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

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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. We show that high emissions are associated with higher credit risk, but this relationship is mitigated by disclosing emissions and climate commitment. After the Paris agreement, firms most exposed to transition risk also saw their ratings deteriorate relative to their peers, with the effect larger for European than US firms, reflecting differential climate policy expectations. These results have policy implications for corporate disclosure and pricing of transition risk.

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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, global GHG emissions need to be substantially reduced by 2050. With this in mind, European countries and the US have pledged to reduce GHG emissions to zero in net terms by this date. But achieving net-zero emissions by 2050 requires much sharper annual reductions in GHG emissions than those which have been observed since 1990.

It is therefore essential for the planet that firms in the economy substantially reduce their GHG emissions in the coming years, at least in net terms. But 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 given the growing appetite of governments to catalyse the transition to a low-carbon economy. 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 recent 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 Principles for Responsible Investment (PRI) in 2016, committing to account for climate

[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.

change related aspects in their assessments of creditworthiness.

In light of these developments, this paper assesses whether and how two key measures of firm-level credit risk – credit ratings issued by rating agencies and the market-implied distance-to-default – are influenced by firms' climate-related transition risk. Importantly, we go beyond considerations of firms' actual current GHG emissions and emission intensities, which are the focus of most existing research, to assess how realised performance in reducing emissions, climate-related disclosure practices, and forward-looking emission reduction targets may all influence credit risk.[2] Although actual emissions proxy a firm's current exposure to climate-related transition risk, we have in mind that past performance, disclosure practices and forward-looking targets and plans may reflect a firm's commitment and strategy to reduce such risks.

We first develop a novel firm-level dataset covering the non-financial corporations included in the S&P 500 and STOXX Europe 600 indices. This provides a rich picture of firms' climate-related transition risk and their strategies to manage such risk, alongside standard financial variables which typically influence credit risk. We then apply a difference-in-differences approach exploiting the Paris agreement - taking inspiration from a wider literature which has exploited this shock in other contexts (Ginglinger and Moreau, 2019) (Ilhan, Sautner, and Vilkov, 2021) - and panel regressions to assess how such climate-related metrics influence credit risk.

In line with the existing literature (e.g. Stellner, Klein, and Zwergel (2015); Capasso, Gianfrate, and Spinelli (2020); Seltzer, Starks, and Zhu (2022)), we confirm that higher GHG emission levels and intensities tend to be associated with higher credit as assessed by both rating agencies and financial markets. But our difference-in-differences analysis shows that firms most exposed to climate transition risk by virtue of their emissions or sector saw their credit ratings deteriorate after the Paris agreement, whereas other comparable firms did not. We also find that the impact of transition risk on credit risk was larger for firms domiciled in Europe than in the US after the Paris agreement. This points to different expectations around government climate policy and commitment both

[2]While cutting the level of emissions is clearly what matters from a societal perspective to transition to a low-carbon economy, emission intensities may also be relevant for an individual firm's credit risk, as we discuss further in Section 2.2 Therefore, throughout our analysis, we consider both of these variables alongside each other when gauging firms' current exposure to transition risk.

after the Paris agreement and across countries. As such, the results are indicative of a causal relationship between some transition risk metrics and credit ratings. This result is consistent with the finding of Ilhan, Sautner, and Vilkov (2021), who use the Paris Agreement and Trump election as shocks to show in the option market that climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation.

We then focus on firms' strategies for managing transition risk in our panel analysis. We find that choosing to disclose emissions is associated with a better credit rating; at the same time, however, rating agencies appear to pay more attention to disclosed emissions than inferred emissions, implying that a firm which discloses high emissions may see an overall worsening in its credit rating. We also find some weaker evidence that disclosing emissions is associated with lower market-implied credit risk.Our results relating to realised past reductions in emissions are mixed. We find that achieving reductions in emissions is associated with better credit ratings but does not appear to influence market-implied credit risk. These results are complementary to those of Bolton and Kacperczyk (2021a), who find based on a sample of US firms that disclosing emissions reduces the stock returns that investors demand for bearing risk and that year-on-year changes in emissions are priced in stock returns.

In terms of climate-related commitments, we find strong evidence that firms who have adopted a forward-looking target to cut emissions have lower credit risk under both of our metrics. There is also some evidence that this effect tends to be stronger for more ambitious commitments, both in terms of the percentage reduction in emissions targeted and the targeted speed of reduction. In a supplementary analysis, we also find that firms with emission reduction targets have historically reduced their emissions by more than firms without targets. While this could partially reflect firms committing to targets if they find it easier to cut their emissions, this finding at least provides some assurance that firms which disclose targets do indeed make tangible progress towards meeting the Paris goals.

The magnitude of most of the effects is also economically meaningful. For example, we estimate that committing to an emission reduction target is associated with a firm's credit rating being about half a notch higher, which is almost as much as the effect from a one standard deviation reduction in leverage.

Taken together, and acknowledging some limitations related to the reliability and comparability of the climate-related metrics, our results suggest that high emitters have a higher risk of failure but that strategies to manage transition risk are also crucial. In particular, firms that are better aware of the low-carbon transition − as indicated by their disclosure practices and announcement of forward-looking commitments − 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, it should be emphasised that the true extent of such risks could still be materially under-estimated by rating agencies and market participants, especially given uncertainties over future climate policies and wider evidence which suggests that climate risks are not 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 emissions reduction targets in a consistent manner. Such action would also have the added benefit of helping investors and credit rating agencies to price 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). Recent work has also focused on the specific link between climate-related transition risk and stock returns (see, for example, Bolton and Kacperczyk (2020, 2021a,b)). This line of research establishes that equity market investors tend to require higher returns for their exposure to those firms with higher levels of GHG emissions, or that appear less well prepared to reduce their emissions. Furthermore divestment seems to be the result of exclusionary screening based on direct emission intensity in specific industries.

There is, however, less empirical research on the relationship between climate-related transition risk and credit risk, and 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). Particularly, Seltzer, Starks, and Zhu (2022) document empirically for the U.S.A. that firms with poorer environmental profile (as measured by environmental score, emissions, or emissions intensity) tend to have lower credit ratings and higher yield spreads. The relationship is particularly evident for firms with facilities located in states with stricter regulatory enforcement relative to other states in the U.S.A. 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. Safiullah, Kabir, and Miah (2021) find a negative, economically meaningful impact of carbon emissions on credit ratings in the US. Finally, further emerging 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). Although some of these studies suggest that credit rating agencies and financial market participants account to some extent for environmental performance as proxied by

[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 in its decisions albeit to a small extent for the environmental performance of a firm in its rating decisions.

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, which may reflect large discretion in methodologies (Berg, Koelbel, and Rigobon, 2019; Billio, Costola, Hristova, Latino, and Pelizzon, 2020; Schnabel, 2020a). As such, environmental scores may not be an adequate proxy for transition risk. By contrast, GHG emissions are likely to be a better proxy 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.

We contribute to the existing literature in three main ways. First, we move beyond backward-looking measures of GHG emissions and environmental scores to develop a rich, novel firm-level dataset which also covers firms' disclosure practices and quantitative information on forward-looking commitments to reduce emissions. Second, we assess credit risk via both credit ratings and market-implied distance-to-default in a common empirical framework. This provides a more holistic picture than the existing literature focusing on credit risk and it also allows us to explore the differential treatment of climate-related transition risk by rating agencies and financial markets. Third, we exploit the Paris agreement shock in a novel application to attempt to ascribe greater causality to the link between climate-related transition risk and credit risk in Europe and in the US.

The rest of the paper is organized as follows. Section 2 describes the dataset, with a particular focus on the range of quantitative climate-related metrics that we employ. Section 3 presents the set of hypotheses and our empirical strategies. Section 4 presents and discusses the results of the difference-in-differences analysis on high emitters and low-carbon transition policy. Section 5 presents and discusses the results on firms' climate disclosure and commitments. Section 6 briefly discusses the credibility of emission reduction targets. Section 7 concludes and discusses policy implications.

2 Dataset and variable selection

For constructing our dataset, we consider the non-financial constituents of the stock indices S&P 500 and STOXX Europe 600 as of December 2019[4]. The set amounts to 859 large firms operating in Europe and in the US. We collect data on credit ratings and exclude firms that do not have a credit rating issued by S&P or Moody's and obtain a set of 558 firms[5]. For these remaining 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, reflecting the two complementary measures of firm credit risk that we analyse. The sample composition by year, country and sector is shown in Table 1. In the following we describe the variables employed for the measurement of credit risk and for the measurement of transition risk as well as the set of controls that we employ in the empirical analysis.

[4] Given that index constituents may vary over time, index constituents are retrieved once for the snapshot December 2019 and not retrieved for each year of the time window 2010-2019.

[5] Out of these 558 firms, a credit rating is observed continuously for 443 firms throughout the time of the sample.

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

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

Year	**Obs.**	**Country**	**Obs.**	**Sector**	**Obs.**
2010	432	Austria	30	B-Mining and quarrying	239
2011	442	Belgium	40	C-Manufacturing other than C19	2348
2012	454	Switzerland	172	C19-Manufacture of coke and refined petroleum products	99
2013	469	Germany	295	D-Electricity, gas, steam and air conditioning supply	485
2014	493	Denmark	40	E-Water supply; sewerage, waste management and remediation	70
2015	508	Spain	100	F-Construction	73
2016	522	Finland	60	G-Wholesale and retail trade; repair of motor vehicles	439
2017	531	France	375	H-Transportation and storage	246
2018	546	United Kingdom	457	I-Accommodation and food service activities	127
2019	558	Ireland	91	J-Information and communication	515
		Italy	94	M-Professional, scientific and technical activities	121
		Luxembourg	24	N-Administrative and support service activities	121
		Netherlands	153	O-Public administration and defence; compulsory social security	10
		Norway	43	Q-Human health and social work activities	49
		Poland	10	R-Arts, entertainment and recreation	13
		Portugal	10		
		Sweden	151		
		US	2810		
Obs.	4955	Obs.	4955	Obs.	4955
Firms	558	Firms	558	Firms	558

2.1 Measures of firm credit risk

Two complementary measures of credit risk are analysed. We rely on credit ratings issued by Standard and Poors (S&P) and Moody's, and on the distance-to-default measure calculated using the approach of Merton (1974) and Bharath and Shumway (2008).

Credit ratings constitute a publicly available source of firm specific 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 panel regression analysis.

Summary scale	**Rating scale**	**Ordinal value**
IG: minimal credit risk	AAA	7
IG: very low credit risk	AA+, AA, AA-	6
IG: low credit risk	A+, A, A-	5
IG: moderate credit risk	BBB+, BBB, BBB-	4
HY: substantial credit risk	BB+, BB, BB-	3
HY: high credit risk	B+, B, B-	2
HY: very high credit risk	CCC+, CCC, CCC-	1

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 and Moody's from the proprietary ECB Ratings Database. For our baseline specification, we use the long-term issuer credit ratings provided by S&P, while we assess the robustness of our results by testing our hypotheses on Moody's ratings. For the purpose of our empirical analysis using panel regressions, we operationalise the ratings by grouping them into seven categories and converting to an ordinal scale 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)). For the purpose of our empirical analysis using difference-in-differences, we employ the alphanumeric mapping of rating grades to values ranging from 1 to 21, without categorization, to capture rating actions such as up- and downgrades.

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[6]. 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 about credit risk (and thus probabilities of default)[7]. 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 im-

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

[7]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.

plement 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:

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

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

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

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[8]. 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 C shows more details on how we implement this approach.

[8]Minor differences may arise between the two samples due to data needs and availability for implementing the distance-to-default calculations. However, in general, to insure consistency and comparability between the DtD and the Credit Rating analyses, the set of companies covered is given by the intersection of the firms covered by the DtD and credit rating data sets.

