HONG KONG INSTITUTE FOR MONETARY AND FINANCIAL RESEARCH

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HKIMR Working Paper No.26/2021

November 2021

Hong Kong Institute for Monetary and Financial Research
香港貨幣及金融研究中心
(a company incorporated with limited liability)

Effect of Climate-Related Risk on the Pricing of Bank Loans: Evidence from Syndicated Loan Markets in Asia Pacific

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November 2021

Abstract

Using a novel dataset that combines syndicated loans originated in the Asia Pacific markets with greenhouse gas emission intensity data of borrowers, this study examines whether and to what extent banks in the region have considered climate-related risk in their loan pricing decisions. Our results suggest that banks in the region started to price-in climate-related risk for loans to emissions-intensive sector since the Paris Agreement. This probably reflects their increased awareness of a climate-transition risk such firms face. In addition, banks' environmental attitude is found to be one key factor in determining the extent of transition risk premium in loan pricing. In particular, more environmentally concerned banks (green banks) tend to charge a higher loan rate than their non-green counterparts when lending to the same "brown" firm in the post-Paris Agreement period.

Keywords: Carbon emissions, Climate policy risk, Loan pricing, Green banks.
JEL classification: G21, G32, Q5.

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* The authors would like to thank Lillian Cheung, Eric Wong and one anonymous referee for their helpful comments and suggestions. This paper represents the views of the authors, which are not necessarily the views of the Hong Kong Monetary Authority, Hong Kong Institute for Monetary and Financial Research, or its Board of Directors or Council of Advisers. The above-mentioned entities except the authors take no responsibility for any inaccuracies or omissions contained in the paper.

I. INTRODUCTION

Climate change has been receiving increasing attention in recent years. Indeed, it has become a core part of the agenda of public and private sectors globally. Policymakers worldwide have shown strong commitment to tackling climate change. Most notably, the United Nations Framework Convention on Climate Change (UNFCCC) reached an agreement to adopt a legally binding international treaty on climate change at the 21st Conference of the Parties in Paris on 12 December 2015 (i.e. the Paris Agreement). The objective is to limit global warming to well below two degrees Celsius, preferably to 1.5 degrees. [1] To achieve this long-term temperature goal, participating countries agreed on the need to reach a global peak of greenhouse gas emissions as soon as possible, and concurrently working towards emissions reductions. The ambitious task of transitioning towards a low-carbon economy will likely have large financial implications for a wide range of industries, as their future business operations could be significantly affected by changes in climate policy and climate-related technology. The transition towards a low-carbon economy could also have strong implications for banks. For example, carbon pricing may be adopted by governments to incentivise corporates to reduce greenhouse gas (GHG) emissions. The future cash flows and valuation of banks' corporate borrowers, particularly for those from the largest-emitting sectors could therefore fall significantly, which could in turn affect the credit risks for banks' loan portfolios (Grippa et al. (2019), BCBS (2021a), Capasso et al. (2020)).

In view of the potential adverse impact arising from transitioning to a low-carbon economy, regulators and other key stakeholders have increasingly emphasised the urgency to manage and pre-emptively mitigate climate-related financial risks in the financial system. Wider policy debates have now emerged over what policy toolkits[2] should be implemented by central banks to ensure that the banking system can weather the coming climate transition more smoothly. In particular, the proposal to integrate climate related financial risks into the prudential capital requirement has recently attracted increased attention from central banks (Berenguer et al., 2020). One of the important questions, which could help contribute to this discussion, is to whether and to what extent banks have taken the associated climate-related

[1] To reach the target of limiting global temperature increase to 1.5 degrees Celsius, it is estimated by the Intergovernmental Panel on Climate Change that net human-caused carbon dioxide equivalent emissions must fall by 45% by 2030 and reach net zero by 2050.

