS)**	**(3 - levels, OLS)**	**(4 - levels, OLS)**
Scope 1 GHG intensity	-511***	-630***		
	(102)	(155)		
Scope 2 GHG intensity	41.6	688		
	(929)	(859)		
Scope 3 GHG intensity	-59.4	-129		
	(125)	(78.5)		
Disclosed intensity change	531	1,819*		
	(831)	(1,029)		
Scope 1 GHG level			-0.021***	-0.022**
			(0.0046)	(0.0091)
Scope 2 GHG level			0.0018	-0.030
			(0.039)	(0.050)
Scope 3 GHG level			-0.0013	-0.00095
			(0.0032)	(0.0023)
Disclosed level change			-0.30	0.093
			(0.35)	(0.13)
TargetPerc Ref	0.014**		0.015***	
	(0.0057)		(0.0058)	
TargetYear Ref	0.0056		0.0044	
	(0.024)		(0.023)	
TargetPerc CDP		0.0072**		0.0072*
		(0.0036)		(0.0037)
TargetYear CDP		-0.00047		-0.000040
		(0.011)		(0.011)
TargetBaseYear CDP		-0.040**		-0.046**
		(0.019)		(0.021)
Firm-level controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	425	588	425	588
R-squared	0.561	0.647	0.558	0.638

We also find that, among the sample of firms that disclose quantitative targets and related timelines, credit ratings are strongly related to the ambitiousness of firms in terms of percentage of emissions to be cut. By contrast, the timing of the target is found to be not significant. This may indicate that the emission reduction target is considered as a better indicator than the timeline to assess the firm commitment towards the low-carbon transition. Within this reduced sample of environmentally aware firms, we do find similar significant results for US firms. However, this result may be driven by the sample selection, as the binary indicator of forward-looking commitments has no impact on ratings.

4.1 Economic significance

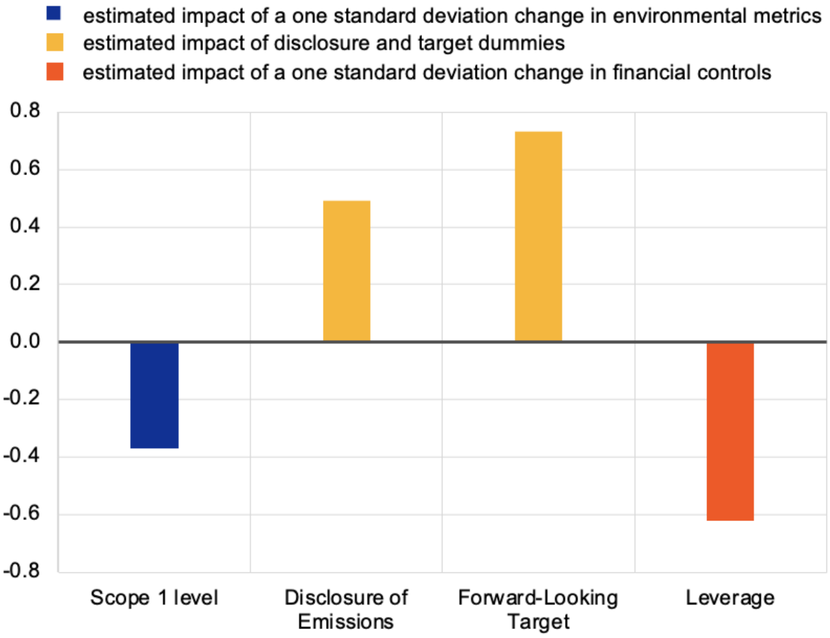
In this section, we compute the magnitude and economic significance of the effect of backward and forward-looking environmental metrics on credit ratings. Given the ordinal nature of our ratings variable, we follow two approaches. First, we compute the impact of a one standard-deviation change in continuous environmental metrics on credit rating notches and compare it with the corresponding impact from changes in leverage. We then consider two dummy variables on disclosure of GHG emissions and the commitment to a forward-looking emission reduction target, for which the impact is purely determined by the magnitude of the coefficient. The results are presented in Figure 3.

The impact of the level of Scope 1 is particularly economically significant, especially when one considers the kurtosis in the distribution of this variable. In particular, a one standard-deviation increase is associated with a reduction of circa 36% of a credit notch. By way of comparison, an equivalent increase in leverage decreases credit ratings by approximately 60% of a credit notch. The stand-alone effect of disclosing GHG intensities or making forward-looking commitments to reduce emissions is also material at around half and 70% of a credit notch respectively, and has the potential to partially offset the negative effect stemming from the level exposure to transition risk, especially for the average firm in the sample. It is important to highlight however that for highly carbon-intensive firms, such as those from the utilities sector, the effect from disclosed Scope 1 levels will be substantially larger than what computed in this exercise, out-weighting the decrease in credit risk yielded by the act of disclosing.

While the quantitative evidence resulting from the exercise based on OLS estimates has the merit of giving simple indications on the magnitude of the effects of different transition risk metrics´ on credit rating, we also compute in a more rigorous setting the average marginal effects of relevant transition risk variables. Following Alali, Anandarajan, and

Figure 3: Magnitude of transition risk metrics on credit ratings vis-a-vis leverage (European firms)

Notes: left-hand axis: percentage of a credit notch. The first column represents the estimated magnitude of a one standard-deviation increase in Scope 1 levels The second and third columns reflect the impact of the decision to disclose of GHG emissions and make a forward-looking commitment respectively. The fourth column shows the impact of a one standard-deviation increase in leverage. The coefficient on the disclosure dummy is significant at the $p<0.05$ level. Coefficients for Scope 1GHG levels, the emission reductions target dummy and leverage at the $p<0.001$ level. All coefficients are taken from the estimation presented in table 5.



Jiang (2012), we undertake some data transformation to facilitate the interpretation of the marginal effects. First, we standardize all continuous transition risk variables and controls used in equation 5. Second, we employ as the dependent variable a transformed binary version of credit ratings, taking the value of 1 for investment grade firms and 0 for high-yield ones. In this way, we are able to interpret the marginal effects as being the change in likelihood of being in the rating group associated with minimal-to-low credit risk (see Table 2) relative to the rating group associated with moderate-to-high credit risk. Results of both the ordered logistic regression and the corresponding average marginal effects are presented in Table 7.

Even with the additional data transformation steps, which increase the variation within the two broad rating groups, we obtain significant positive estimates for the disclosure and forward-looking commitment dummies. Turning to the average marginal effects, we find the act of disclosing GHG emissions increasing the likelihood of firms having lower credit risk by approximately 5%, i.e. the firm being investment-grade. The effect is comparable for firms making a forward-looking commitment related to emissions reduction, who are 4% more likely to have a better rating.

Table 7: Testing the economic significance of H3: ordered logit and average marginal effects (European firms)

Notes: The table shows the results of the ordered logit estimation and the corresponding marginal effects based on equation 5, while employing a binary dependent variable. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**Ordered Logit- Binary rating dependent variable**	**Average Marginal Effect**
Disclosure	0.45**	0.0545**
	(0.19)	
Disclose x Scope 1 GHG int.	-1.16***	-0.09***
	(0.94)	
Disclosed change in Scope 1 GHG int.	0.506	-0.00908
	(1.08)	
Disclose x Scope 3 GHG int.	0.37**	-0.0093
	(0.18)	
Forward-looking commitment	0.32*	0.039*
	(0.19)	
Time fixed-effects	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	4,441	4,441
R-squared	0.29	

5 Results on high emitters and transition policy

In this section, we present the results of the difference-in-differences analysis around the date of the Paris Agreement, as described in Section 3.2. First, we test the existence of a causal relationship between Scope 1, 2, and 3 GHG emissions and our selected measures of credit risk, as specified in Equation 3. The existence of such a relationship is suggested by the literature (Stellner, Klein, and Zwergel, 2015; Capasso, Gianfrate, and Spinelli, 2020; Seltzer, Starks, and Zhu, 2022) and the results of the panel regressions presented in Section 4. Second, we test the differences across jurisdictions (see also Appendix B)[13] and we find that Scope 1 GHG emissions and intensity, and Scope 3 GHG intensity are negatively associated with credit ratings for European firms, but not for US firms. Finally, we find that the EU ETS carbon price is negatively associated with credit ratings of European firms: a high carbon price is associated with worse credit ratings. The results suggest that a causal relationship between the low-carbon transition and credit ratings

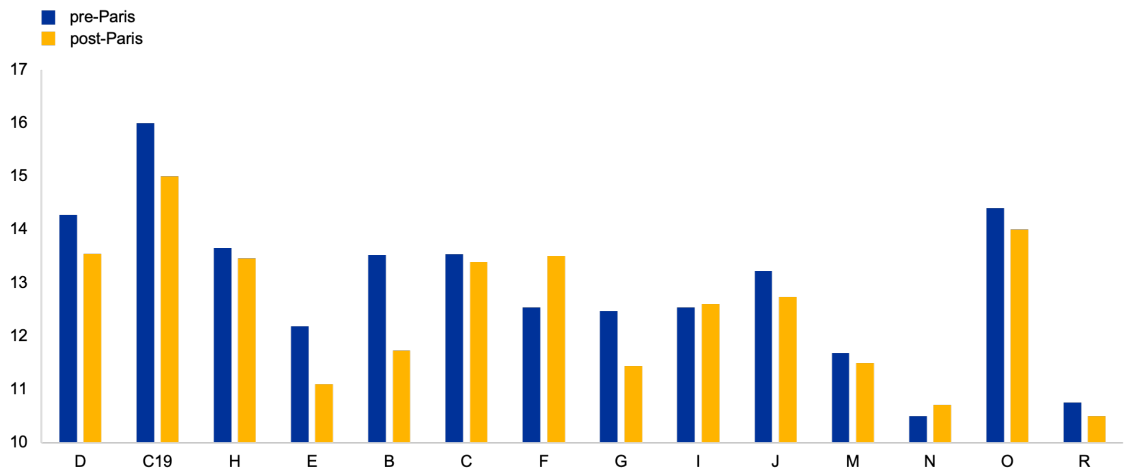
[13] The country of a firm is constructed based on its country of registration (retrieved from Orbis) and, where not available, country of incorporation (retrieved from Datastream) - see Appendix A for a comprehensive description of variables.

may exist for European firms, but not for US firms.

For the difference-in-differences analysis, we consider a balanced panel with the same firms observed throughout the whole period: before the event, ex-ante (2011, 2012, 2013, 2014), and during and after the event, ex-post (2015, 2016, 2017, 2018, 2019). This ensures consistency in the average rating dynamics of the treatment and control groups before and after the Paris Agreement. We focus first on the sample of European firms. We start with a descriptive analysis of changes in credit ratings for high polluting EU firms versus their peers, both before and after the Paris Agreement. Figures 4 and 5 show the average rating for each type of treatment[14] before and after the Paris Agreement.

Figure 4: Average rating of European firms before and after the Paris Agreement in 2015 by NACE1-sector.

Notes: The top polluting sectors, as per Eurostat data for carbon dioxide and methane for EU27+UK, are shown first: Electricity, gas, steam and air conditioning supply (D), Manufacturing (C – and in particular Manufacture of coke and refined petroleum products (C19)), Transportation and storage (H), Mining and quarrying (B), Water supply, sewerage, waste management and remediation activities (E). Y-axis: Alphanumeric rating grade following the mapping of the rating scale to ordinal values ranging from 1 to 21, such that a higher ordinal value indicates a better rating. X-axis: NACE1-sector. Sources: Eurostat, Orbis, ECB Ratings Database, and authors' calculations.