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 Tables 3 and 4, respectively). The backward-looking variables exploit GHG emissions data from Urgentem.[9] 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 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. At the same time, GHG emission intensities may reflect the carbon-efficiency of a firm. From the perspective of individual firms, those which are more carbon-efficient in generating revenues may be better placed than their competitors to withstand policy changes to tackle global warming, such as higher carbon taxes. Such firms may, therefore, also have lower credit risk.[10] In view of this, we consider both emissions levels and emissions intensities alongside each other throughout our analysis.

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

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

[10] To see the potential importance of considering emission intensities from another perspective, consider the hypothetical example of a merger between two identical firms with the same revenues and emission intensities. The merged firm will have the same emission intensity as each individual firm but double the level of emissions. From a credit risk perspective, however, it is not clear that the merged firm would face substantially greater climate-related risks than each individual firm.

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 self-disclosed Scope 1 and 2 GHG emissions in both absolute and relative terms.[11] 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. A dedicated dummy variable indicates whether the firm discloses 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 emis-

[11] 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)).

Table 3: 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
EU ETS Carbon Price	EUA (EU ETS) Futures Price	ICE
Top CO2 NACE	Dummy indicating top 3 carbon polluting NACE1 sectors in EU-27+UK	Eurostat
Top CH4 NACE	Dummy indicating top 3 methane polluting NACE1 sectors in EU-27+UK	Eurostat

sions reported in non-financial statements are verified, but does not necessarily imply that this is the case.

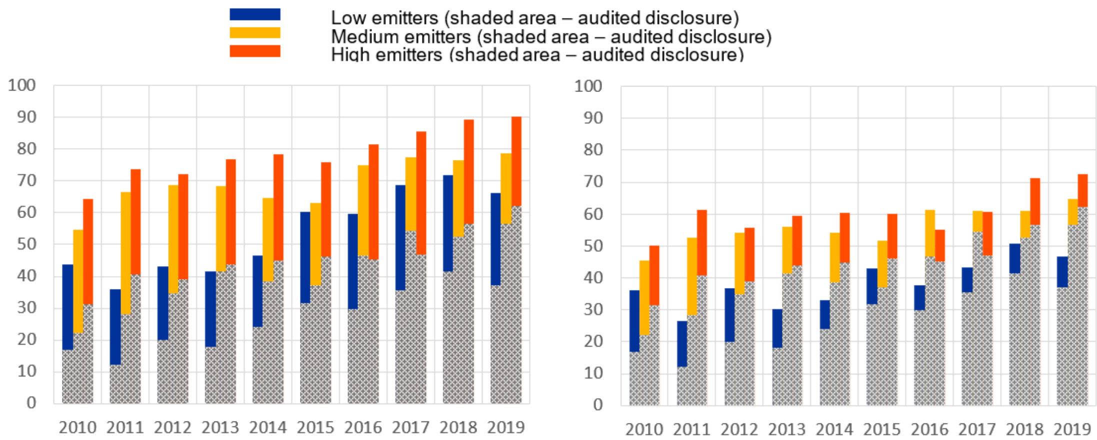
Figure 1 shows that the share of firms disclosing data on GHG emissions and committing to emission reduction targets has increased over time. But despite having similar trends, the firm-level correlation between the two variables is only 47% (see also Table 16), clearly making them of independent interest. 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.

Table 4: 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

Figure 1: Disclosure of backward-looking GHG emissions and forward-looking emissions reduction targets

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 859 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 targets out of a sample of 859 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.

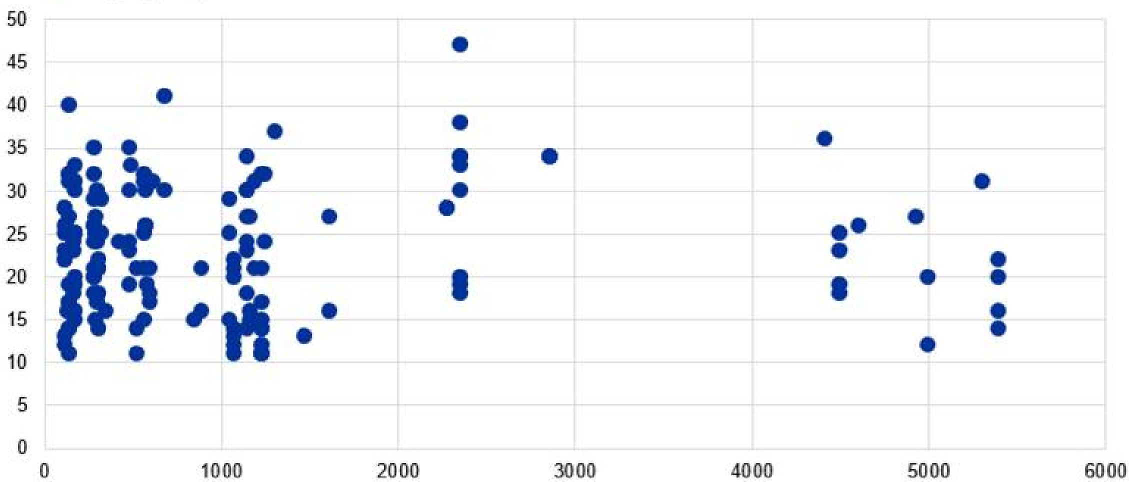


In addition to the assumption establishing the link between GHG emissions/intensities and firms' backward-looking exposure to transition risk, we use the forward-looking variables as proxies of firms' management of such risk. The disclosure variable, albeit being backward-looking, plays a dual role. 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 appear to conform to clear sectoral patterns. For example, the majority of S&P500 utility sector firms have a high climate-related transition risk but significantly variable physical risk dependent on the location of their operations. In view of all 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 15 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. 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.

2.4 Descriptive statistics

Summary statistics on ratings, GHG emissions-related variables and firm-level financial variables are provided in Table 5. Pooled correlations of main variables are shown in the Appendix in Table 16.

Table 5: 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	4762	4.21	4	0.82	1	7
Rating Moody's	4365	4.12	4	0.83	1	7
Size	4944	35761087	17278500	55151427	422868	751216000
Governance	4841	61.47	64.84	21	0	98
Solvency	4936	0.29	0.22	0.23	0	1.39
Leverage	4931	2.83	2.32	2.20	0	13.48
Profitability	4811	20.27	14.98	28.22	-42.2	191.93
Debt service	4923	14.08	7.091	41.91	-16.39	969
Scope 1 GHG intensity	4865	0.000354	0.000019	0.000966	0.0000001	0.010127
Scope 2 GHG intensity	4759	0.000054	0.000029	0.000088	0.0000002	0.001418
Scope 3 GHG intensity	4759	0.004730	0.001256	0.016818	0.000031	0.103110
Scope 1 GHG level	4745	5.55	0.28	17.36	0.000162	178.65
Scope 2 GHG level	4745	1.27	0.29	5.03	0.000948	161.48
Scope 3 GHG level	4745	40.55	8.09	113.88	0.035471	1993.62
Disclosed Scope 1-2 intensity change	4408	0.03	0	0.72	-1	35.08
Disclosed Scope 1-2 level change	4276	0.18	0	5.10	-0.99	326.22
TargetYear	945	5.75	3	5.62	0	33
TargetPerc	898	31.21	25	22.21	0.28	100
DiscloseGHG dummy	4955	0.68	1	0.46	0	1
DiscloseCommit dummy	4955	0.65	1	0.47	0	1
TargetPerc CDP	1257	42.36	30	33.34	0	100
TargetBaseYear CDP	1269	2012	2014	4.75	1990	2020
TargetYear CDP	1268	15.48	11	12.61	0	60
TargetAnnualLevel CDP	771	0.06	0	0.36	0	3.90
TargetLevel CDP	772	1.03	0	7.22	0	121.35
SBTi dummy	4955	0.05	0	0.21	0	1
Audited dummy	4955	0.46	0	0.49	0	1

3 Hypotheses and empirical specifications

As described in Section 2, we consider two measures of firm credit risk for our dependent variable: credit ratings and the market-implied distance-to-default.

The two measures metrics reflect slightly different pricing mechanisms of transition risk. The market-implied distance-to-default reflects transition risk through its potential to disrupt the future earnings and hence dividends of a firm. Credit ratings speak rather to a firm's ability to continue servicing its debt, whereby transition risks may present a greater near-term challenge for firms who already have low ratings but are likely to represent a medium-term challenge for all firms. Despite these differences, we adopt a broadly common empirical framework for both metrics as this allows us to compare results in a more straightforward way. But we acknowledge some of these issues in an extension to our credit rating analysis where we distinguish high yield from investment grade firms.

We test three hypotheses to explore how the various climate-related metrics discussed in section 2 may 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. In particular, 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. 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 estimation methods. Listed firms are often required to disclose on environmental matters, but they can choose which standards to adopt and through this 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 particular, the disclosure of forward-looking targets can convey not only that a firm is aware of the transition risk to which it is exposed, but also that has an active plan to manage these risks. At the same time, disclosed data allow for monitoring the actual performance and effectiveness of the firm in reducing GHG emissions over time. Depending on this performance, disclosure of backward- and forward-looking environmental information can have a moderating effect on the relationship between transition and credit risk. In this context, we test two hypotheses:

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

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.

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 companies. Then a panel regression analysis examines how the relationship between firm transition risk and credit risk 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 more detail the empirical specifications.

3.1 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. The Paris Agreement has been adopted in December 2015, signed in April 2016, and ratified in November 2016, by a group of countries including the US and all European countries in our sample. This represents an exogenous event that may have shifted the assessment of credit rating agencies (see for example Moody's Investors Service (2016), S&P Global

Ratings (2017a)) and the perception of market participants around climate-related transition risk, since it reflected a tightening of the commitment of governments to reduce GHG emissions. At the same time, the impact may have been different across jurisdictions. Before the Paris Agreement, European countries already had an up and running carbon market, the EU Emissions Trading System (ETS). And although the US signed the Paris Agreement, the credibility of the government commitment to reduce emissions was limited by the election of Donald Trump in November 2016, Trump's announcement in June 2017 of withdrawal from the Paris Agreement, and the filing for withdrawal in November 2019. Resenting 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).

Specifically, first we compare 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 3. 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 4.

$$\begin{aligned} CreditRating_{i,t} =& \alpha + \beta_0 Treatment_i \times postParis_t + \\ & \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \rho FirmFE_i + \tau TimeFE_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

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[12]) 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 to 1 for European countries, as described in Equation 4.

$$
\begin{aligned}
CreditRating_{i,t} = & \alpha + \beta_0 Treatment_i \times TransitionPolicy_i \times postParis_t + \\
& \beta_1 Treatment_i \times postParis_t + \\
& \beta_2 TransitionPolicy_i \times postParis_t + \\
& \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \rho FirmFE_i + \tau TimeFE_t + \epsilon_{i,t}
\end{aligned} \tag{4}
$$

3.2 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 distinguishing between disclosed and inferred GHG intensities/emissions, (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.

[12]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.