[2] Some of the proposed policy actions include mandatory requirement for financial institutions to disclose information on material climate-related financial exposures and risks, climate-risk stress testing, targeted asset purchases in quantitative easing programmes, integrating climate related financial risks into the prudential capital requirement, adjusting the pricing or even eligibility of highly emitting counterparties in accessing credit operations by central banks, etc. (Feridun and Güngör (2020), NGFS (2020), NGFS (2021)).

risk (particularly the transition risk[3]) into their lending considerations. If there is evidence to suggest that climate-related risks are largely ignored or overlooked in banks' current business practices, this could justify bank regulators to promptly consider more proactive and stringent strategies to strengthen banks' capacity to withstand the threat of potential abrupt climate transition in future.

This question is highly relevant to policymakers in the Asia Pacific region (APAC), which is home to some of the largest greenhouse gas emission countries in the world. The potential adverse impact of climate transition risks on the region's banks is obvious and could be significant from a financial stability perspective, as they are among the key funding providers for corporates across APAC. In the interests of promoting sustainable finance, having a better understanding of this issue can help inform policymakers about potential action to foster more green financing by the banking sector. However, empirical evidence remains limited as granular information containing both firms' carbon emission data and their loan terms with banks are generally scarce. While some recent studies (Kleimeier and Viehs, 2018; Degryse et al., 2020; Delis et al., 2021; Ehlers et al., 2021) address similar questions, they focus mainly on the US or global markets. By contrast, studies on APAC remain scant, if any. To shed light on the loan pricing of transition risk in the Asia Pacific, this study compiles a novel dataset by combining multiple data sources to construct a sample of syndicated loans originated in the APAC market, with the corresponding financial and environmental characteristics of the borrowers and lenders being matched. The data construction will be discussed in detail in the next section.

There are several advantages in using syndicated loan data in this analysis. Firstly, as a large portion of syndicated loan borrowers are listed firms, we can match their GHG emission data from *S&P Trucost database* which covers mainly listed firms as well. Secondly, as the size of syndicated loans is relatively large by nature, lead arranging banks in a loan syndicate should have stronger incentives to scrutinise all the relevant risks of the borrower (including climate-related risks) compared with those smaller bilateral loans.[4] Thirdly, the rich micro-level information available from syndicated loan data, including loan-level characteristics, and the identity of borrowers and lenders, allows us to strengthen the empirical identification of climate transition risk in loan-pricing after controlling for all other key determinants.

[3] Transition risk is a financial risk which can result from the process of adjustment towards a low-carbon economy prompted by, for example, changes in climate policy, technological changes or a change in market sentiment. Throughout the paper, transition risk and climate transition risk are used interchangeably.

[4] As lead banks are liable to participant banks for the pricing of all relevant risks and effective screening and monitoring of borrowing firms, lead banks have strong incentives to price loans accurately (Delis et al., 2021).

In this analysis, we aim to answer the following questions. Firstly, we seek to investigate whether banks would charge a higher loan spread on firms with higher GHG emissions. In principle, highly emitting firms would be more exposed to the transition risk, in which their future cash flows, and hence their debt repayment ability could be adversely affected in the event of a disorderly transition towards a low-carbon economy. If such a risk is considered by banks at the time of loan origination, a higher loan spread should be charged to compensate banks for the additional credit costs stemming from the transition risk. Therefore, we posit that banks would, on average, charge a higher loan spread on a highly emitting firm (i.e. "brown" firm) compared to an otherwise similar firm but with lower emissions.

Secondly, we examine whether the pricing of climate transition risk by banks (i.e. the transition risk premium) has only recently become apparent, particularly since the adoption of the Paris Agreement in December 2015. Given the Paris Agreement is regarded as one key commitment by both developed and developing countries to set emissions-reduction pledges to slow temperature rises globally, the increased global awareness of climate-related risks since then may prompt banks to consider climate-related risks in their loan origination decisions. Voysey et al. (2016) outlined several risks and opportunity implications of the Paris Agreement for the international financial sector. Kruse et al. (2020) argued that the outcome of the Paris Agreement is surprisingly better than anticipated in having a more ambitious 1.5°C target included in the agreement. In view of its importance, they adopted the event as an exogenous political shock to study stock market reactions. Ardia et al. (2021) also noted a spike in their constructed Media Climate Change Concerns index when the Paris Agreement was sealed, probably reflecting the special attention put on this historical event and its implications as well. Indeed, several recent studies find evidence of the existence of a carbon premium only after the signing of the Paris Agreement. For example, in a related study for the global equity market, Bolton and Kacperczyk (2020b) find that a large and significant carbon premium in stock returns arose only after the Paris Agreement, and this premium is particularly noticeable in Asia. In the context of bank loans, Delis et al. (2021) find that banks generally did not price climate policy exposure regarding borrowers' stranded fossil fuel reserves before 2015. [5]