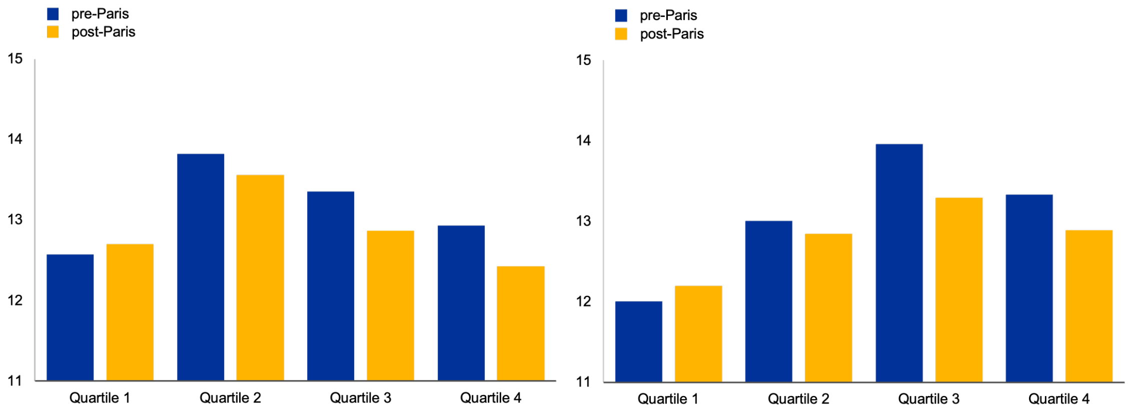


On average, ratings decreased for firms in the top polluting NACE economic activities: Electricity, gas, steam and air conditioning supply (D), Manufacture of coke and refined petroleum products (C19), and Mining and quarrying (B) (Figure 4). In addition, firms in the top quartile of GHG emissions intensity and firms in the top quartile of GHG emissions level had, on average, worse ratings after the Paris Agreement (Figure 5).

[14]The treatment takes three different specifications as defined in 3.2: (i) top GHG NACE – firms in the top polluting economic activities in terms of carbon dioxide and methane emissions, (ii) top GHG intensity – firms in the top quartile of the distribution of GHG emissions intensity, (iii) top GHG level – firms in the top quartile of the distribution of GHG emissions levels.

Figure 5: Average rating of European firms before and after the Paris Agreement in 2015 by firm-level GHG emission intensity (Panel A) and GHG emission level (Panel B).

Notes: Y-axis: Alphanumeric rating grade following the mapping of the rating scale to ordinal values ranging from 1 to 21, such that a higher ordinal value indicates a better rating. Panel A: X-axis: Quartile of GHG emission intensity. Panel B: X-axis: Quartile of GHG emission level. Sources: Eurostat, Orbis, ECB Ratings Database, and authors' calculations.



The results of the difference-in-differences regressions for the three types of treatment are shown in Table 8. The columns 1, 2, and 3 show the estimated coefficients for a basic difference-in-differences specification without controls and without fixed-effects. The columns 4, 5, 6 show the estimated coefficients as per Equation 6. The difference-in-differences estimates for the treatment top GHG NACE (*Top GHG NACE x post-Paris*) and for the treatment top GHG intensity (*Top GHG intensity x post-Paris*) are statistically significant with the treatment having a negative effect as indicated by the negative sign. These results hold both in the basic difference-in-differences specification as well as in the specification augmented with controls, firm and time fixed-effects. The difference-in-differences estimate for the treatment top GHG level (*Top GHG intensity x post-Paris*) is statistically insignificant in the basic difference-in-differences specification, but we do find an effect once we add the controls and the fixed-effects. Both point estimates are negative as expected. These results highlight that following the Paris agreement European firms active in the most polluting economic activities see their ratings fall by more than an additional half a notch relative to the control group. Similarly, following the Paris agreement, most GHG polluting European firms (based on Scope 1 GHG emissions in levels) see their ratings fall by an additional 0.42 notch relative to the control group. These results are indicative of a causal relationship between some transition risk metrics and credit ratings.[15]

The results are also robust to using a narrower event window. Our use of annual data motivates our choice to adopt a relatively wide window of 2011-2019 for our baseline specification. But a wide window can run the risk that changes in average ratings for the treatment and control groups are affected by long-term technological and industry trends. To confront this, we re-run the difference-in-difference exercise for the narrower 2013-2017 window. Our results still hold. For example, point estimates from regressions including controls and time and firm fixed effects for top GHG NACE, top GHG intensity, and top GHG level are -0.39, -0.30, and -0.32, respectively, with the first and third treatment being significant at the 5% level, and top GHG intensity being significant at the 10% level. In addition, the representation of the treatment effect for each year presented below also indicates that the observed effects persist within narrower windows.

Table 8: Difference-in-differences results for changes in credit ratings for European firms following the Paris Agreement in 2015

Notes: The table shows the result of the OLS regressions, testing the relationship between GHG pollution and credit ratings for the subsample of European firms. Models 1 and 4 consider as "treated" firms in the *Top GHG NACE* sectors without and with controls and firm and time fixed-effects, respectively. Models 2 and 3 consider as "treated" firms in the *Top GHG intensity* quartile and in *Top GHG level* quartile, respectively. In models 5 and 6 the later specification is augmented with controls and firm and time fixed-effects.*post-Paris* is the indicator variable taking the value 1 for years following and including 2015, and 0 otherwise. The period of the subsample is from 2011 to 2019. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Top GHG NACE x post-Paris	-0.82***			-0.59***		
	(0.20)			(0.17)		
Top GHG intensity x post-Paris		-0.27**			-0.37*	
		(0.11)			(0.20)	
Top GHG level x post-Paris			-0.31			-0.42**
			(0.21)			(0.18)
Top GHG NACE	0.99***					
	(0.38)					
Top GHG intensity		-0.48				
		(0.32)				
Top GHG level			0.17			
			(0.39)			
Controls	N	N	N	Y	Y	Y
Time fixed-effects	N	N	N	Y	Y	Y
Firm fixed-effects	N	N	N	Y	Y	Y
Observations	1,926	1,926	1,926	1,776	1,776	1,776
Number of firms	214	214	214	211	211	211
R-squared	0.028	0.003	0.012	0.084	0.078	0.080

[15] In addition, we test an alternative specification where we define the treatment group as firms with an economic activity on the EU carbon leakage list and receiving free allowances (dummy variable *EU ETS NACE*). We do not find this treatment specification to be statistically significant in our difference-in-differences setup.

The parallel trend assumption underlying the difference-in-differences design presumes that in the absence of treatment, the difference in rating between the "treated" and the "control" firms is constant over time. We examine the dynamics over time for the treatment specifications *TopGHGNACE*, *TopGHGintensity* and *TopGHGlevel* by estimating yearly coefficients for the treatment. To obtain an estimated coefficient of the treatment for each year, we run the regression for the treatment variable interacted with yearly dummies, instead of the indicator variable *post-Paris*, including all controls, as in the Equation 6. The yearly estimated coefficients are shown in Figure 6. For the treatment specification *TopGHGlevel*, the estimated coefficient for point 0, i.e. the calendar year 2015, is well below the estimates for the period prior to the Paris Agreement event and below 0. The estimates for the four years preceding the Paris Agreement are all close to 0 and above the levels of the estimates post event. The estimates for all the four years following the Paris Agreement remain consistently below 0. This provides strong evidence that the ratings changed post-event for the treated firms and that the parallel trend assumption likely holds for the treatment specification *TopGHGlevel*.

For the treatment specification *TopGHGNACE* and to some extent for *TopGHGintensity* the dynamics of the estimated coefficients in the pre-event period suggest a pre-trend. Malani and Reif (2015) explain that such pre-trends should not discard the analysis as these could be seen as policy anticipation effects that arise naturally out of many theoretical models. And in practice, there may have been some anticipation of the Paris Agreement goals in the preceding years.

Figure 6: Treatment effect for each year of the sample from 2011 to 2019

Notes: Panel A: Treatment corresponds to being a firm in a top polluting economic activity, *TopGHGNACE*. Panel B: Treatment corresponds to being a firm in the top quartile of GHG emissions intensity, *TopGHGintensity*. Panel C: Treatment corresponds to being a firm in the top quartile of GHG emissions level, *TopGHGlevel*. Y-axis: parameter estimate. X-axis: period of the sample where 0 indicates the year of the event, i.e. 2015. Sources: authors' calculations.

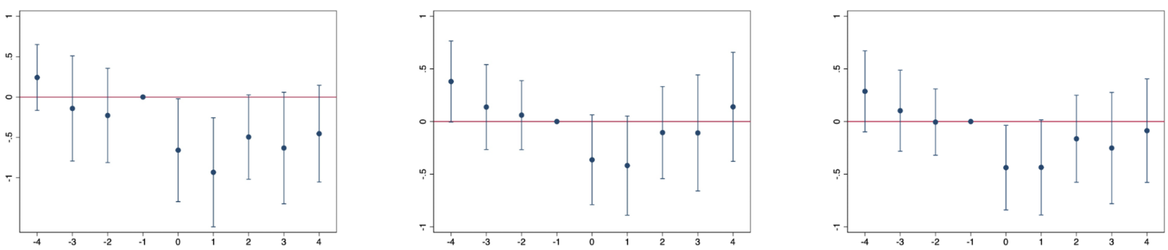
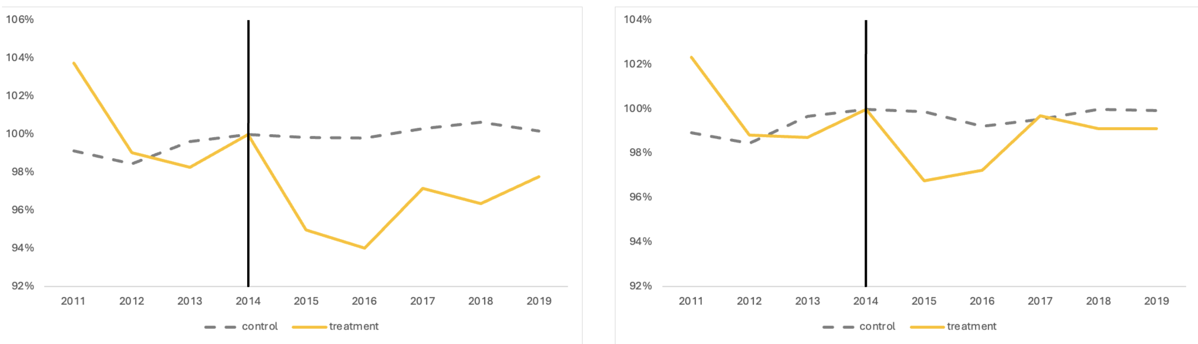


Figure 7 shows the rating dynamics of the treatment group relative to the control group over time for treatments *TopGHGNACE* and *TopGHGlevel*. In Figure 7, observations are scaled at 100 for the year 2014, preceding the event year, 2015. The average rating of "treated" firms (whether using a treatment defined based on *Top GHG NACE* or *Top GHG level*) in the years prior to the Paris Agreement was above the average rating of the "control" group. By contrast, following the Paris Agreement, the average rating of the "treated" firms decreases visibly and remains below the average rating of the "control" group throughout the post-event period. As for the "control" group, the average rating remains relatively stable post-event.

Figure 7: Dynamics of the treatment and control group over the time of the sample.

Notes: Panel A: Treatment corresponds to being a European firm in a top polluting economic activity, while the control group corresponds to European firms in non-top-polluting economic activities. Panel B: Treatment corresponds to being a European firm in the top quartile of polluting firms by GHG emissions level, while the control group corresponds to all other European firms. Y-axis: rating rescaled by the value observed for 2014. X-axis: period in years of the difference-in-differences sample. Sources: authors' calculations.