In the first hypothesis, we analyse the direction and the significance of the relationship between the firm credit risk measures, and Scope 1, 2 and 3 GHG intensities or GHG emissions, which proxy its current exposure to climate-related transition risk. The model is summarised in Equation 5. 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.

$$\begin{aligned} CreditRisk_{i,t} =& \alpha + \beta_1 Scope1_{i,t} + \beta_2 Scope2_{i,t} + \beta_3 Scope3_{i,t} + \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \\ & \rho SectorFE_i + \tau TimeFE_t + \sigma CountryFE_i + \epsilon_{i,t} \end{aligned} \tag{5}$$

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 6. 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.

$$\begin{aligned} CreditRisk_{i,t} =& \alpha + \beta_0 DiscloseGHG_{i,t} + \beta_1 Scope1 + \beta_2 Scope2_{i,t} + \beta_3 Scope3_{i,t} + \\ & \beta_4 DiscloseGHG_{i,t} \times Scope1_{i,t} + \beta_5 DiscloseGHG_{i,t} \times Scope2_{i,t} + \\ & \beta_6 DiscloseGHG_{i,t} \times Scope3_{i,t} + \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \rho SectorFE_i + \\ & \tau TimeFE_t + \sigma CountryFE_i + \epsilon_{i,t} \end{aligned} \tag{6}$$

Finally, for the third hypothesis, we augment the model specification by adding the past year-on-year change in Scope 1 and 2 intensities/emissions, $DisclosedLevelChange_{i,t} = (Scope1and2_{i,t} - Scope1and2_{i,t-1})$, and any information on the forward-looking emission reduction target of a firm, as described in Equation 7. 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.

$$\begin{aligned} CreditRisk_{i,t} = &\alpha + \beta_0 DiscloseGHG_{i,t} + \beta_1 Scope1 + \beta_2 Scope2_{i,t} + \beta_3 Scope3_{i,t} + \\ &\beta_4 DiscloseGHG_{i,t} \times Scope1_{i,t} + \beta_5 DiscloseGHG_{i,t} \times Scope2_{i,t} + \\ &\beta_6 DiscloseGHG_{i,t} \times Scope3_{i,t} + \beta_7 DisclosedLevelChange_{i,t} + \\ &\Sigma_{k=1}^{N} \psi_k Target_{k,i,t} + \Sigma_{j=1}^{N} \gamma_j Controls_{j,i,t} + \\ &\rho SectorFE_i + \tau TimeFE_t + \sigma CountryFE_i + \epsilon_{i,t} \end{aligned} \tag{7}$$

Within this empirical setup, we attempt to tackle potential endogeneity concerns throughout. 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 inferred 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 section 5.2.2 we also repeat the analysis on a sample excluding high-emitters and use firm fixed-effects as opposed to sector and country ones.

4 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 3.1. We start our analysis by testing first the existence of an associative relation between GHG emissions Scope 1, 2, and 3 and our selected measures of credit risk as specified in Equation 5 and suggested by existing related studies[13]. The related panel regression results presented in tables 19 and 20 in Appendix D confirm the existence of such a relationship for both credit ratings and distance-to-default in our sample of firms[14]. Having confirmed the baseline relation between GHG emissions and ratings on our sample, we next present panel regression results for the subsample of European firms and for the subsample of US firms to illustrate our primary that the relation between GHG emissions and ratings differs across these two geographies (see results in Appendix D)[15]. Scope 1 GHG intensity and Scope 3 GHG intensity are negatively associated with credit ratings for European firms, but not for US firms. Similarly, when considering GHG emissions levels instead of GHG emissions intensity, Scope 1 GHG level is negatively associated with credit ratings for European firms, but not for US firms. For regressions on European firms, we further integrate the EU ETS carbon price as a control reflecting the EU carbon market. The carbon price is negatively associated with credit ratings: 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 may exist for European firms, but not for US firms. We test the existence of such a causal relationship by the means of a difference-in-differences methodology.

Having confirmed our intuition of an associative relationship between GHG emissions and credit ratings depending on the geography (Europe versus US), we define the dataset for the difference-in-differences analysis. We consider a balanced panel with the same number of firms observed throughout the whole period: before the event, i.e. ex-ante

[13]See for instance Stellner, Klein, and Zwergel (2015); Capasso, Gianfrate, and Spinelli (2020); Seltzer, Starks, and Zhu (2022)

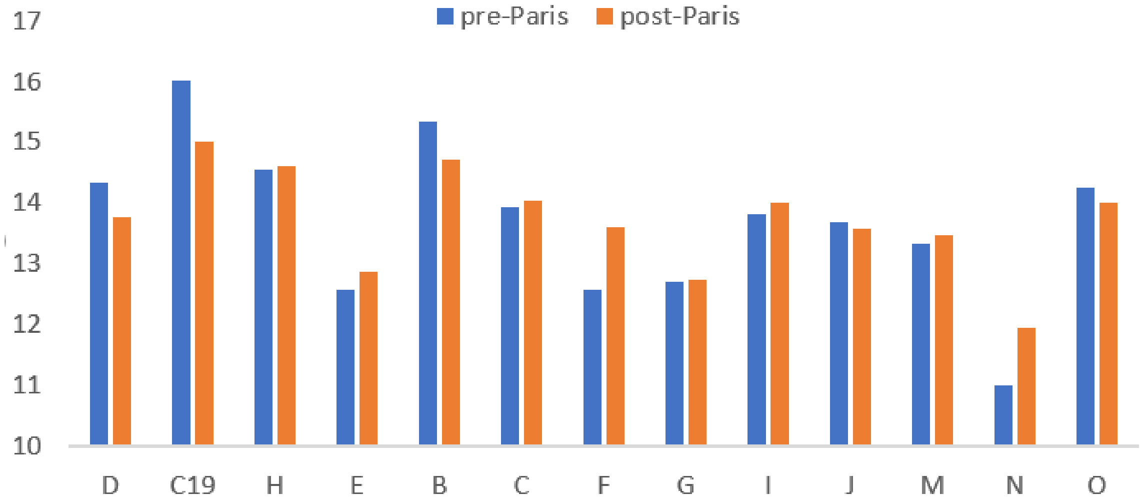
[14]Additional results on the differential effects of transition risk across investment-grade and high-yield firms are reported in Appendix B, tables 17 and 18

[15]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 7 for a comprehensive description of variables.

(2011, 2012, 2013, 2014), and during and after the event, i.e. ex-post (2015, 2016, 2017, 2018, 2019). The *CreditRating* variable is mapped to a granular rating scale of ordinal values ranging from 1 to 21, such that a higher ordinal value indicates a better rating. The more granular rating scale suits better the difference-in-differences approach as it allows us to capture all up- and downgrades undertaken by the credit rating agency. We focus first on the sample of European firms, as presented in section 3.1, and present the US comparison later. We start with a descriptive analysis of changes in credit ratings for high polluting firms operating in the Europe versus other European firms, both before and after the Paris Agreement. Figures 3 and 4 show the average rating for each type of treatment[16] before and after the Paris Agreement.

Figure 3: 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.

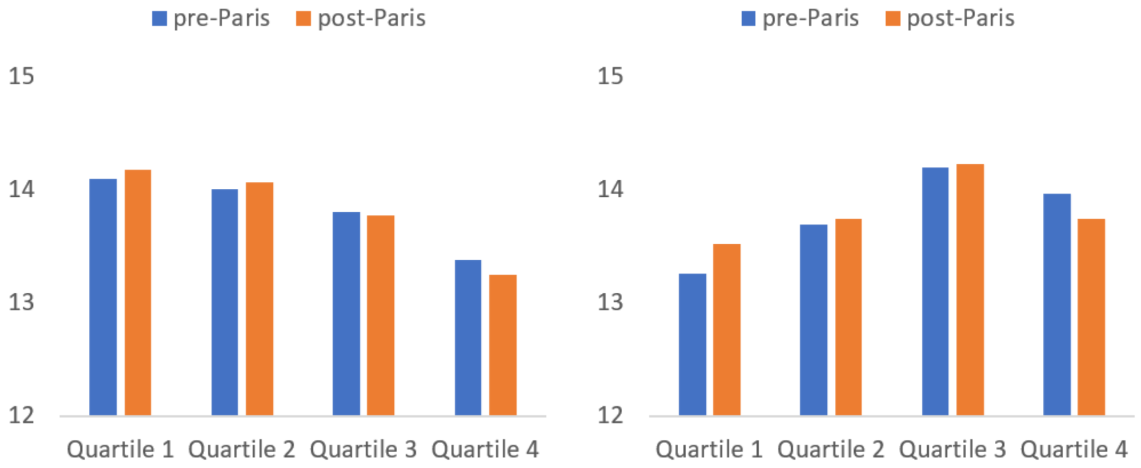


On average, ratings decreased for firms in the top polluting NACE economic activities Electricity, gas, steam and air conditioning supply (D), Manufacture of coke and refined petroleum products (C19), and Mining and quarrying (B) (Figure 3). In addition, firms in the top quartile of GHG emissions intensity and firms in the top quartile of GHG emissions level had, on average, worse ratings after the Paris Agreement (Figure 4).

[16]The treatment takes three different specifications as defined in 3.1: (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 4: 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 6. 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 3. The difference-in-differences estimates for the treatment top GHG NACE (*Top GHG NACE x post-Paris*) and for the treatment top GHG level (*Top GHG level 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 intensity (*Top GHG intensity x post-Paris*) is statistically significant in the basic difference-in-differences specification, but not once we add the controls and the fixed-effects, although the negative sign is still as expected. These results highlight that following the Paris agreement European firms active in the most polluting economic activities see their ratings fall by 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 0.38 notch relative to the control group.

These results are intuitive of a causal relationship between some transition risk metrics[17]

[17] In addition, we test an alternative specification where we define the treatment group as firms with

and credit ratings.

The estimated coefficient for *Top GHG NACE* is positive and statistically significant at 5%, suggesting that, prior to the Paris Agreement, firms in the treatment group *Top GHG NACE* had higher ratings than the firms in the control group.

Table 6: 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	-0.55***			-0.53***		
	(0.17)			(0.16)		
Top GHG intensity x post-Paris		-0.16*			-0.28	
		(0.086)			(0.18)	
Top GHG level x post-Paris			-0.32*			-0.38**
			(0.17)			(0.16)
Top GHG NACE	0.84**					
	(0.34)					
Top GHG intensity		-0.58*				
		(0.35)				
Top GHG level			0.20			
			(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	1,530	1,530	1,530	1,474	1,474	1,474
Number of firms	170	170	170	170	170	170
R-squared	0.028	0.003	0.012	0.063	0.044	0.054

The parallel trend assumption underlying the difference-in-differences design presumes that in the absence of treatment, the difference in rating between the "treated" firms and the "control" firms is constant over time. Since we have observations over many time-points, we examine the dynamics over time for the treatment specifications *TopGHG-NACE*, *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 3. The yearly es-

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.

timated coefficients are shown in Figure 5. 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, i.e. 2016-2019, remain consistently below 0. This provides strong evidence of changes in ratings 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 5: Treatment effect for each period of the sample.

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.

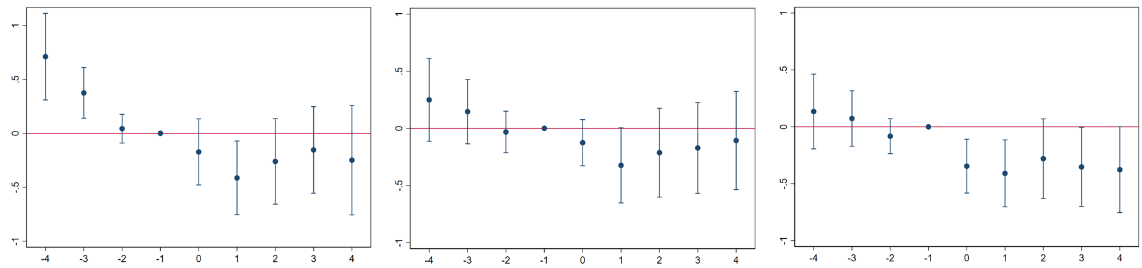
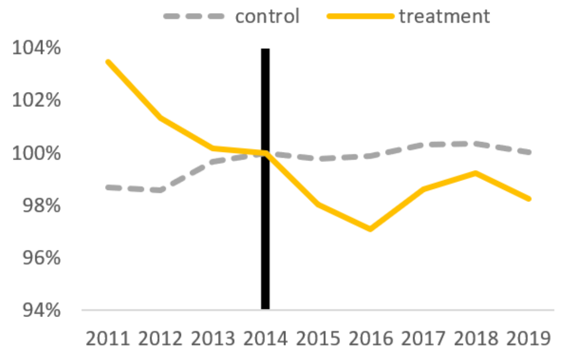
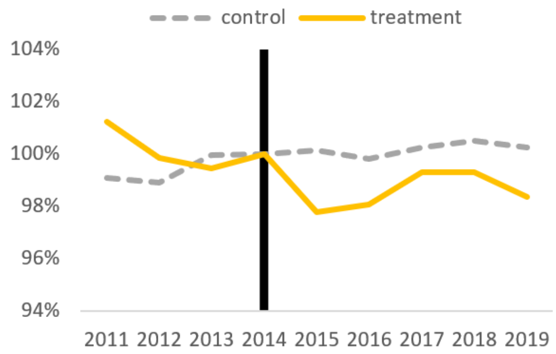


Figure 6 shows the rating dynamics of the treatment group relative to the control group over time for treatments *TopGHGNACE* and *TopGHGlevel*, for which the difference-in-difference estimated coefficients in 6 are consistently statistically significant across different specifications. In Figure 6, 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 6: 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 listed 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)[18]. For this purpose, we run a triple difference-in-differences analysis including an indicator variable differentiating on such countries. The results reported in Table 7 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 specification while columns 4, 5, 6 − for a specification considering in addition firm-level controls and fixed-effects as per Equation 4. 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

[18]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.