Lastly, we examine how far banks' attitude towards green initiatives matters in determining the extent of transition risk in loan pricing. Intuitively, a more environmentally concerned bank (i.e. "green" bank) should make a greater effort to internalise the potential

[5] Ehlers et al. (2021) also find that carbon transition pricing only occurs after the Paris Agreement. Though already observed before the Paris Agreement, Capasso et al. (2020) find that the positive relationship between corporates' distance-to-default risk and carbon footprint becomes stronger after the Paris Agreement.

negative impact on its operations arising from climate-related risk by charging a higher loan spread to a brown borrower relative to non-green banks. Therefore, we conjecture that green banks would tend to charge a higher loan spread to brown firms by a greater extent than other banks.

Overall, our analysis suggests that banks in the region have started to price-in the climate transition risk for loans to emissions-intensive sectors since the Paris Agreement. This probably reflects banks' increased awareness of climate-related risks to corporate borrowers that are more subject to the transition risk. The extent of the transition risk premium is also found to be dependent on the environmental attitude of banks. Specifically, green banks are found to charge a higher loan spread than other banks, when lending to the same brown firm in the post-Paris Agreement period. These findings together provide supportive evidence that banks in the region have started to incorporate climate risk considerations into their existing risk management framework.

The remainder of this paper is structured as follows. Section II describes the data sources employed in this study. Section III discusses the empirical specification settings and associated results for the research questions. Several robustness checks are subsequently conducted and the results are discussed in Section IV. Section V concludes.

II. DATA

To shed light on the loan pricing on climate-transition risk with a particular focus in the APAC, we construct a sample of syndicated loans from the Asia Pacific syndicated market, which is then merged with several data sources to match the relevant financial and environmental characteristics for the corresponding borrowers and lenders of these loans. The main data sources used in constructing the estimation sample are briefly described as follows:

Syndicated loan data

Our analysis covers a sample of syndicated loans over the period 2010 to March 2021. The loan-level information was obtained from Thomson Reuters LPC DealScan Database (via the Refinitiv Loan Connector platform). Following the literature, we measure loan spread by the "All-in-drawn spread" in basis points and thus consider only those loans with information on the loan spreads. Given that our focus is on the APAC syndicated loans market, we further restrict our loan sample to those syndicated in major APAC markets[6] (i.e. where the majority

[6] 13 APAC economies are included, namely Australia, China, Hong Kong, Indonesia, Japan, Malaysia, New Zealand, Singapore, South Korea, Taiwan, Thailand, the Philippines and Vietnam.

of funds were sourced to finance the loan), but also keep a broader set of loan reference rates[7]. Godlewski and Weill (2008) documented that syndicated loans have undergone a major expansion and represented an important source of external finance in emerging markets even before the global financial crisis. To control for the potential heterogeneity in the intercept level of the loan spread over currencies and over different benchmark rates, we added fixed effects on the currencies and types of benchmark rate in all regressions. We further collect loan characteristics such as the borrower (and its parent) names and industries, syndicate structures, loan active date, size, maturity, pricing details, financial covenants, tranche types and purposes and whether the loan is secured as loan controls. In particular, by linking the names of the bank-type lead arrangers[8] in each loans' syndicate structure to the corresponding financial institutions, it enables us to capture the impacts of variations in lenders' financial characteristics and also banks' environmental attitude in loan pricing decisions.

Borrowers' and lenders' financial data

The balance sheet data of loan borrowers and lenders were obtained from S&P Capital IQ to control for the impacts of borrowers' and lenders' financial strength on loan pricing whenever available. S&P Capital IQ additionally provides details on the industry classification, organisation structure, state ownership shares and geographical locations for both borrowers and lenders.[9] We further restrict our sample by excluding loans in which the borrower is a financial institution, or if the lead arranger group consists only of lenders which are not commercial and investment banks based on the information from S&P Capital IQ (i.e., policy banks and non-bank type financial institutions are excluded in our sample).