Overall, the results of this difference-in-differences analysis suggest a potential causal relationship between some metrics of exposure to transition risk and credit ratings for firms operating primarily in Europe. This finding provides support to our hypothesis 1 that high emissions of a firm may be associated with higher credit risk.

Next, we test whether credit rating agencies assess firms in countries with a low-carbon transition policy (European countries) differently from the one without (the US)[16]. For this purpose, we run a triple difference-in-differences analysis including an indicator variable differentiating on such countries. The results reported in Table 9 show a negative estimate for our main coefficients of interest *Treatment x Transition-policy x post-Paris*. Columns 1, 2, 3 show the estimated coefficients for a basic triple difference-in-differences

[16]The country of the firm is defined based on the country of registration retrieved from Orbis that is defined as the country where the firm is primarily conducting business. Where the country of registration is not available (limited number of cases), we use country of incorporation of the firm retrieved from Datastream.

specification while columns 4, 5, 6 − for a specification considering in addition firm-level controls and fixed-effects as per Equation 7. Treatment takes the values Top GHG NACE, Top GHG intensity, and Top GHG level. The sign of the estimate confirms that "treated" firms in European countries have experienced a worsening in credit ratings post-Paris relative to firms in the US. The magnitude of the worsening in credit ratings is of the order of 0.9 notch when considering firms in top GHG-polluting sectors, and of about half a notch when considering firms in the top quartile of GHG intensities and levels. The positive sign of the estimates of the coefficients *Top GHG NACE x post-Paris* and *Top GHG level x post-Paris* suggest that credit ratings actually improved for the most polluting firms in the US in the period following the Paris Agreement. We re-run this test on the event window between 2016-2019 to check whether Trump's 2017 announcement of US withdrawal from the Paris Agreement led to changes in the effect of transition risk on credit risk for European vis-a-vis US high-emitting firms. We do not find evidence of such an effect in the results. [17]

Our difference-in-differences reveals that firms most exposed to climate transition risk experienced a deterioration in their credit ratings after the Paris Agreement, with the effect stronger for European-domiciled firms than those in the US. This probably reflects differing expectations regarding government climate policies and commitments. Our findings are complementary to those of Seltzer, Starks, and Zhu (2022). They find that the credit ratings of high-emitting bond-issuing listed US firms declined after the Paris Agreement in December 2015. But their results also highlight the importance of government commitment both because they find a stronger relationship for firms with facilities located in US states with stricter regulatory enforcement and because they find a partial reversal of the overall effect upon the announcement of US withdrawal from the Paris Agreement in June 2017.[18] For robustness, we repeat the triple DiD analysis on a sample excluding firms active in the Oil and Gas sectors, i.e., corresponding to the NACE codes "B: Mining and Quarrying" and "C-19 Manufacturing of coke oven products and

[17]For the interested reader, results are available upon request.

[18]While Seltzer, Starks, and Zhu (2022) investigate the impact of the Paris Agreement on bond credit ratings for bond-issuing US-listed firms, our paper focuses on firms' credit ratings for listed firms across the S&P 500 and STOXX Europe 600 indices, including firms that do not issue bonds. Our methodology leverages firms' credit ratings from S&P to ensure consistency in creditworthiness assessment methods, which is different from the use of ratings from multiple CRAs and shorter event windows based on monthly data employed in Seltzer, Starks, and Zhu (2022), as opposed to our annual data and longer analysis period.

refined petroleum products". Our results remain consistent, indicating that our findings on the credit ratings for high-emitters post-2015 are not driven by differences in sectoral composition between Europe and the US in the Oil and Gas sectors.[19]

Table 9: Triple difference-in-differences results for changes in credit ratings considering the 2015 Paris Agreement and European countries versus the US

Notes: Model 1 considers as "treated" firms in the *Top GHG NACE* sectors in basic triple-difference-in-differences specification, while in model 4 the basic specification is augmented by firm-level controls and firm time fixed-effects as defined in Equation 7. Models 2 and 3 consider as "treated" firms in the *Top GHG intensity* quartile and in *Top GHG level* quartile, respectively. In models 5 and 6 the later specification is augmented with controls and firm and time fixed-effects. *post-Paris* is the indicator variable taking the value 1 for years following and including 2015, and 0 otherwise. The period of the sample is from 2011 to 2019. *Transition-policy* is an indicator variable taking the value 1 for firms conducting primarily business in European jurisdictions and 0 for those operating primarily in the US. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Top GHG NACE x Transition-policy x post-Paris	-1.30***			-0.86***		
	(0.24)			(0.21)		
Top GHG intensity x Transition-policy x post-Paris		-0.37			-0.46**	
		(0.27)			(0.23)	
Top GHG level x Transition-policy x post-Paris			-0.49*			-0.60***
			(0.27)			(0.23)
Top GHG NACE x post-Paris	0.88***			0.59***		
	(0.17)			(0.13)		
Top GHG intensity x post-Paris		0.22			0.18	
		(0.18)			(0.13)	
Top GHG level x post-Paris			0.26			0.23*
			(0.17)			(0.13)
Top GHG NACE x Transition-policy	1.60***					
	(0.50)					
Top GHG intensity x Transition-policy		0.0017				
		(0.50)				
Top GHG level x Transition-policy			-0.013			
			(0.51)			
Transition-policy x post-Paris	0.36***	0.26**	0.30**	0.11	0.10	0.15
	(0.13)	(0.13)	(0.12)	(0.11)	(0.11)	(0.11)
Firm-level controls	N	N	N	Y	Y	Y
Time fixed-effects	N	N	N	Y	Y	Y
Firm fixed-effects	N	N	N	Y	Y	Y
Observations	4,464	4,464	4,464	4,033	4,033	4,033
Number of firms	496	496	496	487	487	487
R-squared	0.0228	0.0042	0.0056	0.077	0.069	0.072

6 Results on firms' mitigation strategies

6.1 Role and credibility of emissions reduction commitments

Reducing net emissions is fundamental in reaching the Paris goals and for firms' management of climate-related risks. In order to understand the economic rationale as to why indicators of firms' willingness to reduce their emissions can play a role for their credit

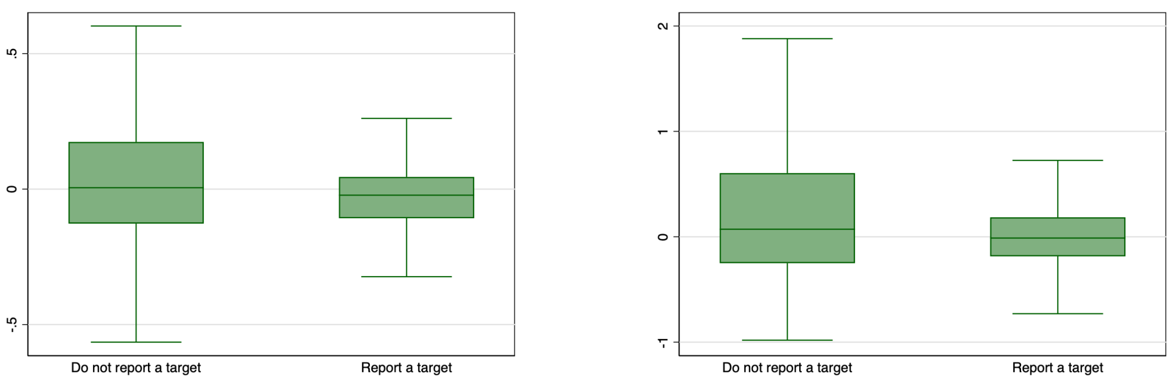
[19]For the interested reader, results are available upon request.

risk assessment, we present evidence on their empirical correlation with changes in emissions. Targets are only meaningful if steps are taken to meet them, which may require an independent assessment of the credibility of the target (NGFS, 2021). In particular, the credibility of a target depends on how realistic it is and how consistent the firm is over time in reducing emissions.

We first ask whether firms with a disclosed target reduce emissions. Figure 8 shows the relative change in Scope 1 GHG emission levels over the last one year (left panel) and over the last three years (right panel) for firms disclosing a target versus those not disclosing a target. The left panel shows that the vast majority of firms that had a disclosed target in 2019 did reduce their GHG emission levels over the last year whereas the firms that did not disclose a target showed little change in GHG emissions. When analysing the relative change of GHG emission intensity over the previous three years, firms with a target had a median emission intensity reduction of 1.5%, while firms without a target in 2019 actually showed a median emission intensity increase of 6.8%. This suggests that firms with a emission reduction target, have tended to reduce their emission intensity by more than firms that did not disclose a target. This is also in line with the findings of Bolton and Kacperczyk (2023b) who find that firms that make commitments subsequently further reduce their emissions.

Figure 8: Change in Scope 1 GHG emission levels for firms disclosing an emissions reduction target and those not disclosing a target

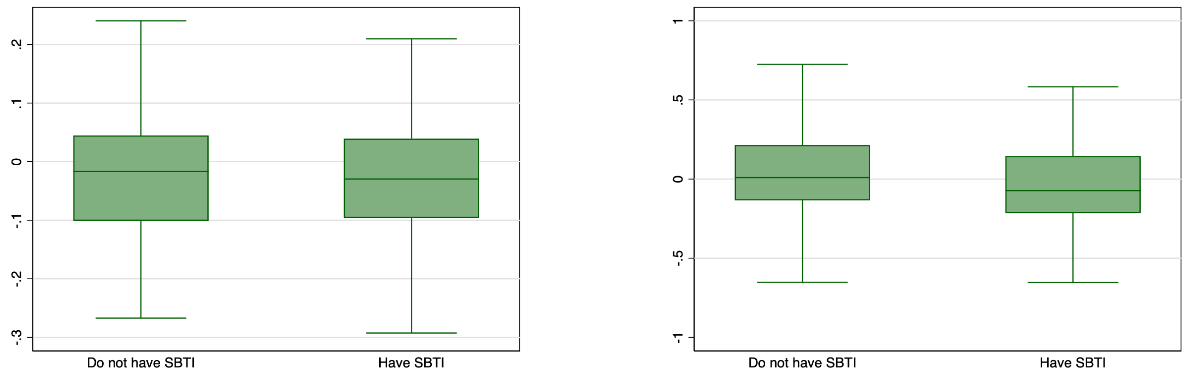
Notes: Left panel: Year-on-year change in 2019 relative to 2018. (Percentage of reduction in Scope 1 emission levels; Bucket of firms out of 728 NFCs). Right panel: 3-year change in 2019 relative to 2016 (Percentage of reduction in Scope 1 and 2 GHG emission intensity; Bucket of firms out of 728 NFCs). In both panels: the blue dot is the median, the shaded area is the interquartile range, bars are the 10th and 90th percentile. Sources: Refinitiv and authors' calculations.



Next, we ask whether firms that have both a self-disclosed emission reduction target – in their financial or non-financial statements – and an SBTi target reduce emissions by more than firms that do not have an SBTi target. An SBTi-verified target is a target which is aligned with the Paris Agreement goals. Figure 9 shows the reduction in emission intensity over the last year (left panel) and over the last three years (right panel) for firms that disclosed a target in 2019. We construct two groups: firms with an SBTi verified target and firms with a self-disclosed emission reduction target only. We find that most firms that self-disclosed a target in 2019 reduced their emission levels over the previous year, independent of whether the target was SBTi verified or not. When looking at changes over the last three years, we find a slightly more left skewed distribution for firms with an SBTi target.