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 intensity x post-Paris* suggest that credit ratings actually improved for the most polluting firms in the US in the period following the Paris Agreement. Overall, the results from this triple difference-in-differences exercise indicate that the potential causal relationship between some transition risk metrics and credit ratings may be dependent on the extent of national climate change / carbon reduction commitments in the country where the firm primarily operates.

Table 7: 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 4. 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	-1.06***			-0.91***		
	(0.23)			(0.21)		
Top GHG intensity x Transition-policy x post-Paris		-0.55**			-0.53**	
		(0.25)			(0.22)	
Top GHG level x Transition-policy x post-Paris			-0.57**			-0.49**
			(0.24)			(0.20)
Top GHG NACE x post-Paris	0.51***			0.39***		
	(0.16)			(0.14)		
Top GHG intensity x post-Paris		0.38**			0.28**	
		(0.16)			(0.14)	
Top GHG level x post-Paris			0.25			0.11
			(0.17)			(0.14)
Top GHG NACE x Transition-policy	1.65***					
	(0.50)					
Top GHG intensity x Transition-policy		0.32				
		(0.54)				
Top GHG level x Transition-policy			0.60			
			(0.54)			
Transition-policy x post-Paris	0.22**	0.12	0.13	0.10	0.024	0.032
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	3,807	3,807	3,807	3,643	3,643	3,643
Number of firms	423	423	423	422	422	422
R-squared	0.026	0.010	0.008	0.094	0.081	0.081

In the above DiD analysis we focus on credit ratings and document a change in assessment performed by the credit rating agencies post 2015. Emerging empirical studies provide complementary evidence on distance-to-default reflecting the assessment performed by stock market participants (Nguyen, Diaz-Rainey, and Kuruppuarachchi, 2021; Kabir, Rahman, Rahman, and Anwar, 2021; Capasso, Gianfrate, and Spinelli, 2020).

By the means of a DiD using the Paris Agreement as a shock, these studies document empirically the existence of a relation between different metrics of GHG emissions and a firm's distance-to-default, suggesting that financial market participants changed their assessment after the Paris Agreement. More broadly, the result of our DiD analysis is comparable to the findings of Ilhan, Sautner, and Vilkov (2021) who show using the option market and the Paris Agreement that climate policy uncertainty makes it difficult for investors to quantify the impact of future climate regulation.

5 Results on firms' climate disclosure and commitments

5.1 Credit ratings

5.1.1 Results of regression analysis

Given the categorical nature of credit ratings, when considering ratings as the dependent variable, we employ both standard ordinary least square estimators as well as ordered logit ones in line with Baghai, Servaes, and Tamayo (2014)[19], 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.

Turning to our second hypothesis, we present results for the specification in Equation 6 in Table 8. It is immediately evident that we find strong results on the relevance of the act of self-disclosing GHG intensities. Firms which disclose such information do 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. As we discuss further below these results are also economically significant. In addition to the standalone effect of being a disclosing firm, we find a significant difference in how GHG emissions/intensities are associated

[19] In line with Baghai, Servaes, and Tamayo (2014), we consider ordered logit estimators suitable for our research question. Given the categorical nature of ratings, ordered logit does not assume that moving from for example BB to BBB is equivalent to moving from AA to AAA. We also report OLS estimators since some of our specifications employ firm fixed-effects to control for unobservable firm-specific heterogeneity, and estimating ordered response models with firm fixed-effects would result in biased and inconsistent point estimates.

with ratings depending on whether emissions are self-reported or inferred by third-party data providers. In particular, the interaction term between the disclosure dummy and Scope 1 intensity is found to be significantly negative. By contrast, inferred intensities do not seem to be reflected in credit ratings and, in contrast to the first set of results in Table 19, Scope 3 emissions are found to be significantly reflected in lower ratings when disclosed. As discussed later in this section, there is a trade-off between the benefit coming from the act of disclosing GHG emissions and the negative impact that the level of disclosed emissions and emission 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 (2020)

Table 8: Panel regression for credit ratings and emissions, Testing H2 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H2, see Equation 6, 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. 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	0.26*** (0.067)	0.84*** (0.21)	0.23*** (0.052)	0.73*** (0.16)
DiscloseGHG x Scope 1 GHG intensity	-113** (46.2)	-359** (149)		
DiscloseGHG x Scope 2 GHG intensity	196 (939)	460 (3,168)		
DiscloseGHG x Scope 3 GHG intensity	-2.49 (1.61)	-5.69 (4.66)		
DiscloseGHG x Scope 1 GHG level			0.0021 (0.0031)	0.0045 (0.0095)
DiscloseGHG x Scope 2 GHG level			-0.0034 (0.017)	0.0087 (0.055)
DiscloseGHG x Scope 3 GHG level			-0.00048* (0.00026)	-0.0015** (0.00075)
Scope 1 GHG intensity	42.8 (51.7)	150 (162)		
Scope 2 GHG intensity	-294 (936)	-661 (3,185)		
Scope 3 GHG intensity	-1.03 (1.13)	-4.09 (3.50)		
Scope 1 level			-0.0049* (0.0028)	-0.014 (0.0086)
Scope 2 level			0.0015 (0.0026)	0.0035 (0.0083)
Scope 3 level			0.00064*** (0.00023)	0.0019*** (0.00070)
Governance	0.0034*** (0.0012)	0.0084** (0.0036)	0.0032*** (0.0012)	0.0077** (0.0036)
Constant	3.98*** (0.097)		4.00*** (0.095)	
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	4,381	4,381	4,373	4,373
R-squared	0.344	0.1753	0.341	0.1746

The third hypothesis, which we formally test via the specifications in Equation 7, relates to the potentially moderating impact of transition risk management on the negative relationship found between current carbon emissions/intensities and credit risk. Table 9 presents the results for past year-on-year changes in (disclosed) emission levels/intensities and the forward-looking commitment dummy in . In addition, we present the results for forward-looking commitment dummy. Table 10 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.

Table 9: Panel regression for credit ratings and emissions, Testing H3 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see Equation 7, 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. 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	0.21***	0.68***	0.18***	0.57***
	(0.067)	(0.21)	(0.053)	(0.17)
DiscloseGHG x Scope 1 GHG intensity	-108**	-359**		
	(52.3)	(171)		
DiscloseGHG x Scope 2 GHG intensity	-36.5	40.2		
	(941)	(3,145)		
DiscloseGHG x Scope 3 GHG intensity	-1.42	-3.46		
	(1.54)	(4.92)		
Disclosed intensity change	-0.015	-0.049*		
	(0.0089)	(0.026)		
DiscloseCommit dummy	0.14***	0.44***	0.14***	0.44***
	(0.050)	(0.16)	(0.051)	(0.16)
DiscloseGHG x Scope 1 GHG level			0.0031	0.0081
			(0.0036)	(0.011)
DiscloseGHG x Scope 2 GHG level			-0.0051	0.0067
			(0.017)	(0.058)
DiscloseGHG x Scope 3 GHG level			-0.00046*	-0.0015*
			(0.00027)	(0.00081)
Disclosed level change			0.00061	0.0025
			(0.0014)	(0.0037)
Governance	0.0030**	0.0076**	0.0029**	0.0072*
	(0.0012)	(0.0038)	(0.0012)	(0.0037)
Constant	3.93***		3.96***	
	(0.10)		(0.097)	
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	3,984	3,984	3,962	3,962
R-squared	0.349	0.1781	0.348	0.1774

In all specifications, the results indicate that committing to a forward-looking emission reduction target is clearly associated with better credit ratings.[20] The magnitude of this effect is comparable to that for the act of disclosure. And noting that making a forward-looking commitment is only partially correlated with the act of disclosing emissions (see Table 16), the wider results in Table 9 imply that the act of disclosure itself is also independently beneficial for a firm's credit rating. In addition, although there appears to be no meaningful relationship between changes in emission levels and credit ratings,

[20]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.

realised reductions in emission intensities do appear to be associated with better ratings in some specifications. Taken together, these results highlight how a range of transition risk management strategies can help to offset the negative effect on credit ratings coming from exposure to high emissions levels and and intensities.

We also find that among the sample of firms who disclose quantitative targets and related timelines, credit ratings appear strongly related to the ambitiousness of firms' in terms of the percentage of emissions to be cut. By contrast, the timing concerning the fulfilment of the quantitative targets is not found to be significantly associated with ratings. This difference might be explained by the stronger information content of the percentage reduction targets, which might summarize the overall commitment of a firm towards reducing its transition risk. Despite the relevant shrinkage in sample size, which is due to the scarcity of quantitative forward-looking information, it would seem that the ambitiousness of firms in reducing their exposure to transition risk, through cuts in their current emissions, is associated with more favourable credit assessments.

Table 10: Panel regression for credit ratings and emissions, Testing H3 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see (7), 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	-66.0	-49.6		
	(42.0)	(88.4)		
Scope 2 GHG intensity	66.7	-21.5		
	(271)	(516)		
Scope 3 GHG intensity	5.58	27.6*		
	(12.2)	(16.1)		
Disclosed intensity change	0.023	-0.014***		
	(0.036)	(0.0049)		
Scope 1 GHG level			-0.0033**	-0.0044
			(0.0017)	(0.0039)
Scope 2 GHG level			0.0076	0.018
			(0.0086)	(0.023)
Scope 3 GHG level			0.00045	0.00045
			(0.00039)	(0.00031)
Disclosed level change			0.0013**	0.0014***
			(0.00049)	(0.00053)
TargetPerc Ref	0.0036**		0.0036**	
	(0.0015)		(0.0015)	
TargetYear Ref	-0.0024		-0.0025	
	(0.0066)		(0.0064)	
TargetPerc CDP		0.0032**		0.0031**
		(0.0014)		(0.0015)
TargetYear CDP		0.0027		0.0031
		(0.0042)		(0.0041)
TargetBaseYear CDP		-0.014*		-0.013
		(0.0083)		(0.0084)
Constant	4.80***	11.2	4.80***	6.72
	(0.21)	(19.7)	(0.21)	(21.2)
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	815	1,116	808	1,111
R-squared	0.335	0.395	0.333	0.394

5.1.2 Robustness checks

To further assess the reliability of the results discussed in section 5.1.1, we perform two further robustness exercises. 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. But as Table 22 shows, the 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. The results corresponding to H3 are summarized in Table 23. 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.