Firms' GHG emission data

We gauge firms' exposure to the transition risk by their GHG emissions. The GHG emissions data of corporates are obtained from *S&P Trucost.* It provides annual corporate Carbon Dioxide and other Greenhouse gas (CO_2e) emission data between 2005 to 2019 for

[7] These include Bank Bill Swap Bid Rate (BBSY) for Australian dollars, Euro Interbank Offered Rate (Euribor) for Euro, Hong Kong Interbank Offered Rate (HIBOR) for Hong Kong dollar, London interbank offered rates (LIBOR) for US dollar, Singapore Interbank Offered Rate (SIBOR) and Singapore Swap Offer Rate (SWOR) for Singapore dollar, TAIBOR (Taiwan Interbank offered rates) for Taiwanese dollar, Tokyo Interbank offered rates (TIBOR) and Yen LIBOR for Japanese Yen.
[8] The lead arrangers are usually responsible for ex ante due diligence and ex post monitoring on the borrower. They usually retain substantial stake in the syndicate (Sufi (2007)).
[9] Specifically, we first match the names of borrowers and lead arranger from DealScan with S&P Capital IQ using the SPCIQ Identifier Converter Excel Template. As a borrower and a lead arranger could negotiate and reach the loan deals through their solely owned subsidiaries or branches, we typically look up the corporate's organisation tree until a parent corporate is identified, which usually would be either a publicly listed firm or have financial data reported. Second, we match S&P Trucost with S&P Capital IQ conveniently given the availability of International Securities Identification Number (ISIN) for most of the firms under the Trucost Platform. Finally, we merge the three sources, whenever available, to construct the firm-loan-bank relationship data.

more than 17,000 companies globally (covering more than 90% of global market capitalisations according to the S&P Global). Consistent with the standards set out by the GHG Protocol[10], three types of GHG emission data of a corporate are available from *S&P Trucost* - namely scope 1, 2 and 3 emissions. Generally speaking, scope 1 emissions cover all emissions generated during fuel combustion activities from a firm (or its controlled affiliates) while scope 2 emissions cover indirect generation relating to the purchase of energy. Scope 3 emissions include all other indirect emissions that occur in a company's value chain (See Figure 1 extracted from GHG Protocol).

In practice, scope 1 and 2 emissions data are more widely applied in the assessment of firms' GHG emissions performance, given their clearer and more standardised measurement provided. Such property of consistency allows us to treat the estimated data by Trucost as reasonably comparable to other reported data for corporates' scope 1 and 2 emissions.[11] Thus, and in line with existing literature, our study focuses primarily on non-financial corporates' scope 1 and 2 emissions only, and disregards scope 3 emissions.

It is also noteworthy that the absolute amount of GHG emissions is highly correlated with a firm's size. To ensure the comparability of GHG emission performance across firms, we divide their emissions by their total revenue, which is equivalent to firms' GHG emission intensity. In addition, measuring a firm's GHG emissions relative to its revenue also helps capture the severity of the potential financial impact from a tightening of carbon emission regulations, such as an imposition of a higher carbon tax. For instance, among two firms which have the same amount of total GHG emissions, the firm with a higher GHG emission intensity will find the financial impact of a carbon tax more material compared to the other firm with a low GHG emission intensity.

It is also noteworthy that the level of emission intensity generally varies across sectors. Figure 2 presents the average emission intensity of firms across economic sectors by the Global Industry Classification Standards (GICS). As shown, mainly reflecting the nature of their business activities, "utilities", "materials", and "energy" sectors are the largest emitting sectors (denoted as emission-intensive sectors hereafter). This observation leads us to investigate whether there could be a difference in the loan pricing of transition risk between borrowers

[10] The GHG Protocol is considered to be the most widely recognised international accounting tool for the measurement of GHG emissions.
[11] Bolton and Kacperczyk (2020a, 2020c), Dai et al. (2021), Jondeau et al. (2021) and Ehlers et al. (2021) similarly employed the Trucost data to study the pricing of carbon risk. Box 2 in BCBS (2021) also documented that bank respondents confirmed that they look at scope 1 and 2 emissions relatively more than scope 3 emissions.

from the emissions-intensive sectors and those from other sectors, as the transition for the former may be much higher than the latter.