Figure 9: Change in Scope 1 GHG emission levels for firms disclosing a target, grouped by availability of an SBTi aligned target

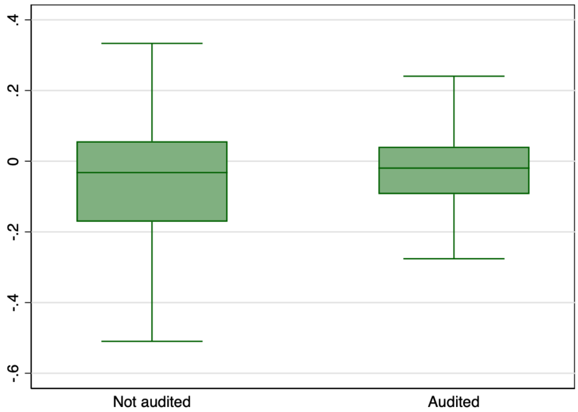
Notes: Left panel: Year-on-year change in GHG emission levels in 2019 relative to 2018 (Percentage of reduction in Scope 1 GHG emission levels; Bucket of firms out of 728 NFCs). Right panel: 3-year change in GHG emission levels in 2019 relative to 2016 (Percentage of reduction in Scope 1 and 2 GHG emission intensity ; Bucket of firms out of 728 NFCs). In both panels: the blue dot is the median, the shaded area is the interquartile range, bars are the 10th and 90th percentile. Sources: Refinitiv and authors' calculations.



Finally, we ask whether firms that disclose an emission reduction target and have their non-financial statements audited reduce emissions by more than firms that disclose a target but have no audit. The audit of non-financial statements is a proxy of the assurance of the rigorousness of the emission reduction target (see section 2). Figure 10 shows the boxplot of observed year-on-year changes in emission levels of a subsample of listed non-financial firms that reported a target in 2019 and had or did not have their non-financial statements audited in 2019. There is no major difference observed between the two groups in terms of the median reduction, albeit an higher standard deviation for non-audited firms. It is important to note that in our sample more than twice as many firms had their non-financial statements audited.

Figure 10: Change in Scope 1 GHG emission levels for firms disclosing a target, grouped by audit status of non-financial statements

Notes: Percentage of reduction in Scope 1 GHG emission levels; Bucket of firms out of 728 NFCs. In both panels: the blue dot is the median, the shaded area is the interquartile range, bars are the 10th and 90th percentile. Sources: Refinitiv and authors' calculations.



6.2 Results of dynamic difference in differences

We now investigate whether emission targets and the disclosure dummy are reflected in credit ratings by applying the dynamic difference-in-differences approach discussed in section 3.3 . In doing so, we integrate the results from our static DiD analysis and estimate the model separately for European and US domiciled firms. For consistency, we restrict the sample in the same way as in section 5, which yields a balanced panel of firms over 2011-2019.

Table 10: Dynamic difference in differences results for emissions reduction target and disclosure, European sample

Notes: The table shows the result of the Dynamic DiD estimation as described in section 3.3. Individual difference-in-differences estimators are computed through OLS with the inclusion of firm and time fixed-effects. The results on DiscloseCommit are robust to employing firm-level controls in the estimation, following De Chaisemartin and d'Haultfoeuille (2024). Column 1 presents the results for forward-looking target, while column 2 shows results for the disclosure dummy. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

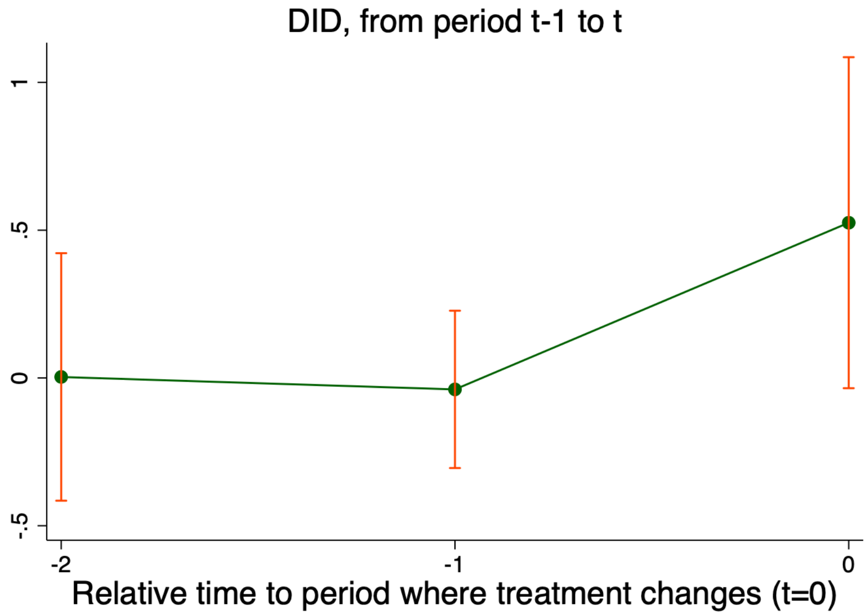
Variable	**DiscloseCommit**	**DiscloseGHG**
DiD_M	0.463**	-0.140
	(0.213)	(0.083)
$Placebo_{t-1}$	0.021	0.398
	(0.156)	(0.259)
$Placebo_{t-2}$	0.046	-0.013
	(0.254)	(0.123)
Observations	224	1712
Number of switchers	28	239

Table 10 displays the results from the two estimations conducted for the sample of European domiciled firms. The point estimate obtained for the forward-looking target indicates a 46% of a credit notch increase in average ratings upon adopting a commitment to reduce emissions. This result is statistically significant at the 5% level after conducting 1000 bootstrap replications for standard errors. Comfortingly, as visualized in figure 11, parallel trends seem to hold given the insignificant differences in average rating up to the moment when firms change adopt an emission reduction target. We also compute event-study coefficients up to a lead of three years, retaining the estimation only on switchers, and find that the positive effect on ratings retains its significance and magnitude over this horizon.

Turning to disclosure of carbon emissions, we find no significant effect on credit ratings, with the point estimate even being negative. While potentially counterintuitive at first, this result could be explained by the inherently different role that disclosing GHG emissions has in communicating management of transition risk relative to a commitment to cut emissions. Recalling that we are estimating the impact on ratings from firms starting to disclose their emissions, it can conceivably be argued that for some firms, providing emission metrics that market participants previously had to infer could elicit negative risk pricing if those emissions turn out to be above ex-ante market expectations. Therefore, the positive signaling role of disclosure, whereby firms who disclose emissions might be perceived as more aware of transition risk relative to their non-disclosing peers, might not materialize upon the initial disclosure since it could be overshadowed by this mechanism. Alternatively, it could simply be the case that a clear ambition to reduce emissions is seen to be more important for credit risk assessment than mere awareness of transition risk. This is because a commitment to reduce emissions is an explicit and, in most cases, verifiable statement about reducing exposure to transition risk.

Looking across jurisdictions, we do not find any significant effects of either emission reduction targets or disclosure on ratings for firms domiciled in the United States. This heterogeneity of results seems to imply that ambitiousness of climate policies in the jurisdiction where firms are domiciled is of the same fundamental nature for both backward and forward-looking indicators of transition risk, as also highlighted in our panel regressions and difference-in-difference analysis around the Paris agreement.

Figure 11: Heterogeneous difference-in-differences results for changes in credit ratings for European firms reporting an emissions reduction target.



7 Additional analysis: Distance to default

In this section we analyse the relationship between climate-related transition risk metrics and our second measure of credit risk: Merton's measure of the firm's distance-to-default (DtD) as specified in Equation 13. The panel regressions outlined in Tables 11, 12, 13 and 14 take DtD as the measure of credit risk, using the full sample of monthly data, spanning the period from 2010 to 2019. As mentioned in section 2, this monthly dataset only includes European firms. Given the continuous nature of the DtD as the dependent variable, we employ only standard ordinary least square estimators, controlling for sector and country fixed-effects.

The first hypothesis tests the relationship between Scope 1, 2, and 3 emissions and firms' DtD. Table 11 shows that firms with lower Scope 1 and 3 emissions and intensities are considered as less exposed to credit risk by market participants, i.e. are associated with a higher DtD. The magnitude of the Scope 3 intensity coefficient is lower than that of the Scope 1 intensity coefficient, which may indicate that market participants acknowledge the limitations on the proper accounting and disclosure of Scope 3 emission intensities. These findings are fully consistent with those on credit ratings in Table 3 of Section 4.

Table 11: Panel regression for DtD and emissions, Testing H1 from 2010-2019

Notes: The table presents the panel regression results for Distance-to-Default (DtD) and emissions, relevant for H1, using Equation 3. DtD decreases as credit risk increases, meaning a negative coefficient for emissions supports H1. Models 5 and 6 employ OLS estimators, with emissions expressed in intensity (Model 1) and levels (Model 2). Firm-level clustered standard errors are in parentheses. Statistical significance is denoted by *** ($p < 0.01$), ** ($p < 0.05$), and * ($p < 0.10$).

Variable	**(1 - int., OLS)**	**(2 - levels, OLS)**
Scope 1 GHG intensity	-173***	
	(61.2)	
Scope 2 GHG intensity	-487	
	(303)	
Scope 3 GHG intensity	-53.6**	
	(22.5)	
Scope 1 GHG level		-0.0060***
		(0.0021)
Scope 2 GHG level		-0.017
		(0.020)
Scope 3 GHG level		0.00068
		(0.00057)
Governance	0.0041*	0.0039*
	(0.0023)	(0.0023)
Constant	5.97***	5.92***
	(0.18)	(0.18)
Controls	Y	Y
Time fixed-effects	N	N
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	19,538	19,538
R-squared	0.282	0.277

Our second hypothesis tests both how decisions to disclose emissions affect a firm's DtD and whether information on emissions is treated differently depending on whether it is self-reported by firms or inferred by third party data providers. Table 12 shows that choosing to disclose GHG-emissions seems to increase a firm's DtD. Similar as for ratings in Section 4, we find a strong negative relationship between Scope 1 intensities and DtD, which is again found to not depend on whether firms' disclose the metrics. The net effect for Scope 2 and 3 GHG levels seems to be overall close to zero when accounting for the opposite signs and similar magnitudes of the plain and interacted coefficients.

Our third tested hypothesis focuses on firms' forward-looking commitments in relation to the reduction of the GHG-emissions alongside past performance in reducing emissions. These results are summarised in Table 13. We find a positive and statistically significant relationship between the communication of future emission targets and DtD. This implies that financial markets assess it as credit-positive that firms communicate such forward-looking targets, since this is associated with an increase in the distance-to-default, and thus with lower market-based credit risk. We also document a negative and significant association between changes in past emissions and DtD. Taken together with the results on commitments it would appear that financial markets are pricing transition strategies more than the backward-looking exposure of firms to transition risk. Indeed, while we do find similarly to table 12 a significant coefficient for non-interacted Scope 1 intensity, all other coefficients for intensities/levels are either non significant or average out to zero when summing interacted and non-interacted point estimates.