5.1.3 Economic significance

In the previous section, we have documented how both backward and forward-looking environmental metrics related to transition risk seem to be reflected in credit ratings. We now aim to provide quantitative indications on the magnitude and economic significance of the estimated coefficients. To do so, 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 also consider two dummy variables on disclosure of GHG intensities and the commitment to a forward-looking emission reduction target, for which the impact is purely determined by the magnitude of the coefficient. Formally, we have

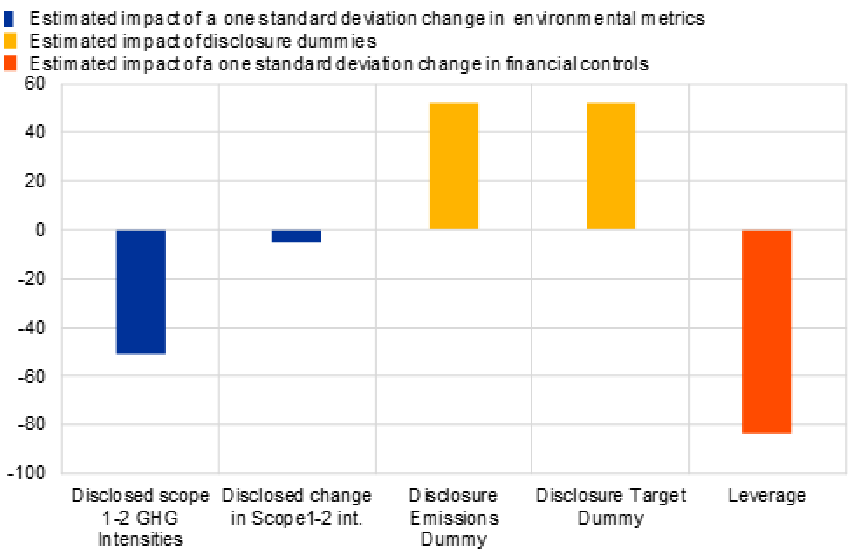
$$Impact\ on\ credit\ rating\ notch = 3 * \beta_i * \sigma_i \tag{8}$$

where β_i is the relevant coefficient and σ_i is the standard-deviation of continuous metrics. We multiply by a factor of 3 as the credit rating variable used in the regressions groups 3 credit notches into one categorical value. The results are presented in Figure 7.

As is clear, the impact of the level of Scope 1 and 2 intensities is particularly economically significant, especially when one considers the wide distribution of this variable. In particular, a one standard-deviation increase in intensities is associated with a reduction of more than half a credit notch. By way of comparison, an equivalent increase in leverage decreases credit ratings by approximately 80% 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 a rating notch for each variable, 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 1-2 intensities will be larger than what computed in this exercise, out-weighting the decrease in credit risk yielded by the act of disclosing.

Figure 7: Magnitude of transition risk metrics on credit ratings vis-a-vis leverage.

Notes: left-hand axis: percentage of a credit notch. The first two columns represent the estimated magnitude of a one standard-deviation increase in disclosed Scope 1 and 2 GHG intensities and disclosed changes in Scope 1 and 2 GHG intensities respectively. The third and fourth columns reflect the impact of the decision to disclose of GHG emissions and make a forward-looking commitment respectively. The fifth column shows the impact of a one standard-deviation increase in leverage. The coefficients on the two dummies and leverage are significant at the $p<0.01$ level. Coefficients for disclosed GHG intensities and changes in intensities are significant at the $p<0.05$ level.



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 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 7. Second, we employ as the dependent variable a transformed binary version of credit ratings, taking the value of 1 for $Rating = AAA, AA, A$ and 0 for $Rating = BBB, BB, B$. 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 11.

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. Changes in disclosed Scope 1 and 2 intensities retain modest significance. 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 belonging to the AAA, AA, A group. The effect is even stronger for firms making a forward-looking commitment related to emissions reduction, who are 10% more likely to have a better rating.

Table 11: Testing the economic significance of H3: ordered logit and average marginal effects

Notes: The table shows the results of the ordered logit estimation and the corresponding marginal effects based on equation 7, 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	0.35***	0.0529**
	(0.15)	
Disclose x Scope 1 and 2 GHG int.	-0.46	-0.0387
	(0.28)	
Disclosed change in Scope 1-2 GHG int.	-0.14*	-0.0078
	(0.081)	
Disclose x Scope 3 GHG int.	-0.091	-0.303*
	(0.13)	
Forward-looking commitment	0.56***	0.0940***
	(0.19)	
Time fixed-effects	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	3,810	2,175
R-squared	0.223	

5.2 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 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 a complement, the Appendix provides sub-sample estimates for the periods before and after the Paris Agreement. 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.

5.2.1 Results of the regression analysis

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 summarises these results. Similar as for ratings in Section 5.1.1, we find that choosing to disclose GHG-emissions seems to increase a firm's DtD as shown with statistically significant parameter estimates equal to 0.15 for GHG-emission levels and 0.12 for GHG-emission intensities. Regarding the differentiation of the coefficients of published and inferred GHG emission intensities, the regression results lend support to two empirical observations. On the one hand, there is a highly statistically significant inverse relationship between disclosed Scope 1 GHG-emission intensities and DtD, whereas inferred Scope 1 GHG-emission intensities have a statistically insignificant coefficient of lower magnitude, which suggests the market pricing of credit risk is more attentive to disclosed Scope 1 intensities. On the other hand, the DtD for Scope 3 emission intensities seems to be rather influenced by inferred than by disclosed metrics as shown by the smaller magnitude and statistical significance of the latter ones, which can be related to the inherent uncertainty for capturing Scope 3 emissions, where apparently market data vendor inference methodologies seem to play a more important role for the market expectation of credit risk.

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 (6), 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 *Disclosure*. 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	0.12	0.15**
	(0.081)	(0.069)
DiscloseGHG x Scope 1 GHG intensity	-357**	
	(150)	
DiscloseGHG x Scope 2 GHG intensity	-159	
	(597)	
DiscloseGHG x Scope 3 GHG intensity	-57.0**	
	(27.2)	
DiscloseGHG x Scope 1 GHG level		-0.018
		(0.011)
DiscloseGHG x Scope 2 GHG level		0.032
		(0.051)
DiscloseGHG x Scope 3 GHG level		0.00054
		(0.0011)
Inferred Scope 1 GHG intensity	-287	
	(200)	
Inferred Scope 2 GHG intensity	60.7	
	(151)	
Inferred Scope 3 GHG intensity	-73.4***	
	(24.9)	
Inferred Scope 1 level		-0.0021
		(0.0071)
Inferred Scope 2 level		-0.0081
		(0.018)
Inferred Scope 3 level		0.0011
		(0.00077)
Governance	0.0034***	0.0084**
	(0.0012)	(0.0036)
Constant	6.28***	6.21***
	(0.15)	(0.15)
Controls	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	20,829	20,829
R-squared	0.350	0.345

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 for the full sample, both for GHG intensities and levels. 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. As annex 7 shows in Table 27, this finding also holds in both sub-samples, though the magnitude of the effect is slightly stronger after the Paris agreement. Conversely, changes in past emissions are not found to be associated with market implied estimates of credit risk as indicated by the low magnitude and statistical significance of the corresponding parameter estimates relating to the change in disclosed Scope 1&2 GHG-emission intensities or levels. We attribute this finding to the fact that the financial markets are inherently forward-looking when assessing the creditworthiness of a company and therefore abstract from past achievements.

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

Notes: The table shows the result of the panel regression relevant for H3, see (7), 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. 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	0.25***	0.17**
	(0.078)	(0.072)
DiscloseGHG x Scope 1 GHG intensity	-317**	
	(135)	
DiscloseGHG x Scope 2 GHG intensity	-214	
	(616)	
DiscloseGHG x Scope 3 GHG intensity	-43.6	
	(26.6)	
Disclosed intensity change	75.7	
	(307)	
DiscloseCommit dummy	0.42***	0.43***
	(0.085)	(0.086)
DiscloseGHG x Scope 1 GHG level		-0.018*
		(0.011)
DiscloseGHG x Scope 2 GHG level		0.021
		(0.050)
DiscloseGHG x Scope 3 GHG level		0.00089
		(0.0010)
Disclosed level change		0.040
		(0.031)
Governance	0.0011	0.00095
	(0.0020)	(0.0020)
Constant	5.73***	5.74***
	(0.17)	(0.17)
Controls	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	18,490	18,490
R-squared	0.357	0.354

As a final complement to the testing of hypothesis 3, Table 13 summarises the empirical testing of the relationship between DtD and the ambitiousness of targets as reflected in the

(*TargetPerc*) relative to current emissions, and the duration until the target is expected to be reached (*TargetYear*). 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* based on Refinitiv data, which amounts to -0.021 for GHG-emission intensities and -0.02 for GHG-emission levels. However, due to the sparse data coverage of forward-looking commitments[21] 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. This highlights an importance of understanding how credible such targets are, an issue to which we now turn.

[21]It is noted that forward-looking commitments only became available following the Paris agreement, so that no sub-sample analysis into pre- and post-Paris agreement can be made.

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

Notes: The table shows the result of the panel regression relevant for H3, see (7). 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	-72.2	-634**		
	(129)	(293)		
Scope 2 GHG intensity	-147	289		
	(784)	(1,373)		
Scope 3 GHG intensity	-19.0	-63.9		
	(24.7)	(44.4)		
Disclosed intensity change	96.9	1,040		
	(261)	(639)		
Scope 1 GHG level			-0.0064	-0.029***
			(0.0041)	(0.010)
Scope 2 GHG level			0.031	0.027
			(0.049)	(0.071)
Scope 3 GHG level			-0.00067	-0.0034*
			(0.0012)	(0.0019)
Disclosed level change			-0.016	0.010
			(0.027)	(0.046)
TargetPerc Ref	0.0018		0.0020	
	(0.0021)		(0.0021)	
TargetYear Ref	-0.021*		-0.020*	
	(0.011)		(0.010)	
TargetPerc CDP		0.0027		0.0020
		(0.0025)		(0.0025)
TargetYear CDP		-0.00093		0.00011
		(0.0087)		(0.0081)
TargetBaseYear CDP		-0.012		-0.025**
		(0.014)		(0.011)
Constant	5.72***	29.3	5.72***	53.3*
	(0.34)	(33.8)	(0.34)	(27.2)
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	3,793	3,917	3,793	3,917
R-squared	0.549	0.521	0.549	0.530

5.2.2 Robustness checks

We run the same two robustness exercises used for the credit ratings analysis. When we 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 (Table 24).

We also re-run our panel regressions again using firm fixed-effects as opposed to sector and country ones. The results shown in Table 25 for H3 confirm the continued significance of forward-looking commitments to reduce GHG emissions, though the disclosure dummy and Scope 1 emission levels and intensities lose their significance. But 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.

6 The credibility of climate targets and commitments

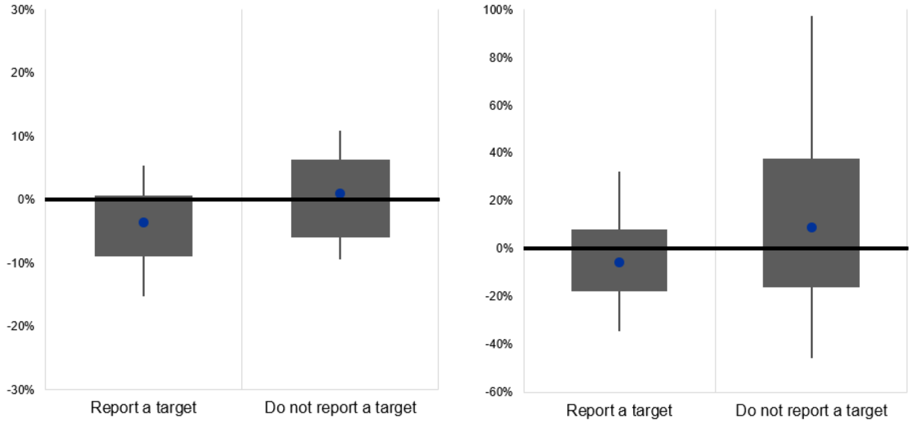
Disclosing an emission reduction target is an important first step in supporting the Paris goals and managing climate-related risks. The evidence we present also suggests that this is recognised by rating agencies and market participants. But ultimately such targets are only meaningful if they are credible and 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. In addition, targets may be not ambitious enough, in the sense that they may be not aligned with the overall global goal of achieving net-zero by 2050 or with country-level intermediate goals.