Proxy for banks' environmental attitude

Lastly, we use bank membership in the United Nations Environment Programme Finance Initiatives (UNEP FI) as a proxy for a bank's attitude toward green issues. Following the practice of Delis et al. (2020) and Degryse et al. (2020), we consider a bank (at the group parent level)'s membership signature in UNEP FI as revealing its attitude towards climate change issues. UNEP FI is a partnership between the UN and the financial sector to encourage private sector funding in financing sustainable development. Signatory banks signal the public and their investors that they are committed to working towards integrating environmental considerations into their operations and business decisions. If a lead arranger has already been a member of the UNEP FI at the time of loan originations, we consider the lead arranger to be a green bank (i.e. $Green\ bank_{b,t}$=1).

Despite this public commitment, the signature action could also be in part motivated by the reputational benefits from enhanced corporate image[12] and, therefore, not necessarily reflecting those banks have committed tangible efforts to promote greenness. As such, we propose another more restrictive "green" classification for a lead arranger by requiring additional green effort from banks. Specifically, the narrow green bank measure ($Green\ bank''_{b,t}$) takes the value of 1 only if the lead arranger has already been a member of UNEP FI and, at the same time, it or the ultimate parent holding firm, have been self-disclosing CO_2e emission information of the organisation. As shown in Figure 3, about 22% of the lead arrangers in our sample had already joined the UNEP FI before 2010, while the share had increased to around 35% by the end of 2020. As a result, based on those that have become members within the sample period, we can exploit the "within bank variation" in memberships alongside the lead arranger fixed effect.

Overview of the final sample

By combining all relevant data from different sources described above and removing those loans with missing data, our final sample covers 2,842 loans for estimations which span 704 unique borrowing firms and 157 unique banking corporations. In Table 1, we provide a descriptive statistic table of the final sample of loans. In panel A, we report the summary statistics of the variables at the loan-level, the middle panel is the data for borrowers and the lower panel for lead arrangers. The all-in-spread-drawn to firms is, on average, 166 basis points

[12] Cao et al. (2015) find that a US company with a higher reputation score obtains a lower cost of equity capital after controlling for other factors.

(bps) over the reference rates, with a standard deviation of 106.7 bps. The median number of lead arrangers in the syndicate is 5, which is consistent with the characteristics of the global syndicated loan market outside the United States (see, for instance, Ferreira and Matos (2012), Europe Economics (2019), Tanjung et al. (2013)).[13] The average size and tenor of the loans are 18.9 in logarithm of US dollar equivalent (that is, US$161.5 million), and 51.6 months respectively. Loans are roughly evenly distributed before and after the Paris Agreement, with the mean value of post-Paris Agreement dummy equal to 0.54. For the borrower's CO_2e emission intensity, the average emission intensity for scope 1 and scope 2 are 457.1 and 75.6 (both in tonnes per US$ millions) respectively. Regarding the geographical distribution of the borrowers, the majority of the 704 borrowers are also headquartered in the Asia Pacific region, with firms from China having the strongest presence (around 20%) in the sample. Borrowers from Taiwan, Hong Kong, Australia, Japan, and ASEAN economies also constituted sizeable shares (ranging from 8-19% of the firms for each group) in the sample. Roughly 10% of the borrowers are from the other regions (such as the Americas, EMEA and other parts of Asia). As such, our sample should be representative of the corporate lending situation in APAC.