Table 12: Panel regression for Distance-to-Default (DtD) and emission disclosures, testing H2 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H2, see (4), where the relationship between emission disclosures and distance-to-default (DtD) is tested for the data sample covering the full data sample from January 2010 to December 2019, using a monthly observation frequency. The relevance of disclosure, in itself, is tested via the dummy variable denoted by *DiscloseGHG dummy*. Similarly, the market assessment of the source of the GHG-emission data is investigated by including dummy interaction terms capturing whether a given firm's emission statistics are self-reported (*Disclosed*), or whether they are *inferred* by a third-party data provider. DtD falls when credit risk increases, so a negative estimate for the emission-coefficients implies the acceptance of H2. Model 1 shows the OLS results considering GHG emission intensity, while model 2 shows the OLS results considering GHG emission level. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int.)**	**(2 - levels)**
DiscloseGHG dummy	0.37***	0.34***
	(0.087)	(0.075)
DiscloseGHG x Scope 1 GHG intensity	58.2	
	(81.6)	
DiscloseGHG x Scope 2 GHG intensity	-220	
	(624)	
DiscloseGHG x Scope 3 GHG intensity	-54.1	
	(37.4)	
DiscloseGHG x Scope 1 GHG level		-0.0036
		(0.0029)
DiscloseGHG x Scope 2 GHG level		0.076**
		(0.037)
DiscloseGHG x Scope 3 GHG level		-0.0027***
		(0.00077)
Scope 1 GHG intensity	-221**	
	(91.0)	
Scope 2 GHG intensity	-363	
	(306)	
Scope 3 GHG intensity	-8.49	
	(37.1)	
Scope 1 level		-0.0031
		(0.0028)
Scope 2 level		-0.083**
		(0.034)
Scope 3 level		0.0030***
		(0.00093)
Governance	0.0034***	0.0084**
	(0.0012)	(0.0036)
Constant	5.87***	5.85***
	(0.18)	(0.18)
Controls	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	19,538	19,538
R-squared	0.290	0.287

Table 13: Panel regression for Distance-to-Default (DtD) and emission targets, testing H3 (binary reduction target measure) from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see (5), where the relationship between emission-disclosure targets and distance-to-default (DtD) is tested for the full data sample from January 2010 to December 2019, using a monthly observation frequency. DtD falls when credit risk increases, so if a firm communicates a future emission target, and this event is interpreted by financial markets as a credit-positive event, a positive parameter estimate would be obtained. Model 1 shows the OLS results considering GHG emission intensity, while model 2 shows the OLS results considering GHG emission level. Non-interacted terms form intensities and levels are included in the estimation but not reported. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int.)**	**(2 - levels)**
DiscloseGHG dummy	0.28***	0.27***
	(0.093)	(0.082)
DiscloseGHG x Scope 1 GHG intensity	91.1	
	(77.1)	
DiscloseGHG x Scope 2 GHG intensity	-226	
	(752)	
DiscloseGHG x Scope 3 GHG intensity	-47.4	
	(40.2)	
Disclosed intensity change	-0.18*	
	(0.10)	
DiscloseCommit dummy	0.47***	0.45***
	(0.097)	(0.097)
DiscloseGHG x Scope 1 GHG level		-0.0013
		(0.0037)
DiscloseGHG x Scope 2 GHG level		0.10*
		(0.053)
DiscloseGHG x Scope 3 GHG level		-0.0031***
		(0.00092)
Disclosed level change		-0.23**
		(0.11)
Governance	0.0011	0.00095
	(0.0020)	(0.0020)
Constant	5.75***	5.72***
	(0.19)	(0.18)
Controls	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	16,078	16,112
R-squared	0.299	0.293

As a final complement to the investigation of hypothesis 3, Table 14 summarises the empirical testing of the relationship between DtD and the ambitiousness of targets as reflected in the (*TargetPerc Ref*) relative to current emissions, and the duration until the target is expected to be reached (*TargetYear Ref*). While we cannot confirm a statistically significant relationship between credit risk and larger emissions reduction targets for the DtD analysis as is the case with credit ratings, we find some empirical evidence that suggests that financial markets penalise companies with less ambitious timing targets. Concretely, companies that communicate more distant emission reduction targets in the course of time seem to get penalised with a lower DtD as seen with the statistically significant coefficients for *TargetYear Ref*, which amounts to -0.026 for GHG-emission intensities and -0.027 for GHG-emission levels. However, due to the sparse data coverage of forward-looking commitments[20] and potentially different information content among data providers, this relationship can neither be confirmed nor rejected when looking at the CDP data with statistically and economically insignificant coefficients, so that the empirical relationship is still somewhat inconclusive. Nevertheless, our results from both metrics of credit risk highlight the potential importance of forward-looking targets and strategies in gauging firm' vulnerability to climate-related transition risk.

Table 14: Panel regression for Distance-to-Default (DtD) and emission targets, testing H3 (quantitative reduction target measures) from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see (5). The impact on distance-to-default (DtD) of a communicated emission-reduction target (*Emission target percentage*) relative to current emissions and the duration until the target should be reached *Emission target arrival*, are investigated. Here the analysis is performed only for the full sample of data covering the period from 2010 to 2019, using a monthly observation frequency. It is assumed that the higher the communicated target is, as long as it is perceived to be credible, the better the market based credit risk assessment i.e. a higher DtD, so it is expected that a positive coefficient will be associated with the *Emission target arrival*. And, it is assumed that the sooner the communicated is expected to be achieved, the better it is for the market based credit risk assessment: as such we expect a negative coefficient for the *TargetYear* variables. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int., OLS)**	**(2 - int., OLS)**	**(3 - levels, OLS)**	**(4 - levels, OLS)**
Scope 1 GHG intensity	-109	8.20		
	(99.5)	(345)		
Scope 2 GHG intensity	-1,793	-568		
	(1,535)	(1,610)		
Scope 3 GHG intensity	12.2	-6.68		
	(27.7)	(67.5)		
Disclosed intensity change	-0.45	-0.25		
	(0.30)	(0.29)		
Scope 1 GHG level			-0.0037	-0.018
			(0.0046)	(0.020)
Scope 2 GHG level			-0.085	-0.033
			(0.068)	(0.049)
Scope 3 GHG level			0.0020	-0.00095
			(0.0014)	(0.0018)
Disclosed level change			-0.44	-0.25
			(0.36)	(0.29)
TargetPerc Ref	0.0035		0.0034	
	(0.0036)		(0.0041)	
TargetYear Ref	-0.026*		-0.027*	
	(0.014)		(0.015)	
TargetPerc CDP		0.0022		0.0015
		(0.0035)		(0.0035)
TargetYear CDP		-0.00042		0.0011
		(0.012)		(0.011)
TargetBaseYear CDP		-0.015		-0.019
		(0.017)		(0.016)
Constant	58.9**	35.8	60.6**	40.3
	(28.5)	(44.1)	(29.5)	(43.1)
Firm-level controls	Y	Y	Y	Y
Macroeconomic controls	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	2,719	2,872	2,187	2,896
R-squared	0.372	0.431	0.436	0.435

We run the same two robustness exercises used for the credit ratings analysis. When we

[20]It is noted that forward-looking commitments only became available following the Paris agreement.

exclude the highest emitting companies, we find that the act of disclosure and making an emissions-reduction commitment are still both associated with lower market-implied credit risk[21].

We also re-run our panel regressions again using firm fixed-effects as opposed to sector and country ones. The results for H3 confirm the continued significance of realized changes in both GHG emissions and intensities, while the disclosure and commitment dummies' effects are absorbed by the time-invariant characteristics of the firm. However, for the same reasons discussed in the robustness checks for credit ratings, we argue that the use of fixed-effects by sector and country in our baseline analysis is more appropriate for the empirical characteristics of our data set than the use of firm fixed-effects.

8 Conclusion and policy implications

This paper examines how the low-carbon transition risk affects firm credit risk, as measured by credit rating and market-implied distance-to-default. First, we construct a novel firm-level dataset for listed non-financial corporations that includes not only actual GHG emissions and emission intensities, which are the focus of most existing research, but also disclosure practices and forward-looking emission reduction targets. Then, we conduct panel regressions and apply two complementary difference-in-differences approaches to assess how climate-related metrics influence firm credit risk.

In line with the literature, our panel regressions show that firms with higher GHG emissions and emission intensities tend to face higher credit risk, as reflected in both credit ratings and market-based measures of default probability. Choosing to disclose emissions is also associated with a better credit rating for European firms, but does not affect much market-implied credit risk. Instead, European firms with forward-looking climate commitments, such as ambitious emission reduction targets, benefit from better credit ratings and lower market-implied credit risk. These findings suggest that credit rating agencies and financial markets recognize the relevance of low-carbon transition strategies in assessing firms' long-term viability and creditworthiness.

[21] Both tables described in this section are available upon request.

Our difference-in-differences analyses further provide causal evidence that (expectations around) national government climate policies influence how markets and rating agencies assess transition risk. First, we find that after the Paris agreement, firms most exposed to climate transition risk saw their ratings deteriorate by more than other firms with similar characteristics. This effect is larger for European firms than their US peers, probably reflecting differential (expectations around) climate policies across jurisdictions. Strong and credible climate policies seem to enhance the financial materiality of corporate climate commitments, thereby reinforcing the link between transition risk management and creditworthiness. Second, our dynamic difference-in-differences analysis shows that European firms who make a climate commitment experience an improvement in their credit rating relative to comparable firms who do not set a target, with the effects tending to be stronger for more ambitious targets. The same is not true for US firms, likely due to the different national climate policies. At the same time, we do not find evidence of a causal impact of disclosure on credit ratings. While disclosing emissions could have signaling value Bolton and Kacperczyk (2021c), the relatively weaker evidence we find for climate disclosures in affecting credit risk compared to both current emissions and forward-looking commitments suggest that actual transition risk and the clear ambition to reduce emissions are more important for credit risk assessment than awareness of transition risk.

Overall, our results suggest that high emitters have a higher risk of failure but that active strategies to manage transition risk are also crucial. Despite the limitations related to the reliability and comparability of climate-related metrics, credit rating agencies and investors reward firms that have a clear plan to reduce their emissions with better ratings and market-based credit risk assessments, compared to firms that show less commitment.

Our results have several important policy implications. First, the fact that credit risk estimates reflect transition risk metrics underscores the need for improvements in the coverage, quality, credibility and comparability of disclosure of GHG emissions and emission reduction strategies. Enhanced transparency in forward-looking metrics is particularly crucial, as these reflect a firm's strategy to mitigate transition risk. More comprehensive and harmonized disclosures would enable financial institutions and investors to better assess transition-related credit risks within their portfolios, reducing the likelihood of mispricing carbon transition risk (see for example Schnabel (2020a,b, 2021); Panetta (2021); Hauser (2021); Thomä and Chenet (2017)). Such improvements would also make it easier for authorities to gauge overall risks in the financial sector (De Guindos, 2021). The climate change-related disclosure standards under the European Union's Corporate Sustainability Reporting Directive is set to be applied for the first time in annual reports for 2024, that will be released in 2025. Our findings emphasize the importance of ambitious standards within this framework, particularly regarding forward-looking targets and strategies. Furthermore, they provide support for broader initiatives aimed at implementing mandatory, standardized, and audited reporting requirements across additional jurisdictions, and ideally, at the global level.

Second, our findings have implications for how central banks integrate climate-related transition risk in their monetary and non-monetary policy operations. In particular, they highlight how climate change and the carbon transition affect the value and the risk profile of assets held on central bank balance sheets. Partly with these considerations in mind, several central banks have started to take action. For example, the ECB has decided to introduce disclosure requirements for private sector assets as a new eligibility criterion or as a basis for a differentiated treatment for collateral and asset purchases.[22] Also, when reviewing the design of the operational framework, the ECB decided to incorporate climate change-related considerations into the structural monetary policy operations.[23] Such measures can both promote more consistent disclosure practices in the market and improve the alignment of central banks' valuation and risk management frameworks with firm-level transition risk. The ECB and the Bank of Englang also adjusted the framework guiding the allocation of corporate bond purchases to incorporate climate change criteria, in line with their mandates, placing particular emphasis on realised reductions in emissions, disclosure practices and emissions reduction targets when assessing the climate performance of firms.[24] Our findings are supportive of such approaches. In particular, they highlight the importance of central banks focussing on firms' forward-looking targets and strategies, alongside how well they are doing in actually cutting their emissions, when considering their monetary and non-monetary policy portfolios.