With these considerations in mind, this sections exploits our sample of 859 non-financial firms to analyse the credibility of targets descriptively. We first ask whether firms with a disclosed target reduce emissions. Figure 8 shows the relative change in Scope 1 and 2 GHG emission intensity 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 intensity over the last year whereas the firms that did not disclose a target showed little change in GHG emission intensity. 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 6%, while firms without a target in 2019 actually showed a median emission intensity increase of 9%. 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 (2021c) who find that firms that make commitments subsequently further reduce their emissions.

Figure 8: Change in Scope 1 and 2 GHG emission intensity 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 and 2 GHG emission intensity; Bucket of firms out of 859 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 859 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.

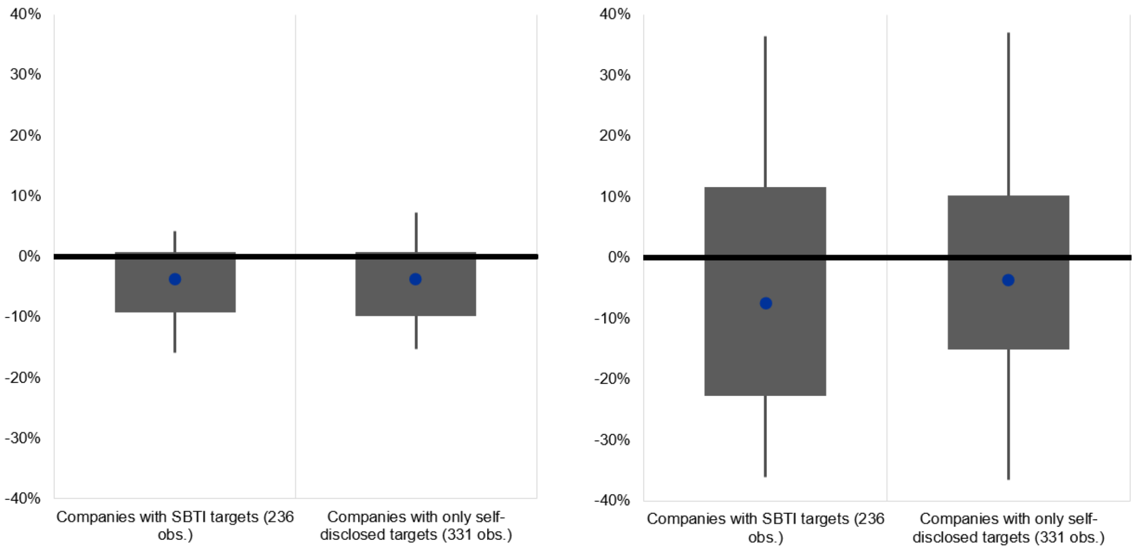


Next, we ask whether firms that have both a self-disclosed emission reduction target – in their financial or non-financial statements – and an SBTi target reduce emissions by more than firms that do not have an SBTi target. An SBTi-verified target is a target which is aligned with the Paris Agreement 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 intensity over the previous year, independent of whether the target was SBTi verified or not. We find broadly similar patterns between these two groups also in the distribution of observed changes in emission intensity over the three years preceding 2019. It is possible to observe however that the median firm with an SBTI target reported over this period slightly stronger reductions compared to the self disclosed group.

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

Figure 9: Change in Scope 1 and 2 GHG emission intensity for firms disclosing a target, grouped by availability of an SBTi aligned target

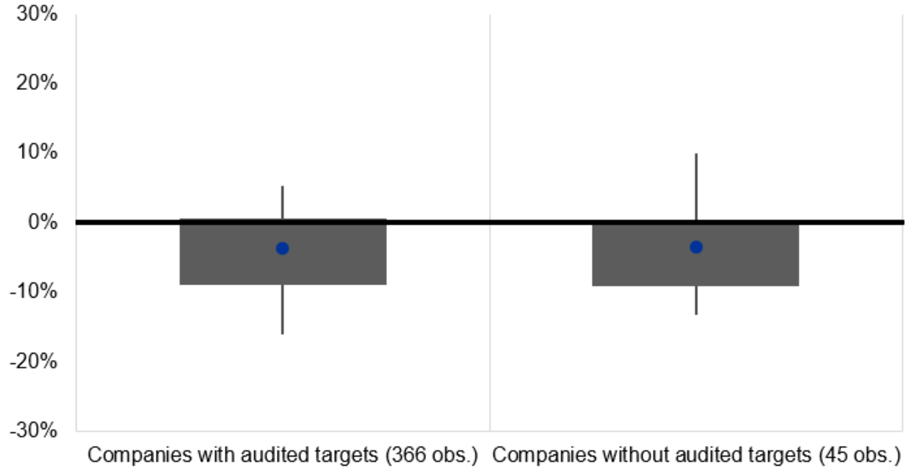
Notes: Left panel: Year-on-year change in GHG emission intensity in 2019 relative to 2018 (Percentage of reduction in Scope 1 and 2 GHG emission intensity in the range (+40%;-40%); Bucket of firms out of 859 NFCs). Right panel: 3-year change in GHG emission intensity in 2019 relative to 2016 (Percentage of reduction in Scope 1 and 2 GHG emission intensity in the range (+40%;-40%); Bucket of firms out of 859 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.



boxplot of observed year-on-year changes in emission intensity 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 significant difference observed between the two groups in terms of emission intensity reduction, albeit the external validity of the result is limited by the fact that the vast majority of firms that reported a target in 2019 had their non-financial statements audited (331 firms) by comparison with a minority of firms without audited non-financial statements (41 firms).

Figure 10: Change in Scope 1 and 2 GHG emission intensity for firms disclosing a target, grouped by audit status of non-financial statements

Notes: Percentage of reduction in Scope 1 and 2 GHG emission intensity in the range (+30%;-30%); Bucket of firms out of 859 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.



7 Conclusion and policy implications

This paper examines how climate-related transition risk is reflected in firm credit risk, as measured by credit rating and market-implied distance-to-default. Our results show that credit rating agencies and financial markets consider quantitative metrics of transition risk to some extent when assessing the ability of a company to repay and service its debt. First, while higher GHG-emissions and emission intensities are associated with higher credit risk under both of our metrics, governments' climate policies and expectations around such policies affect the transition risk of firms, and therefore their credit risk. 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, with the effect larger for European firms than their US peers, probably reflecting differential (expectations around) climate policies both after the Paris agreement and across countries. Second, the practice of disclosing emissions is associated with better credit ratings and, to some extent, with a lower market-implied distance-to-default. Finally, committing to an emission reduction target is associated with lower credit risk estimates, with the effects tending to be stronger for more ambitious targets. Overall, our results suggest that firms that are better prepared for the low-carbon transition have lower credit risk. At the same time, it is important to emphasise that the true extent of climate-related credit risks could still be materially under-estimated by rating agencies and market participants, and to acknowledge that there are naturally some limitations related to the reliability and comparability of climate-related transition risk metrics.

Our results have several important policy implications. First, the fact that credit risk estimates reflect disclosed transition risk metrics to some extent highlights how an improvement in the coverage, quality and comparability of disclosure of GHG emissions and emission reduction strategies would facilitate better assessment and pricing of firm-level climate risk. The disclosure and monitoring of forward-looking metrics seem particularly important in this regard, since these reflect a firm's strategy to reduce transition risk. Better and more harmonised information would allow financial institutions and investors to improve their assessment of the transition-related credit risk of their portfolios and reduce the likelihood that financial markets misprice carbon transition risk (see for example Schnabel (2020a,b, 2021); Panetta (2021); Hauser (2021); Thomä and Chenet (2017)). It 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 will be used by companies for the first time in 2024 for the financial year 2023. Our results call for ambition in such standards, especially around forward-looking targets and strategies. They also provide support for wider efforts to introduce mandatory and standardized reporting and disclosure standards with an audit requirement across further jurisdictions, and where possible at the global level.

Second, our results have potential implications for the way that central banks approach climate-related transition risk in their monetary and non-monetary policy operations. In particular, they highlight how climate change and the carbon transition will affect the value and the risk profile of the 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 recently 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]. This type of measure can both promote more consistent disclosure practices in the market and allow the valuation and risk control frameworks

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

used by central banks to better reflect firm-level transition risk. The ECB also plans to adjust the framework guiding the allocation of corporate bond purchases to incorporate climate change criteria, in line with its mandate, including a focus on the alignment of issuers with the goals of the Paris agreement. And the Bank of England has set out details of how it will green its corporate bond purchase scheme, placing particular emphasis on realised reductions in emissions, disclosure practices and emissions reduction targets when assessing the climate performance of firms [23]. Our findings are supportive of such approaches. In particular, they highlight the importance of central banks focussing on firms' disclosures and 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.

Third, our findings are relevant for the regulatory framework for banks and insurance companies. In particular, they highlight the importance of assessing whether the climate-related transition risk faced by firms is adequately and consistently reflected in prudential and supervisory standards. Under capital adequacy regulations, the risk-weighted level of capital related to credit risk is determined based on risk weights. Institutions may determine these weights either based on external ratings provided by credit rating agencies in the Standardised Approach or internal ratings in the Internal Ratings-Based Approach. Our results suggest that credit rating agencies do reflect – to some extent – transition risk considerations in their ratings. At the same time, it remains important for regulators to consider whether risk weights based on credit ratings sufficiently reflect transition risk, and this needs 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 based on internal models reflect climate-related transition risk is less clear (see for example ECB (2021b)). Overall, our results highlight the importance of regulators and supervisors assessing whether climate-related transition risk is appropriately reflected in risk weights, irrespective of how they are calculated, and in the wider 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

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

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)).

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Appendix A

Table 15: Data description

Variable name	**Description**	**Source**
	Firm credit risk related variables	
Credit rating	Long-term ratings issued by S&P and Moody's	ECB Ratings DB
DtD	Market-implied distance-to-default	Constructed
	Firm-level controls (yearly)	
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
	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 for EA firms	Refinitiv

Continuation of Table 15		
Variable name	**Description**	**Source**
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 16: Pooled correlations

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
1. Rating S&P	1.000															
2. Rating Moody's	0.868	1.000														
3. Size	0.335	0.373	1.000													
4. Governance	0.168	0.189	0.128	1.000												
5. Solvency	-0.017	-0.030	0.056	0.099	1.000											
6. Leverage	-0.255	-0.263	0.143	-0.004	0.108	1.000										
7. Profitability	0.140	0.157	-0.053	0.038	-0.079	-0.229	1.000									
8. Debt service	0.200	0.199	-0.006	-0.019	-0.066	-0.229	0.124	1.000								
9. Scope 1 GHG intensity	-0.024	-0.053	0.037	0.102	0.433	0.188	-0.121	-0.077	1.000							
10. Scope 2 GHG intensity	-0.040	-0.047	-0.038	0.077	0.259	0.066	-0.068	-0.047	0.241	1.000						
11. Scope 3 GHG intensity	-0.114	-0.109	-0.051	-0.043	0.056	0.026	-0.037	-0.040	0.020	0.063	1.000					
12. Scope 1 GHG level	0.063	0.091	0.303	0.102	0.282	0.100	-0.107	-0.046	0.474	0.168	0.010	1.000				
13. Scope 2 GHG level	0.107	0.130	0.279	0.070	0.130	0.008	-0.043	-0.014	0.098	0.241	0.030	0.338	1.000			
14. Scope 3 GHG level	0.156	0.207	0.403	0.108	0.137	-0.005	-0.067	-0.007	0.046	0.043	0.043	0.467	0.392	1.000		
15. DiscloseGHG dummy	0.189	0.221	0.163	0.232	0.038	0.027	0.029	0.005	0.062	0.031	-0.066	0.113	-0.022	0.068	1.000	
16. DiscloseCommit dummy	0.228	0.240	0.185	0.265	0.055	0.007	0.041	-0.007	0.074	0.049	-0.039	0.109	0.092	0.067	0.475	1.000

Appendix B

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.