III. EMPIRICAL SPECIFICATIONS AND RESULTS

<u>3.1 Do banks charge a higher lending rate on "brown" firms than their non-"brown" industry peers?</u>

To answer this research question, we compare the loan spread charged on a highly emitting firm with an otherwise identical firm in the same industry but with a lower CO_2e emission intensity, after controlling for all relevant loan-level, borrower and lender characteristics. Specifically, we run the following firm-loan level regression model (1):

$$loan\ spread_{i,t} = \alpha + FE_{i,t} + \beta_1 High\_CO2_{i,t-1} + \delta' Z_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

The dependent variable $loan\ spread_{i,t}$ denotes the lending spread over reference rates in basis points for loan *i* issued in year *t*. $High\_CO2_{i,t-1}$ is a dummy variable defined as one if the borrower of loan i's CO_2e scope 1 emission intensity is higher than its respective industry-average level at year *t-1*. By construction, $High\_CO2_{i,t-1}$ captures the average impact for a

[13] Consistent with the characteristics of the Europe market, the number of lead arrangers in loans originated in APAC is also higher than those observed in the US market. One of the reason is that foreign banks (i.e. banks from US or Europe) also actively participate in the APAC syndicated loan market, and they usually pair up with local banks which possess soft information on borrowers from the same region to arrange the loan package. Tanjung et al. (2013) studied the trend in syndicated loan market in the Asia Pacific region and found that most of the loans have at least two lead arrangers. This is significantly different from the US market as found by Ivashina (2009) that 98% of US syndicated loans were led by one arranger only.

borrower being "brown" relative to its same-industry-peers at year *t-1* on the pricing of loan at year *t*. [14] Details about the CO_2e emission intensity and the industry-average level are provided in Section II. $FE_{i,t}$ is a vector of fixed effects which includes borrower's country-, borrower's industry-, year-, country of loan syndication-, loan reference rates-, loan currency- and loan type-fixed effects to control for unobserved differences in the cost of bank loans across various dimensions. $Z_{i,t}$ and $X_{i,t-1}$ are vectors of loan-level, and one-year lagged borrower-level characteristics control variables, respectively. Loan-level and lender-control variables include logarithm of loan size, loan maturity, number of lead arrangers in the syndicate, dummies for the existence of financial covenants or being secured by collateral, the average profitability, Tier-1 capital ratio and size of the lead arranger consortium. The borrower firm control variables are intended for controlling for the impacts from other borrower features being considered during loan pricing. [15] These include a borrower's return-on-assets (RoA), debt-to-asset ratio, logarithm of firm's total assets, and dummy for identifying whether the borrower is under state controls. $\varepsilon_{i,t}$ denotes the idiosyncratic error term.

The coefficient of interest here is β_1, which is the difference in average loan spreads between loans to brown firms and that of similar loans to non-brown firms (i.e. the control group) in the same industry and country, and originated in the same year. A statistically significant and positive β_1 would imply that banks tend to charge a higher loan spread to brown firms on average relative to non-brown industry-peers to compensate for the associated climate transition risk, all else being held constant.

We further study whether banks have started to price in the transition risk since the Paris Agreement by extending equation (1). Specifically, we consider a modified regression model (2) by adding a Post-Paris Agreement dummy and an interaction term of $High\_CO2_{i,t-1}$ with the Post-Paris Agreement dummy:

$$loan\ spread_{i,t} = \alpha + FE_{i,t} + \beta_1 High\_CO2_{i,t-1} + \beta_2 High\_CO2_{i,t-1} * Dum\_Paris_t + \mu Dum\_Paris_t + \delta' Z_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

[14] An alternative dummy which is based on the industry-region average of the emission intensity has been considered as a robustness check, where the regions are Asia & Oceania, EMEA and the America respectively. The results remain quantitatively robust and they are available upon request.

[15] Ideally, one would include credit ratings of borrowers as one of the control variables as it provides a holistic summary of the firms' financial strength. However, as credit ratings are generally limited in our sampled borrowers, this precludes us from including this variable in our analysis as it will substantially reduce the number of observation. Therefore, we control for borrowers' financial strength by their balance sheet characteristics, namely leverage, profitability and size, instead.

where Dum_Paris_t takes the value one if loans are issued in and after 2016. The coefficient β_2 in essence tests whether there is a significant change in the average loan spread charged among the group of highly emitting firms after the Paris Agreement relative to that during pre-Paris Agreement period.