[22]See the ECB action plan to include climate change considerations in its monetary policy strategy (ECB, 2021a)

[23]See https://www.ecb.europa.eu/press/pr/date/2024/html/ecb.pr240313 807e240020.en.html

[24]See https://www.bankofengland.co.uk/markets/greening-the-corporate-bond-purchase-scheme

Third, our findings are relevant for the regulatory framework for banks and insurance companies. Specifically, they highlight the importance of ensuring that climate-related transition risks faced by firms are adequately and consistently reflected in prudential and supervisory standards. Under capital adequacy regulations, risk-weighted capital requirements for credit risk depend on risk weights, which institutions determine either based on external ratings provided by credit rating agencies (Standardised Approach) or internal models (Internal Ratings-Based Approach). Our findings indicate that credit rating agencies incorporate transition risk considerations to some extent in their assessments. At the same time, regulators must evaluate whether risk weights based on credit ratings sufficiently capture transition risk or need to be supported by the adoption of systematic, consistent and transparent disclosure practices and enhanced methodologies by credit rating agencies. The extent to which risk weights derived from internal models reflect climate-related transition risk is less clear (see for example ECB (2021b)). Overall, our results highlight the need for regulators and supervisors to assess whether climate-related transition risk is appropriately accounted for in risk weights, regardless of the calculation method, and more broadly within the regulatory framework.

Future work could consider how credit ratings and market-based gauges of credit risk reflect the mobilization efforts of the firm to transition to a low carbon economy. For example, metrics related to green investment and innovation efforts, such as R&D investment and green patents could be considered, though these present significant data challenges. In addition, further research assessing the credibility of different emission targets and their alignment with country-level Nationally Determined Contributions (NDC) targets would deepen understanding of how well firms' plans are aligned with the Paris climate change goals. Finally, future research on financing constraints of firms would enhance understanding of how to help close the investment gap related to the low-carbon transition (see for instance Maurin, Barci, Davradakis, Gereben, Tueske, and Wolski (2021) and Kacperczyk and Peydró (2021)).

References

Alali, F., A. Anandarajan, and W. Jiang (2012): "The effect of corporate governance on firm's credit ratings: further evidence using governance score in the United States", *Accounting & Finance*, 52(2), 291–312.

Alogoskoufis, S., N. Dunz, T. Emambakhsh, T. Hennig, M. Kaijser, C. Kouratzoglou, M. Muñoz, L. Parisi, and C. Salleo (2021): "ECB economy-wide climate stress test. Methodology and results", ECB Occasional Paper Series No. 281 [Accessed: 2021 10 01].

Aswani, J., A. Raghunandan, and S. Rajgopal (2023a): "Are Carbon Emissions Associated with Stock Returns?*", *Review of Finance*, 28(1), 75–106.

——— (2023b): "Are Carbon Emissions Associated with Stock Returns?—Reply*", *Review of Finance*, 28(1), 111–115.

Attig, N., S. El Ghoul, O. Guedhami, and J. Suh (2013): "Corporate social responsibility and credit ratings", *Journal of business ethics*, 117(4), 679–694.

Baghai, R. P., H. Servaes, and A. Tamayo (2014): "Have rating agencies become more conservative? Implications for capital structure and debt pricing", *The Journal of Finance*, 69(5), 1961–2005.

Barth, F., B. Hübel, and H. Scholz (2020): "ESG and corporate credit spreads", *Available at SSRN 3179468*.

BCBS (2021): "Climate-related risk drivers and their transmission channels", Report [Accessed: 2021 06 29].

Berg, F., J. F. Koelbel, and R. Rigobon (2022): *Aggregate confusion: The divergence of ESG ratings*, vol. 26.

Bharath, S., and T. Shumway (2008): "Forecasting Default with the Merton Distance to Default Model", *Review of Financial Studies*, 21, 1339–1369.

Billio, M., M. Costola, I. Hristova, C. Latino, and L. Pelizzon (2020): "Inside the ESG Ratings:(Dis) agreement and performance", *University Ca'Foscari of Venice, Dept. of Economics Research Paper Series No*, 17.

Black, F., and M. Scholes (1973): "The Pricing of Options and Corporate Liabilities", *Journal of Political Economy*, 81, 637–654.

Bolton, P., and M. Kacperczyk (2021a): "Do investors care about carbon risk?", *Journal of Financial Economics.*

——— (2021b): "Global pricing of carbon-transition risk", Discussion paper, National Bureau of Economic Research.

——— (2023a): "Are Carbon Emissions Associated with Stock Returns? Comment", *Review of Finance*, 28(1), 107–109.

——— (2023b): "Firm commitments", .

Bolton, P., and M. T. Kacperczyk (2021c): "Signaling through carbon disclosure", *Harvard Law School Forum on Corporate Governance.*

Busch, T., M. Johnson, and T. Pioch (2020): "Corporate carbon performance data: Quo vadis?", *Journal of Industrial Ecology.*

Capasso, G., G. Gianfrate, and M. Spinelli (2020): "Climate change and credit risk", *Journal of Cleaner Production*, 266, 121634.

Chava, S. (2014): "Environmental externalities and cost of capital", *Management science*, 60(9), 2223–2247.

De Chaisemartin, C., and X. d'Haultfoeuille (2024): "Difference-in-differences estimators of intertemporal treatment effects", *Review of Economics and Statistics*, pp. 1–45.

De Chaisemartin, C., and X. d'Haultfoeuille (2020): "Two-way fixed effects estimators with heterogeneous treatment effects", *American economic review*, 110(9), 2964–2996.

De Guindos, L. (2021): "Climate change and financial integration", speech at the joint ECB and European Commission conference on "European Financial Integration and Stability", Frankfurt am Main, 27 May.

Doumpos, M., D. Niklis, C. Zopounidis, and K. Andriosopoulos (2015): "Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms", *Journal of Banking & Finance*, 50, 599–607.

ECB (2021a): "ECB presents action plan to include climate change considerations in its monetary policy strategy", Retrievable online at: https://www.ecb.europa.eu/press/pr/date/2021/html/ecb.pr210708$_1$ $f104919225.en.html$.

——— (2021b): "The state of climate and environmental risk management in the banking sector", Report on the supervisory review of banks' approaches to manage climate and environmental risks [Accessed: 2021 11 30].

Edmans, A. (2021a): "Does sustainability reduce the cost of capital?", VoxEU CEPR article.

——— (2021b): *Grow the Pie: How Great Companies Deliver Both Purpose and Profit–Updated and Revised*. Cambridge University Press.

El Ghoul, S., O. Guedhami, H. Kim, and K. Park (2018): "Corporate environmental responsibility and the cost of capital: International evidence", *Journal of Business Ethics*, 149, 335–361.

Elderson, F. (2021): "Patchy data is a good start: from Kuznets and Clark to supervisors and climate", speech at the ECB-EBRD joint conference on "Emerging climate-related risk supervision and implications for financial institutions", Frankfurt am Main, 16 June.

Eliwa, Y., A. Aboud, and A. Saleh (2019): "ESG practices and the cost of debt: Evidence from EU countries", *Critical Perspectives on Accounting*, p. 102097.

Ghisetti, C., and K. Rennings (2014): "Environmental innovations and profitability: How does it pay to be green? An empirical analysis on the German innovation survey", *Journal of Cleaner production*, 75, 106–117.

Ginglinger, E., and Q. Moreau (2019): "Climate risk and capital structure", *Université Paris-Dauphine Research Paper*, (3327185).

Hauser, A. (2021): “It’s not easy being green – but that shouldn’t stop us: how central banks can use their monetary policy portfolios to support orderly transition to net zero”, speech given at Bloomberg, 21 May.

Höck, A., C. Klein, A. Landau, and B. Zwergel (2020): “The effect of environmental sustainability on credit risk”, *Journal of Asset Management*, pp. 1–9.

Ilhan, E., Z. Sautner, and G. Vilkov (2021): “Carbon tail risk”, *The Review of Financial Studies*, 34(3), 1540–1571.

IPCC (2021): “Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change”, [Masson-Delmotte, V., P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu and B. Zhou (eds.)]. Cambridge University Press. In Press.

Jiang, X., S. Kim, and S. Lu (2025): “Limited accountability and awareness of corporate emissions target outcomes”, *Nature Climate Change*, pp. 1–8.

Jones, S., D. Johnstone, and R. Wilson (2015): “An empirical evaluation of the performance of binary classifiers in the prediction of credit ratings changes”, *Journal of Banking & Finance*, 56, 72–85.

Kabir, M. N., S. Rahman, M. A. Rahman, and M. Anwar (2021): “Carbon emissions and default risk: International evidence from firm-level data”, *Economic Modelling*, 103, 105617.

Kacperczyk, M. T., and J.-L. Peydró (2021): “Carbon Emissions and the Bank-Lending Channel”, *Available at SSRN 3915486.*

Kalesnik, V., M. Wilkens, and J. Zink (2020): “Green Data or Greenwashing? Do Corporate Carbon Emissions Data Enable Investors to Mitigate Climate Change?”, *SSRN Electronic Journal.*

Kiesel, F., and F. Lücke (2019): “ESG in credit ratings and the impact on financial markets”, *Financial Markets, Institutions & Instruments*, 28(3), 263–290.

Lagarde, C. (2021): "Towards a green capital markets union for Europe", speech at the European Commission's high-level conference on the proposal for a Corporate Sustainability Reporting Directive, Frankfurt am Main, 6 May.

Malani, A., and J. Reif (2015): "Interpreting pre-trends as anticipation: Impact on estimated treatment effects from tort reform", *Journal of Public Economics*, 124, 1–17.

Marquis, C., M. W. Toffel, and Y. Zhou (2016): "Scrutiny, norms, and selective disclosure: A global study of greenwashing", *Organization Science*, 27(2), 483–504.

Maurin, L., G. Barci, E. Davradakis, A. Gereben, A. Tueske, and M. Wolski (2021): "Leveraging the financial system to green the European economy", European Investment Bank Investment Report 2020/2021, Part II Investing in the transition to a green and smart economy. [Accessed: 2021 06 29].

Merton, R. C. (1973): "Theory of Rational Option Pricing", *Bell Journal of Economics and Management Science*, 4, 141–183.

——— (1974): "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", *Journal of Finance*, 29, 449–470.

Misani, N., and S. Pogutz (2015): "Unraveling the effects of environmental outcomes and processes on financial performance: A non-linear approach", *Ecological economics*, 109, 150–160.

Moody's Investors Service (2016): "Moody's To Analyse Carbon Transition Risk Based On Emissions Reduction Scenario Consistent with Paris Agreement", study published on 28 June.

NGFS (2021): "Progress report on bridging data gaps", Technical document [Accessed: 2021 06 29].

Nguyen, P.-A., A. Kecskés, and S. Mansi (2020): "Does corporate social responsibility create shareholder value? The importance of long-term investors", *Journal of Banking & Finance*, 112, 105217.

Nguyen, Q., I. Diaz-Rainey, and D. Kuruppuarachchi (2021): "In search of climate distress risk", [Paper presentation] 3rd Summer School on Sustainable Finance organized by the European Commission's Joint Research Centre.

OECD (2022): "ESG ratings and climate transition: An assessment of the alignment of E pillar scores and metrics", *OECD Business and Finance Policy Papers*.

Panetta, F. (2021): "A global accord for sustainable finance", blog post, Frankfurt am Main, 11 May.

Rexhäuser, S., and C. Rammer (2014): "Environmental innovations and firm profitability: unmasking the Porter hypothesis", *Environmental and Resource Economics*, 57(1), 145–167.