Table 17 presents the results 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.

Table 17: Panel regression for credit ratings by credit quality: IG vs HY and emissions, Testing H1 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H1, see Equation 5, where the relationship between GHG emissions − expressed in intensity (Models 1 and 2) and in levels (Models 3 and 4) − and credit ratings is tested for the full data sample covering the period from 2010 to 2019. The results are shown for two groups of credit quality: investment grade and high yield. We employ both OLS (Models 1 and 3) and ordered logit estimators (Models 2 and 4). 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)**
Scope 1 GHG intensity				
HY	-140***	-653***		
	(47.3)	(205)		
IG	-18.1	-66.3		
	(27.3)	(91.4)		
Scope 2 GHG intensity				
HY	-7,279***	-39,401***		
	(1,122)	(9,579)		
IG	367	997		
	(226)	(752)		
Scope 3 GHG intensity				
HY	-3.78*	-19.2		
	(1.97)	(12.0)		
IG	0.078	-0.36		
	(0.85)	(2.80)		
Scope 1 GHG level				
HY			-0.013***	-0.049***
			(0.0041)	(0.017)
IG			-0.0015	-0.0057
			(0.0014)	(0.0042)
Scope 2 GHG level				
HY			-0.028	-0.47
			(0.042)	(0.52)
IG			0.00057	0.0015
			(0.0026)	(0.0089)
Scope 3 GHG level				
HY			-0.0020	-0.0046
			(0.0014)	(0.0045)
IG			0.00058***	0.0017***
			(0.00020)	(0.00061)
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	4,381	4,381	4,373	4,373

Turning to consider past performance in reducing emissions, disclosure practices and climate commitments, Table 18 presents key results 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.

Table 18: Panel regression for credit ratings by credit quality: IG vs HY, Testing H3 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H3, see Equation 7, where the relationship between disclosure, its interaction with GHG emissions, disclosed change in emissions, forward-looking commitment and credit ratings is tested for the full data sample covering the period from 2010 to 2019. The results are shown for two groups of credit quality: investment grade and high yield. We employ both OLS (Models 1 and 3) and ordered logit estimators (Models 2 and 4). 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				
HY	0.023	-0.45	0.037	0.087
	(0.060)	(0.93)	(0.053)	(0.99)
IG	1.40***	58.7	1.38***	153
	(0.055)		(0.052)	(182)
DiscloseGHG x Scope 1 GHG intensity				
HY	74.6	531		
	(60.8)	(953)		
IG	-81.3*	-331*		
	(43.9)	(194)		
Disclosed intensity change				
HY	0.029*	0.42		
	(0.016)	(1.07)		
IG	-0.016**	-0.075*		
	(0.0074)	(0.041)		
DiscloseGHG x Scope 1 GHG level				
HY			0.0068	-1.01
			(0.0061)	(1.98)
IG			0.0048	0.014
			(0.0036)	(0.014)
Disclosed level change				
HY			0.00052	0.012
			(0.0077)	(0.11)
IG	0.0012	0.0044*		
			(0.00074)	(0.0023)
DiscloseCommit dummy				
HY	-0.049	-0.18	-0.049	-0.58
	(0.058)	(1.00)	(0.057)	(1.06)
IG	0.099**	0.45**	0.11**	0.47***
	(0.041)	(0.18)	(0.042)	(0.18)
Constant	3.08***		3.06***	
	(0.064)		(0.062)	
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	3,984	3,984	4,373	4,373
R-squared	0.613	0.477	0.611	0.469

Appendix C (intended for Internet Appendix only)

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.

Appendix D (intended for Internet Appendix only)

The set of results for the baseline uses the specification presented in Equation 5 to describe the relationship between firms' exposure to transition risk and their credit rating. We present the results in Table 19.

Table 19: Panel regression for credit ratings and emissions, Testing H1 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H1, see Equation 5, where the relationship between GHG emissions − expressed in intensity (Models 1 and 2) and in levels (Models 3 and 4) − and credit ratings is tested for the full data sample covering the period from 2010 to 2019. We employ both OLS (Models 1 and 3) and ordered logit estimators (Models 2 and 4). 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)**
Scope 1 GHG intensity	-66.6**	-194**		
	(29.4)	(93.0)		
Scope 2 GHG intensity	259	900		
	(283)	(918)		
Scope 3 GHG intensity	-2.01**	-6.26**		
	(0.86)	(2.71)		
Scope 1 GHG level			-0.0037***	-0.012***
			(0.0012)	(0.0038)
Scope 2 GHG level			0.0017	0.0058
			(0.0023)	(0.0073)
Scope 3 GHG level			-0.000093	-0.00024
			(0.00016)	(0.00050)
Profitability	0.00044	0.0021	0.00045	0.0021
	(0.00046)	(0.0030)	(0.00046)	(0.0031)
Size	4.2e-09***	1.3e-08***	4.2e-09***	1.3e-08***
	(8.0e-10)	(2.4e-09)	(8.1e-10)	(2.5e-09)
Leverage	-0.13***	-0.40***	-0.13***	-0.41***
	(0.012)	(0.042)	(0.012)	(0.043)
Solvency	-0.18	-0.46	-0.21	-0.53
	(0.13)	(0.41)	(0.13)	(0.39)
Debt servicing capacity	0.0012**	0.0050**	0.0012**	0.0050**
	(0.00052)	(0.0025)	(0.00052)	(0.0025)
Governance	0.0039***	0.011***	0.0038***	0.010***
	(0.0011)	(0.0036)	(0.0012)	(0.0036)
Constant	4.21***		4.22***	
	(0.091)		(0.091)	
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	4,201	4,201	4,194	4,194
R-squared	0.343	0.1697	0.343	0.1698

Results suggest an overall negative relationship between GHG emissions, intensities and credit ratings, with more carbon intensive firms having on average lower ratings. The main drivers of this association are Scope 1 emissions and the corresponding intensity. We also find a negative relationship for Scope 3 GHG intensities, although this variable is more sensitive than Scope 1 emissions to the set of environmental metrics included in the specification. This variation is likely to be explained by the existing limitations on the proper accounting and disclosure of Scope 3 emissions, which ought to encompass all emissions related to the value-chain of a firm's products. On the non-environmental metrics, we do find an higher governance score to be associated with better credit ratings. Controlling for this effect is particularly relevant given the theoretical arguments on the relationship between the management structure of a firm, its environmental practices and credit risk.

Table 20 summarises the results of the relationship between Scope 1, 2, and 3 emissions and DtD. The negative coefficients found for Scope 1 and Scope 3 emission intensities suggest that firms with lower overall emissions are viewed by market participants as being less exposed to credit risk: lower emission intensities are associated with a higher DtD. Similar to the credit ratings, given their strong correlation, the variability of the Scope 2 emission intensities seems to be overshadowed by those of the Scope 1 intensities and therefore induce the statistical insignificance of the Scope 2 intensity coefficient.[24] Furthermore, similar to the empirical conclusions on H1 for credit ratings, it can be seen that the magnitude of the Scope 3 intensity coefficient is lower than that of the Scope 1 intensity coefficient, which indicates that also market participants are acknowledging the limitations on the proper accounting and disclosure of Scope 3 emission intensities. The emission levels Scope 1, 2 and 3 are, however, statistically insignificant for DtD, which can be explained by the fact that, due to a better longitudinal comparability between companies, both within and across sectors, it is the emission intensities that have emerged as the market's preferred key performance indicators for assessing the environmental footprint of a company, as further explained in TCFD (2017). To sum up, for H1, our findings for the H1 for the DtD are fully consistent with those of the credit ratings in Section 5.1.1 in that higher emission intensities are associated with higher credit risk and they also apply for the sub-samples before and after the Paris Agreement as shown in Appendix Table 26

[24] This becomes further clear when omitting Scope 1 intensities, in which case the Scope 2 coefficient becomes highly statistically significant. Nevertheless, given the remaining set of regression coefficients is shown to be robust regardless of whether or not the Scope 1 intensities are included, we maintain in the following the same set of explanatory variables as in Section 5.1 for the benefit of direct comparability of the results.

Table 20: Panel regression for Distance-to-Default (DtD) and emissions, Testing H1 from 2010-2019

Notes: The table shows the result of the panel regression relevant for H1, see Equation (5), where the relationship between emissions and distance-to-default (DtD) is tested for the full data sample covering the period from January 2010 to December 2019 using a monthly observation frequency. DtD falls when credit risk increases, so a negative estimate for the emission-coefficients implies the acceptance of H1. 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)**
Scope 1 GHG intensity	-348***	
	(124)	
Scope 2 GHG intensity	26.8	
	(212)	
Scope 3 GHG intensity	-65.1***	
	(21.7)	
Scope 1 GHG level		-0.0069
		(0.0065)
Scope 2 GHG level		-0.0016
		(0.023)
Scope 3 GHG level		0.00086
		(0.00079)
Profitability	0.0055***	0.0056***
	(0.0020)	(0.0020)
Size	1.7e-09***	1.4e-09**
	(5.1e-10)	(5.7e-10)
Leverage	-0.056	-0.047
	(0.039)	(0.041)
Solvency	-0.22	-0.36
	(0.25)	(0.25)
Debt servicing capacity	0.00093*	0.00097*
	(0.00050)	(0.00051)
Governance	0.0032	0.0027
	(0.0019)	(0.0020)
Market	-0.027***	-0.027***
	(0.0024)	(0.0025)
Oil	-0.0045***	-0.0044***
	(0.00045)	(0.00045)
Inflation	0.061***	0.041*
	(0.024)	(0.023)
Industrial Production	0.034***	0.036***
	(0.0030)	(0.0030)
Gold	-0.022***	-0.022***
	(0.0011)	(0.0011)
Bills	0.60***	0.57***
	(0.067)	(0.066)
Volatility	-0.091***	-0.090***
	(0.0029)	(0.0029)
Constant	6.29***	6.23***
	(0.15)	(0.15)
Controls	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	20,829	20,829
R-squared	0.348	0.342

Table 21: Panel regression for credit ratings and emissions for European firms and for US firms

Notes: The table shows the result of the panel regression relevant for H1, see (5), where the relationship between GHG emissions and credit ratings is tested for the subsample of European firms and the subsample of US firms. Model 1 tests the relationship between GHG emissions intensity and credit rating for European firms; Model 2 tests the relationship between GHG emissions level and credit rating for European firms. Model 3 and model 4 test for US firms the relationship between GHG emissions intensity and credit rating and between GHG emissions level and credit rating, respectively. The period of the subsamples is from 2010 to 2019. We report ordered logit estimators. 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-EU)**	**(2-EU)**	**(3-US)**	**(4-US)**
Scope 1 GHG intensity	-396***		-7.35	
	(140)		(118)	
Scope 2 GHG intensity	-1,956		380	
	(1,643)		(1,009)	
Scope 3 GHG intensity	-14.7***		0.91	
	(3.72)		(3.50)	
Scope 1 GHG level		-0.015***		-0.00079
		(0.0049)		(0.0088)
Scope 2 GHG level		-0.018*		0.018
		(0.010)		(0.018)
Scope 3 GHG level		0.00035		0.00090
		(0.0012)		(0.00079)
EU ETS Carbon Price	-0.075***	-0.053***		
	(0.020)	(0.020)		
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	1,818	1,817	2,563	2,556
R-squared	0.2334	0.2314	0.1739	0.1737