All regressions are estimated using the ordinary least square method. Given the existence of multiple-ways of fixed effects in the specifications, we adopt the linear estimator proposed by Correia (2016) which is a feasible and computationally efficient estimator for large and complex datasets. Robust standard errors are reported, unless otherwise specified.

Results for the loan-level regression equation (1) are presented in columns 1 to 3 of Table 2, while results for equation (2) are shown in columns 4 to 6. As shown in Table 1, the control variables are mostly statistically significant across specifications and are consistent with their underlying economic intuitions respectively, suggesting they are important determinants of the loan spreads in our sample. However, there appears to be no significant difference in the loan pricing between brown firms and non-brown firms in the same industry over the whole sample period, as indicated in column 1. The same result held true even if we re-estimate equation (1) by splitting the sample into two subgroups – namely the CO_2e emissions-intensive industries group (i.e. firms in the Utilities, Materials and Energy industries) in column (2) and the other industry group in column (3). This finding appears to suggest that for the whole sampling period from 2010 to 2021, the climate transition risk was not priced on average for loans originated in the Asian syndicated loan market.[16]

When the interaction term is added to differentiate loans originated before and after the Paris Agreement, we find some evidence that banks would charge a higher loan spread to brown firms relative to their non-brown peers, albeit only statistically significant for borrowers in the emissions-intensive industries in the post-Paris Agreement period (i.e. column 5). As indicated in column (5), we find a positive and statistically significant coefficient for the interaction term (i.e. $\widehat{\beta_2}$ = 44.59), suggesting that brown firms in the emissions-intensive industries are, on average, charged higher by almost 45 bps for their loans in the post-Paris Agreement period relative to the pre-Paris Agreement period. The cross-sectional difference in loan spreads between brown firms and their non-brown counterparts in the post-Paris Agreement period is

[16] The insignificant finding does not necessarily imply an inconsistency with the findings in Chava (2014) and other related works, where they find that the environmental performance of a borrower will affect the pricing term of a syndicated loan even before the Paris Agreement. We offer two plausible explanations here. First, the dataset used in existing literature for the syndicated loan market is largely reflecting results for loans originated in the US. This could differ from the Asian syndicated loan market which we focused on. Second, while the climate transition risk of a corporate in principle could be one important environmental constraint faced by borrowers, banks may simply look at the holistic ratings of the borrowers' environmental profiles, rather than focusing solely on the dimension of transition risk.

jointly determined by $\widehat{\beta_1} + \widehat{\beta_2}$.[17] The tests for the cross-sectional difference are also reported in the Table 2. The reported magnitude in column (5) suggests that banks on average charge a 23 bps loan spread higher on "brown" borrowers relative to their non-brown peers in emissions-intensive industries after the signing of the Paris Agreement.[18] The higher loan spread charged on highly emitting firms in emissions-intensive industries is consistent with the view that reaching the Paris Agreement in Dec 2015 had updated creditors' expectations on the stringency of the environmental policy into the future, as discussed in Bolton and Kacperczyk (2020b), Delis et al. (2021) and Ehlers et al. (2021). Importantly, this result is not only statistically significant but also economically meaningful. Given that the average loan spread over the reference rate in our sample is 166 bps[19], this implies these brown firms are, on average, being charged around 13% more than their non-brown peers after the Paris Agreement, *ceteris paribus*.

By contrast, the relatively muted effects in our full sample (i.e. column (4)), appear to be driven by loans borrowed by firms from the other industry group as we do not find any statistically significant coefficients for both β_1 and β_2 in columns 4 and 6. A plausible explanation is that, on average, firms in these lower emission industries generally have relatively low scope 1 emission intensity (see Panel A in Figure 1), so the associated climate transition risk may not be significant enough to trigger concern among arranging banks. As a result, banks may be less inclined to consider their scope 1 emission profile as an important factor in the loan pricing decision for firms in these industries. Instead, the loan spreads charged on these firms will largely be determined by their financial characteristics and the specific loan features as captured in the control variables.