Safiullah, M., M. N. Kabir, and M. D. Miah (2021): "Carbon emissions and credit ratings", *Energy Economics*, p. 105330.

Schnabel, I. (2020a): "Never waste a crisis: COVID-19, climate change and monetary policy", speech at a virtual roundtable on "Sustainable Crisis Responses in Europe" organised by the INSPIRE research network, 17 July.

——— (2020b): "When markets fail – the need for collective action in tackling climate change", speech at the European Sustainable Finance Summit, Frankfurt am Main, 28 September.

——— (2021): "From market neutrality to market efficiency", speech at the ECB DG-Research Symposium "Climate change, financial markets and green growth", Frankfurt am Main, 14 June.

Seltzer, L., L. Starks, and Q. Zhu (2022): "Climate Regulatory Risks and Corporate Bonds", *National Bureau of Economic Research*.

Sharfman, M. P., and C. S. Fernando (2008): "Environmental risk management and the cost of capital", *Strategic management journal*, 29(6), 569–592.

S&P Global Ratings (2015): "How Environmental And Climate Risks Factor Into Global Corporate Ratings", study published on 21 October.

——— (2017a): "How Does S&P Global Ratings Incorporate Environmental, Social, And Governance Risks Into Its Ratings Analysis", study published on 21 November.

——— (2017b): "How Environmental And Climate Risks And Opportunities Factor Into Global Corporate Ratings - An Update", study published on 9 November.

S&P Global, Trucost ESG analysis (2019): "Understanding Climate Risk at the Asset Level: The Interplay of Transition and Physical Risks", study published in 2019.

Stellner, C., C. Klein, and B. Zwergel (2015): "Corporate social responsibility and Eurozone corporate bonds: The moderating role of country sustainability", *Journal of Banking & Finance*, 59, 538–549.

Stoll, H. R. (1969): "The Relationship Between Put and Call Option Prices", *Journal of Finance*, 24, 801–824.

Thomä, J., and H. Chenet (2017): "Transition risks and market failure: a theoretical discourse on why financial models and economic agents may misprice risk related to the transition to a low-carbon economy", *Journal of Sustainable Finance & Investment*, 7(1), 82–98.

Appendix A

Table 15: Backward-looking transition-risk metrics

Variable	Description	Source
Scope 1 GHG intensity	Scope 1 GHG emissions of a firm Expressed in million tonnes of eCO2 per million unit of revenue. May be self-disclosed or 3rd-party-estimated.	Urgentem
Scope 2 GHG intensity	Scope 2 GHG emissions of a firm Expressed in million tonnes of eCO2 per million unit of revenue. May be self-disclosed or 3rd-party-estimated.	Urgentem
Scope 3 GHG inten sity	Scope 3 GHG emissions of a firm Expressed in million tonnes of eCO2 per million unit of revenue. May be self-disclosed or 3rd-party-estimated.	Urgentem
Scope 1 GHG level	Scope 1 GHG emissions of a firm Expressed in million tonnes of eCO2. May be self-disclosed or 3rd-party-estimated.	Urgentem
Scope 2 GHG level	Scope 2 GHG emissions of a firm Expressed in million tonnes of eCO2. May be self-disclosed or 3rd-party-estimated.	Urgentem
Scope 3 GHG level	Scope 3 GHG emissions of a firm Expressed in million tonnes of eCO2. May be self-disclosed or 3rd-party-estimated.	Urgentem
DiscloseGHG dummy	Dummy indicating whether a firm's Scope 1, 2, and/or 3 GHG emissions are self-disclosed	Urgentem
Disclosed intensity change	Year-on-year change in self-disclosed Scope 1 and 2 GHG emissions intensity of a firm	Constructed
Disclosed level change	Year-on-year change in self-disclosed Scope 1 and 2 GHG emissions level of a firm	Constructed

Table 16: Forward-looking transition-risk metrics

Variable	Description	Source
DiscloseCommit dummy	Dummy indicating whether a firm self-discloses a forward-looking commitment to reduce GHG emissions	Refinitiv
TargetPerc Ref	Percentage by which the firm commits to reduce GHG emissions	Refinitiv
TargetYear Ref	Number of years until reaching the target year by which firm commits to reduce GHG emissions	Refinitiv
TargetPerc CDP	Percentage reduction from the base year that the most ambitious absolute emissions reduction target relates to. The information is directly from the company's response to the CDP climate change information request.	Bloomberg
TargetBaseYear CDP	Base year of the most ambitious absolute emission reduction target. The information is directly from the company's response to the CDP climate change information request.	Bloomberg
TargetYear CDP	Number of years until reaching the target year of the most ambitious absolute emissions reduction target. The information is directly from the company's response to the CDP climate change information request.	Bloomberg
SBTi	Dummy indicating whether the firm's target is aligned with the Paris Agreement goal	SBTi
Audited	Dummy indicating whether the non-financial statement of the firm has been audited	Refinitiv

Table 17: Data description

Variable name	Description	Source
	Firm credit risk related variables	
Credit rating	Long-term ratings issued by S&P	ECB Ratings DB
DtD	Market-implied distance-to-default	Constructed
	Firm-level controls (yearly)	
InIndex dummy	Dummy indicator for whether a firm is listed in an index	Refinitiv
Profitability	Return on equity	Refinitiv
Size	Total assets	Refinitiv
Leverage	Ratio of total debt (short-term and long-term debt) and EBITDA	Refinitiv
Debt service	Ratio of EBIT and interest expenses	Refinitiv
Solvency	Ratio of property, plant, and equipment (PPE) and Total assets	Refinitiv
Governance	Score of the quality of governance of the firm	Refinitiv
Sector	Sector of economic activity (NACE1) of the firm. NACE1-sector Manufacturing (C) is devided into two subclasses: firms in manufacturing of coke and refined petroleum products (C19) and other manufacturing firms.	Orbis
Country	Country of the firm constructed based on country of registration and, where not available, country of incorporation	Constructed
Country of registration	Country where the firm is registered and is primarily conducting business. May be different from the country of incorporation.	Orbis
Country of incorporation	Country of incorporation of the firm. A firm may be incorporated only in one country and registered in other country(s) where conducting business.	Datastream
Year	Fiscal year of the firm's financial and non-financial statements	Refinitiv
Year	Fiscal year of the firm's financial and non-financial statements	Refinitiv
	Macroeconomic controls (monthly)	
Market return	MoM local currency market return of S&P 500 for US firms and of STOXX600 for EA firms	Refinitiv
Oil	MoM local currency return of oil spot, WTI for US firms, Brent for EA firms	Refinitiv
Inflation	YoY change, PCE deflator for the US firms, core HCPI	Refinitiv

Continuation of Table 17		
Variable name	**Description**	**Source**
	for EA firms	
Industrial production	YoY change, US industrial production for US firms, EA industrial production for EA firms	Refinitiv
Gold	MoM return of gold in terms of USD	Refinitiv
Bills	End of month Bill rates, T-Bills for US firms, Bubills for EA firms	Refinitiv
Volatility	End of month implied market volatility, VIX for US firms, VSTOXX for EA firms	Refinitiv

Table 18: Summary statistics of firm-level variables

Notes: The definition of all variables is given in Appendix.

Variable	**Observations**	**Mean**	**Median**	**Standard deviation**	**Minimum**	**Maximum**
Rating S&P	6099	13.13	13	2.74	1	21
InIndex dummy	6099	0.81	1	0.39	0	1
Size	5910	32498433	14309696	54186368	0	751216000
Governance	5749	60.45	63.68	21.22	0	98.72
Solvency	5901	0.30	0.22	0.24	0	1.39
Leverage	5886	3.03	2.38	2.99	0	35.86
Profitability	5704	18.24	14.21	32.07	-163.64	231.45
Debt service	5875	14.03	6.36	59.02	-64.88	1878.79
Scope 1 GHG intensity	5443	.00038	.00001	.00201	0.0000001	0.010127
Scope 2 GHG intensity	5443	.00012	.00002	.00419	0.0000002	0.001418
Scope 3 GHG intensity	5443	0.004730	0.001256	0.016818	0.000031	0.103110
Scope 1 GHG level	5443	5.74	0.25	18.04	0	250.21
Scope 2 GHG level	5443	.96	.27	2.67	0	111.31
Scope 3 GHG level	5443	20.89	2.83	68.35	0	1318.99
Disclosed Scope 1-2 intensity change	4723	0.00009	-0.0000001	0.005	-0.017	0.3301285207271576
Disclosed Scope 1-2 level change	4723	-0.09	-0.002	8.17	-183	143
TargetYear	1055	2023	2021	5.64	2018	2050
TargetPerc	1002	30.39	25	21.79	0	100
DiscloseGHG dummy	6099	.61	1	.49	0	1
DiscloseCommit dummy	6099	.59	1	.49	0	1
TargetPerc CDP	1342	41.21	30	32.9	0	100
TargetBaseYear CDP	1356	2012.37	2014	4.84	1990	2020
TargetYear CDP	1356	2027.44	2025	11.1	2015	2050
SBTi dummy	6099	0.04	0	0.2	0	1
Audited dummy	6099	0.42	0	0.49	0	1

Appendix B

In this section we report the results of the panel regressions on our second and third hypotheses for the subsample of US firms and credit ratings.

Table 19: Panel regression for credit ratings and emissions for US firms, Testing H2 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H2, see Equation 4, where the relationship between disclosure, its interaction with GHG emissions and credit ratings is tested for the full data sample covering the period from 2010 to 2019. Model 1 shows the OLS results considering GHG emission intensity, while model 2 shows the corresponding ordered logit results. Model 3 shows the OLS results considering GHG emission level, while model 4 shows the ordered logit results. Non-interacted terms form intensities and levels are included in the estimation but not reported. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int., OLS)**	**(2 - int., logit)**	**(3 - levels, OLS)**	**(4 - levels, logit)**
DiscloseGHG dummy	0.52**	0.54***	0.62***	0.65***
	(0.20)	(0.18)	(0.18)	(0.17)
DiscloseGHG x Scope 1 GHG intensity	-438***	-372***		
	(154)	(133)		
DiscloseGHG x Scope 2 GHG intensity	892	610		
	(1,258)	(1,210)		
DiscloseGHG x Scope 3 GHG intensity	136*	123*		
	(75.0)	(66.0)		
DiscloseGHG x Scope 1 GHG level			-0.019**	-0.017**
			(0.0091)	(0.0083)
DiscloseGHG x Scope 2 GHG level			-0.18	-0.20*
			(0.11)	(0.12)
DiscloseGHG x Scope 3 GHG level			0.0048**	0.0044**
			(0.0023)	(0.0019)
Scope 1 GHG intensity	219	196		
	(145)	(129)		
Scope 2 GHG intensity	-911	-619		
	(1,255)	(1,209)		
Scope 3 GHG intensity	-68.4	-62.3		
	(76.9)	(68.1)		
Scope 1 level			0.0023	0.0016
			(0.0094)	(0.0087)
Scope 2 level			0.17	0.20*
			(0.11)	(0.12)
Scope 3 level			-0.0017	-0.0015
			(0.0017)	(0.0014)
Governance	0.0046	0.0015	0.0040	0.00083
	(0.0042)	(0.0037)	(0.0041)	(0.0037)
Constant	11.6***		11.6***	
	(0.40)		(0.39)	
Firm-level controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	2,952	2,952	2,952	2,952
R-squared	0.406	0.11	0.406	0.11