Appendix E (intended for Internet Appendix only)

Table 22: Panel regression for credit ratings and emissions, Testing H3 for the sub-sample excluding high emitters

Notes: The table shows the result of the panel regression relevant for H3, see Equation 7, where the relationship between quantitative backward and qualitative forward-looking metrics (commitment to reduce emissions) and credit ratings is tested for the data sample excluding high emitters, covering the period from 2010 to 2019. High emitters are defined as the firms belonging to the top tercile of the distribution of Scope 1 and 2 emissions. 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. 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	0.27***	0.87***	0.21***	0.66***
	(0.095)	(0.30)	(0.066)	(0.21)
DiscloseGHG x Scope 1 GHG intensity	-443**	-1,298**		
	(203)	(642)		
DiscloseGHG x Scope 2 GHG intensity	25.0	-108		
	(998)	(3,138)		
DiscloseGHG x Scope 3 GHG intensity	-108	-318		
	(66.8)	(208)		
Disclosed intensity change	-0.014	-0.048		
	(0.012)	(0.034)		
DiscloseCommit dummy	0.19***	0.63***	0.19***	0.62***
	(0.061)	(0.19)	(0.062)	(0.19)
DiscloseGHG x Scope 1 GHG level			-0.0099	-0.031
			(0.0089)	(0.027)
DiscloseGHG x Scope 2 GHG level			-0.0037	0.021
			(0.030)	(0.10)
DiscloseGHG x Scope 3 GHG level			-0.0034***	-0.0098***
			(0.00098)	(0.0031)
Disclosed level change			-0.031***	-0.096***
			(0.011)	(0.032)
Constant	3.82***		3.86***	
	(0.13)		(0.11)	
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	2,885	2,885	2,872	2,872
R-squared	0.384	0.1781	0.381	0.1774

Table 23: Panel regression for credit ratings and emissions, Testing H3 for the full-sample employing firm-level fixed-effects

Notes: The table shows the result of the panel regression relevant for H3, see Equation 7, where the relationship between quantitative backward and qualitative forward-looking metrics (commitment to reduce emissions) and credit ratings is tested for the data sample covering the period from 2010 to 2019. Firm-level fixed-effects are employed in place of sector, country and year. Model 1 shows the OLS results considering GHG emissions intensity, while model 2 shows the corresponding result for GHG emissions 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., OLS)**	**(2 - levels., OLS)**
DiscloseGHG dummy	0.027	0.022
	(0.025)	(0.023)
DiscloseGHG x Scope 1 GHG intensity	-11.2	
	(24.3)	
DiscloseGHG x Scope 2 GHG intensity	-136	
	(231)	
DiscloseGHG x Scope 3 GHG intensity	-0.56	
	(0.90)	
Disclosed intensity change	-0.019*	
	(0.011)	
DiscloseCommit dummy	0.014	0.0022
	(0.026)	(0.027)
DiscloseGHG x Scope 1 GHG level		0.0038
		(0.0027)
DiscloseGHG x Scope 2 GHG level		0.00022
		(0.0088)
DiscloseGHG x Scope 3 GHG level		-0.00043***
		(0.00017)
Disclosed level change		-0.00051
		(0.00055)
Constant	4.07***	4.07***
	(0.092)	(0.088)
Firm-level controls	Y	Y
Firm fixed-effects	Y	Y
Observations	3,970	3,945
R-squared	0.882	0.882

Table 24: Panel regression for Distance-to-Default (DtD) and emissions, Testing H3 for the sub-sample excluding high emitters

Notes: The table shows the result of the panel regression relevant for H3, see Equation 7, where the relationship between quantitative backward and qualitative forward-looking metrics (commitment to reduce emissions) and distance-to-default (DtD) is tested for the data sample excluding high emitters, covering the period from 2010 to 2019. High emitters are defined as the firms belonging to the top tercile of the distribution of Scope 1 and 2 emissions. Model 1 shows the OLS results considering GHG emissions intensity, while model 3 shows the OLS results considering GHG emissions 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., OLS)**	**(2 - levels)**
DiscloseGHG dummy	0.28**	0.16
	(0.12)	(0.12)
DiscloseGHG x Scope 1 GHG intensity	-555***	
	(162)	
DiscloseGHG x Scope 2 GHG intensity	159	
	(1,160)	
DiscloseGHG x Scope 3 GHG intensity	-196	
	(189)	
Disclosed intensity change	696***	
	(264)	
DiscloseCommit dummy	0.50***	0.46***
	(0.10)	(0.099)
DiscloseGHG x Scope 1 GHG level		-0.040*
		(0.021)
DiscloseGHG x Scope 2 GHG level		-0.015
		(0.17)
DiscloseGHG x Scope 3 GHG level		0.020
		(0.033)
Disclosed level change		0.094
		(0.076)
Constant	5.69***	5.79***
	(0.18)	(0.19)
Controls	Y	Y
Sectoral fixed-effects	Y	Y
Country fixed-effects	Y	Y
Observations	13,001	12,602
R-squared	0.326	0.322

Table 25: Panel regression for Distance-to-Default (DtD) and emissions, Testing H3 for the full-sample employing firm-level fixed-effects

Notes: The table shows the result of the panel regression relevant for H3, see Equation 7, where the relationship between quantitative backward and qualitative forward-looking metrics (commitment to reduce emissions) and distance-to-default (DtD) is tested for the data sample covering the period from 2010 to 2019. Firm-level fixed-effects are employed in place of sector and country. Model 1 shows the OLS results considering GHG emissions intensity, while model 2 shows the corresponding result for GHG emissions 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	0.019	-0.0031
	(0.055)	(0.050)
DiscloseGHG x Scope 1 GHG intensity	-43.5	
	(96.0)	
DiscloseGHG x Scope 2 GHG intensity	93.5	
	(485)	
DiscloseGHG x Scope 3 GHG intensity	-3.78	
	(16.5)	
Disclosed intensity change	-58.6	
	(310)	
DiscloseCommit dummy	0.16**	0.16**
	(0.075)	(0.076)
DiscloseGHG x Scope 1 GHG level		-0.0023
		(0.0063)
DiscloseGHG x Scope 2 GHG level		0.037
		(0.028)
DiscloseGHG x Scope 3 GHG level		-7.7e-06
		(0.00045)
Disclosed level change		0.025
		(0.022)
Constant	6.29***	6.29***
	(0.21)	(0.21)
Controls	Y	Y
Firm fixed-effects	Y	Y
Observations	18,573	18,573
R-squared	0.565	0.565

Table 26: Panel regression for Distance-to-Default (DtD) and emissions, Testing H1 for the sub-samples 2010-2015 and 2016-2019

Notes: The table shows the result of the panel regression relevant for H1, see Equation (5), where the relationship between emissions and distance-to-default (DtD) is tested for the sub-sample before the Paris agreement (i.e. 2010-2015) and thereafter (i.e. 2016-2019) using a monthly observation frequency. DtD falls when credit risk increases, so a negative estimate for the emission-coefficients implies the acceptance of H1. Models 1 and 3 show the OLS results considering GHG emission intensity, while models 3 and 4 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.)** (2010-2015)	**(2 - levels)** (2010-2015)	**(3 - int.)** (2016-2019)	**(4 - levels)** (2016-2019)
Scope 1 GHG intensity	-573**		-310**	
	(226)		(123)	
Scope 2 GHG intensity	65.2		-121	
	(151)		(677)	
Scope 3 GHG intensity	-102***		-59.9**	
	(24.4)		(28.2)	
Scope 1 GHG level		-0.00094		-0.0097
		(0.0081)		(0.0070)
Scope 2 GHG level		-0.013		-0.00072
		(0.018)		(0.047)
Scope 3 GHG level		0.0011		0.00036
		(0.00076)		(0.0010)
Profitability	0.0040**	0.0041**	0.0076***	0.0077***
	(0.0019)	(0.0020)	(0.0025)	(0.0026)
Size	2.3e-09***	1.9e-09***	1.3e-09**	1.2e-09**
	(6.1e-10)	(6.8e-10)	(5.2e-10)	(6.0e-10)
Leverage	-0.025	-0.011	-0.066	-0.058
	(0.065)	(0.068)	(0.042)	(0.043)
Solvency	-0.14	-0.32	-0.30	-0.45
	(0.28)	(0.30)	(0.29)	(0.28)
Debt servicing capacity	0.0018***	0.0018***	0.00043	0.00048
	(0.00054)	(0.00058)	(0.00056)	(0.00057)
Governance	0.0031	0.0025	0.0052**	0.0049**
	(0.0022)	(0.0023)	(0.0023)	(0.0024)
Market	-0.039***	-0.040***	-0.036***	-0.035***
	(0.0023)	(0.0023)	(0.0039)	(0.0040)
Oil	-0.0011	-0.0014	0.0033***	0.0033***
	(0.00100)	(0.00100)	(0.00051)	(0.00052)
Inflation	-0.18***	-0.21***	0.12***	0.11***
	(0.038)	(0.037)	(0.026)	(0.025)
Industrial Production	-0.12***	-0.11***	0.044***	0.045***
	(0.011)	(0.011)	(0.0027)	(0.0027)
Gold	-0.0100***	-0.0094***	-0.018***	-0.018***
	(0.0012)	(0.0012)	(0.0018)	(0.0018)
Bills	0.65***	0.59***	-1.57***	-1.59***
	(0.079)	(0.079)	(0.15)	(0.16)
Constant	6.61***	6.48***	4.18***	4.13***
	(0.17)	(0.17)	(0.22)	(0.23)
Controls	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	9,624	9,624	11,205	11,205
R-squared	0.354	0.344	0.414	0.407

Table 27: Panel regression for Distance-to-Default (DtD) and emission targets, testing H3 for the sub-samples 2010-2015 and 2016-2019

Notes: The table shows the result of the panel regression relevant for H3, see (7), where the relationship between emission-disclosure targets and distance-to-default (DtD) is tested for the sub-sample before the Paris agreement (i.e. 2010-2015) and thereafter (i.e. 2016-2019) 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. 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.)** (2010-2015)	**(2 - levels)** (2010-2015)	**(3 - int.)** (2016-2019)	**(4 - levels)** (2016-2019)
DiscloseGHG dummy	0.48***	0.31***	0.16*	0.10
	(0.13)	(0.099)	(0.097)	(0.091)
DiscloseGHG x Scope 1 GHG intensity	-524		-313**	
	(435)		(124)	
DiscloseGHG x Scope 2 GHG intensity	-823		-241	
	(1,413)		(697)	
DiscloseGHG x Scope 3 GHG intensity	-74.0		-40.5	
	(53.2)		(28.6)	
Disclosed intensity change	864		96.4	
	(7,890)		(276)	
DiscloseCommit dummy	0.49***	0.50***	0.34***	0.34***
	(0.11)	(0.11)	(0.099)	(0.099)
DiscloseGHG x Scope 1 GHG level		-0.040**		-0.014
		(0.015)		(0.012)
DiscloseGHG x Scope 2 GHG level		0.098		0.0019
		(0.080)		(0.058)
DiscloseGHG x Scope 3 GHG level		0.0012		0.00084
		(0.00085)		(0.0012)
Disclosed level change		0.55		0.031
		(1.82)		(0.027)
Governance	0.00048	0.00019	0.0030	0.0029
	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Constant	5.95***	5.97***	4.02***	4.02***
	(0.21)	(0.21)	(0.22)	(0.23)
Controls	Y	Y	Y	Y
Sectoral fixed-effects	Y	Y	Y	Y
Country fixed-effects	Y	Y	Y	Y
Observations	7,499	7,499	10,991	10,991
R-squared	0.290	0.291	0.422	0.417