Table 20: Panel regression for credit ratings and emissions for US firms, Testing H3 (binary reduction target measure) from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see Equation 5, where the relationship between quantitative backward and qualitative forward-looking metrics (commitment to reduce emissions) and credit ratings is tested for the full data sample covering the period from 2010 to 2019. Model 1 shows the OLS results considering GHG emissions intensity, while model 2 shows the corresponding ordered logit results. Model 3 shows the OLS results considering GHG emissions level, while model 4 shows the ordered logit results. Non-interacted terms form intensities and levels are included in the estimation but not reported. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int., OLS)**	**(2 - int., logit)**	**(3 - levels, OLS)**	**(4 - levels, logit)**
DiscloseGHG dummy	0.52***	0.51***	0.67***	0.65***
	(0.20)	(0.18)	(0.18)	(0.17)
DiscloseGHG x Scope 1 GHG intensity	-460***	-390***		
	(154)	(133)		
DiscloseGHG x Scope 2 GHG intensity	1,322	1,089		
	(1,151)	(870)		
DiscloseGHG x Scope 3 GHG intensity	165**	150**		
	(81.2)	(71.1)		
Disclosed intensity change	0.019	0.013		
	(0.013)	(0.010)		
DiscloseCommit dummy	0.039	0.084	0.035	0.084
	(0.18)	(0.16)	(0.18)	(0.16)
DiscloseGHG x Scope 1 GHG level			-0.023**	-0.020**
			(0.0097)	(0.0090)
DiscloseGHG x Scope 2 GHG level			-0.17	-0.16
			(0.11)	(0.12)
DiscloseGHG x Scope 3 GHG level			0.0046*	0.0041**
			(0.0025)	(0.0019)
Disclosed level change			0.019	0.011
			(0.015)	(0.012)
Governance	0.0051	0.0021	0.0044	0.0014
	(0.0044)	(0.0040)	(0.0043)	(0.0039)
Constant	11.5***		11.5***	
	(0.43)		(0.42)	
Firm-level controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	2,598	2,599	2,598	2,599
R-squared	0.415	0.1204	0.414	0.1202

Table 21: Panel regression for credit ratings and emissions for US firms, Testing H3 (quantitative reduction target measure) from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see (5), where the relationship between quantitative backward and, where available, quantitative forward-looking transition metrics and credit ratings. Model 1 and 2 show the OLS estimates considering GHG emissions intensity and quantitative forward-looking metrics from Refinitiv and from CDP, respectively. Model 3 and 4 show the OLS estimates considering GHG emissions level and quantitative forward-looking metrics from Refinitiv and from CDP, respectively. Ordered logit estimators lead to similar conclusions and are not reported here for brevity. Firm-level clustered standard errors are indicated in parentheses. The statistical significance of the estimated parameters is indicated by *** for a p-value of 0.01, ** for a p-value of 0.05, and * for a p-value of 0.10.

Variable	**(1 - int., OLS)**	**(2 - int., OLS)**	**(3 - levels, OLS)**	**(4 - levels, OLS)**
Scope 1 GHG intensity	-107	-331		
	(210)	(207)		
Scope 2 GHG intensity	650	-1,111		
	(1,007)	(957)		
Scope 3 GHG intensity	52.5	72.9***		
	(34.6)	(24.8)		
Disclosed intensity change	409	-1,017*		
	(650)	(527)		
Scope 1 GHG level			-0.017	-0.023*
			(0.012)	(0.012)
Scope 2 GHG level			0.094	0.023
			(0.077)	(0.100)
Scope 3 GHG level			0.0018	0.0014
			(0.0019)	(0.0024)
Disclosed level change			-0.052	-0.064
			(0.056)	(0.078)
TargetPerc Ref	0.013*		0.013**	
	(0.0066)		(0.0065)	
TargetYear Ref	-0.056*		-0.052*	
	(0.030)		(0.029)	
TargetPerc CDP		0.016**		0.015**
		(0.0070)		(0.0071)
TargetYear CDP		-0.0099		-0.0080
		(0.019)		(0.019)
TargetBaseYear CDP		-0.045		-0.040
		(0.038)		(0.038)
Constant	65.8*	121***	65.4*	116***
	(39.1)	(43.2)	(37.4)	(44.1)
Firm-level controls	Y	Y	Y	Y
Time fixed-effects	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	433	548	433	548
R-squared	0.421	0.393	0.425	0.392

Appendix C

Credit ratings may be more sensitive to changes in risk for firms which are already closer to default. It is, therefore, interesting to consider whether our results depend on the existing credit-worthiness of firms – in particular, on whether they are stronger for riskier high-yield (HY) firms than for those with an investment-grade (IG) rating. To explore this, we define an indicator variable allocating firms to either the HY or IG category based on their credit rating, as defined in Table 2. This results in 84% of the observations belonging to IG firms and 16% to HY. We then re-run the regressions related to H1 and H3, focusing on the interaction of our main transition risk metrics with the two credit quality groups.

When running the specification related to H1, we find that higher Scope 1 GHG levels and intensities are associated with worse ratings for HY firms but that this is not the case for IG firms. The post-estimation test for both specifications also confirms that estimates of scope 1 GHG levels and intensities for the group of observations with HY ratings differs in a statistically significant manner from those estimates corresponding to IG observations. These results suggest that firms which have worse credit ratings do indeed exhibit stronger sensitivity to their current exposure to transition risk than firms which are IG, though the limited sample of HY firms makes it challenging to draw strong conclusions.

Turning to consider past performance in reducing emissions, disclosure practices and climate commitments, we also re-run the specification for H3 on GHG intensities and GHG emission levels. Strikingly, we find that the credit ratings of IG firms – who are further away from default – remain sensitive to practices related to transition risk management. In particular, there is strong evidence across specifications that committing to an emission-reduction target is positively associated with better credit ratings for IG firms. There is also some evidence that disclosure and realised performance in cutting emissions are associated with better ratings for IG firms. While post-estimation tests provide only limited evidence that the IG estimates are statistically significantly different from the HY ones, the results clearly dismiss the idea that transition risk only matters for the credit risk of firms which are already close to default. This may be because credit rating agencies maintain a strong focus on the management of medium-term transition risks for relatively credit-worthy firms even if, in contrast to HY firms, they are less concerned about their immediate vulnerability to transition risks. Both tables described in this section are available upon request.

Additional robustness checks on credit ratings and transition risk

To further assess the reliability of the results discussed in section 4, we perform three additional robustness exercises. Tables on the robustness tests described in this section are available upon request. We first repeat the analysis on a sample excluding high-emitters, defined as those firms belonging to the top tercile of the Scope 1 and 2 GHG intensities' distribution. The main rationale for excluding such firms is that high-emitters, which are more environmentally damaging and therefore exposed to greater scrutiny, choose to disclose more (Marquis, Toffel, and Zhou, 2016), a finding also confirmed in our own sample by their higher disclosure rate of GHG emissions and their greater propensity to commit to emission-reduction targets (see Figure 1). This could have particular implications for our results relating to H3. Comfortingly, key results relating to disclosure and forward-looking commitments being associated with better credit ratings continue to hold in this sub-sample.

Second, we re-run our panel regressions using firm fixed-effects as opposed to sector and country ones. While some results continue to hold, it is evident that some key variables − including those related to the act of disclosure and the commitment to an emission-reduction target − lose their significance under firm fixed-effects. It should be noted, however, that firm fixed-effects require a large amount of degrees of freedom in the estimation and that within-firm variation on the environmental metrics might not be sufficient, especially given the yearly nature of our environmental data. As such, the firm fixed-effects setup has strong limitations to its applicability, which is why we use time, sector and country fixed-effects in our baseline specification and place significantly more weight on those results.

Finally, we also repeat the panel regressions on a sample including only firms in the highest emitting sectors (NACE codes A, B, C, D, E, H). The main results on the significance of Scope 1 emissions, as well as the moderating role of disclosure and emissions reduction targets are found in this exercise. Tables with detailed results are available upon request.

Appendix D

Following Merton we solve the following system of equations (9) and (10) to obtain distance-to-default measures, with firm equity (E), assets (A), time to expiry (T) of the debt (e.g. next debt repayment date), the nominal amount of the debt (D), the risk-free rate (r), with N denoting the cumulative normal distribution:

$$E = A \cdot N(d_1) D \cdot e^{rT} \cdot N(d_2) \tag{9}$$

$$\sigma_E = \frac{A}{E} \cdot N(d_1) \cdot \sigma_A. \tag{10}$$

where d1 and d2 are given by:

$$d_1 = \frac{log\left(\frac{A}{D}\right) + \left(r + \frac{1}{2}\sigma_A^2\right) \cdot T}{\sigma_A \cdot \sqrt{T}} \tag{11}$$

$$d_2 = d_1 - \sigma_A \cdot \sqrt{T} \tag{12}$$

The solution to equations (9) and (10) provides estimates for the unknown variables $\{A, \sigma_A\}$, which are then used to compute the distance-to-default (DtD) as:

$$DtD = \frac{1}{\sigma_A \cdot \sqrt{T}} \cdot \left(log(A) + \left(r - \frac{1}{2}\sigma_A^2 \right) - log(D) \right) \tag{13}$$

giving rise to the expression that computes the probability of default (PD):

$$PD = 1 - N(DtD). \tag{14}$$

Finally, it is worth recalling that the market based credit risk measures, by virtue of relying on market prices, will be influenced by the general risk perception of the agents that trade in the markets. In other words, risk premia will influence the market-implied default probabilities. Conversely, ratings issued by rating agencies are presumably expressed as through-the-cycle gauges for credit risk, and should as such not be as affected by the current state of financial markets. To the extent that risk premia vary considerably over time, differences in conclusions may materialise as a consequence of this difference.

Recent Issues

No. 441	Kamila Duraj, Daniela Grunow, Michael Haliassos, Christine Laudenbach, Stephan Siegel	Rethinking the Stock Market Participation Puzzle: A Qualitative Approach
No. 440	Chiara Mio, Marco Fasan, Antonio Costantini, Francesco Scarpa, Aoife Claire Fitzpatrick	Unveiling the Consequences of ESG Rating Disagreement: An Empirical Analysis of the Impact on the Cost of Equity Capital
No. 439	Florian Berg, Florian Heeb, Julian F. Kölbel	The Economic Impact of ESG Ratings
No. 438	Florian Heeb, Julian F. Kölbel, Stefano Ramelli, Anna Vasileva	Green Investing and Political Behavior
No. 437	Florian Heeb, Julian F. Kölbel	The Impact of Climate Engagement: A Field Experiment
No. 436	Tobias Berg, Lin Ma, Daniel Streitz	Out of Sight, Out of Mind: Divestments and the Global Reallocation of Pollutive Assets
No. 435	Alexander Morell	Should Cartel Sanctions Be Reduced in Case the Offender Runs a Corporate Compliance Program?
No. 434	Peter Andre, Joel P. Flynn, George Nikolakoudis, Karthik A. Sastry	Quick-Fixing: Near-Rationality in Consumption and Savings Behavior
No. 433	Nikolai Badenhoop, Max Riedel	Reforming EU Car Labels: How to Achieve Consumer-Friendly Transparency?
No. 432	Alexander Ludwig, Jochen Mankart, Jorge Quintana, Mirko Wiederholt	Heterogeneity in Expectations and House Price Dynamics
No. 431	Jakob Famulok, Emily Kormanyos, Daniel Worring	Do Investors Use Sustainable Assets as Carbon Offsets?
No. 430	Satchit Sagade, Stefan Scharnowski, Erik Theissen, Christian Westheide	A Tale of Two Cities – Inter-Market Latency and Fast-Trader Competition
No. 429	Christine Laudenbach, Ulrike Malmendier, Alexandra Niessen-Ruenzi	The Long-Lasting Effects of Experiencing Communism on Attitudes Towards Financial Markets