To ensure the above empirical findings are not driven by different groups of borrowers with different characteristics across the two periods (i.e. pre-Paris Agreement and post-Paris Agreement), a robustness check was conducted, in which we restrict our sample to those borrowers that have borrowed a loan at least once in both periods.[20] The estimation results

[17] Interestingly, we find a negative and significant coefficient for β_1. This could partly be attributable to an unobserved heterogeneity among borrowers before the Paris Agreement. As shown in a fixed sample robustness analysis in Table 3 (which will be discussed shortly after), β_1 is estimated to be statistically insignificant, while β_2 remains positive and statistically significant. This finding suggests that banks may not have taken the transition risk of firms in the loan pricing consideration prior the Paris Agreement.

[18] One may argue that the difference can be merely driven by correlation with other factors such as rating. However, Ehlers et al. (2021) find that there is virtually no correlation between firms' carbon emission intensity with corporate ratings in their sample.

[19] The average lending spreads, charged on loans for firms in the three emissions-intensive industries after the Paris Agreement, is quantitatively similar (164.5 bps).

[20] The fixed sample analysis enables us to include time invariant borrower fixed effects to control for unobserved characteristics of borrowers. As borrowing country- and borrower industry- fixed effects

based on the fixed sample are presented in Table 3. As can be seen, the estimation results remain quantitatively similar, suggesting our baseline results are robust. Importantly, we continue to find evidence that banks would on average charge a higher lending spread to brown firms by around 35 basis points as compared to that of non-brown firms in the emissions-intensive sectors in the post-Paris Agreement period.

Taken together, our empirical results find supportive evidence that banks in the region have started to consider climate transition risk in their loan pricing after the Paris Agreement, at least in their syndicated loans. The existence of the transition risk premium is found mainly in those loans extended to firms from emissions-intensive industries, probably reflecting banks' increased awareness of climate-related risk to those corporates that are more subject to the transition risk.

3.2 Does the environmental attitude of banks play a role in determining the extent of climate transition risk in loan pricing?

Given the findings above, an important related question is whether the green attitude of banks matters in determining the extent of a transition risk premium charged on brown firms. As discussed in Section II, there is no consensus on which indicator can perfectly measure a bank's green status. Therefore, we employ two measures to proxy whether or not a bank is green in this analysis. For a broad measure, we consider a bank is green if it was already a member of the UNEP FI before the loan was originated. For a narrow measure, conditional on the bank already being a member of the UNEP FI, we further require that particular bank (or its ultimate parent holding company) to have already disclosed its own CO_2e emission information. The latter condition attempts to narrow down those green banks that have committed tangible measures and costs in implementing climate-related practices in their operations.

To empirically separate the effect of banks' environmental attitudes from other banks' financial characteristics, we further decompose loan-level observations into loan-lead arranger level observations following Degryse et al. (2020) and Delis et al. (2021).[21] This decomposition allows us to define a time-varying bank-level dummy variable (i.e. $GreenBank_{b,t}$) to capture the bank's green attitude to estimate its standalone and interaction effects on loan spreads, and also

are being absorbed by including the borrower fixed effects, the former two fixed effects are therefore omitted in Table 3.

[21] Ferreira and Matos (2012) and Liu and Pogach (2017) also include bank characteristics as control variables when loan spread is used as the dependent variable.

to include the lead arranger fixed effects whenever possible. Specifically, we consider the following firm-loan-lead arranger level regression model (3):

$$loan\ spread_{i,b,t} = \alpha + FE_{i,b,\,t} + \beta_1 High\_CO2_{i,t-1} + \beta_2 Green\ bank_{b,t} + \beta_3 High\_CO2_{i,t-1} * Dum\_Paris_t + \beta_4 High\_CO2_{i,t-1} * Green\ bank_{b,t} + \beta_5 Green\ bank_{b,t} * Dum\_Paris_t + \beta_6 High\_CO2_{i,t-1} * Green\ bank_{b,t} * Dum\_Paris_t + \mu Dum\_Paris_t + \delta' Z_{i,t} + \gamma' X_{i,t-1} + \theta' Y_{b,t-1} + \varepsilon_{i,t} \quad (3)$$

where $Green\ bank_{b,t}$ takes the value of one if the lead arranger *b* is classified as green bank at loan origination year *t* and zero otherwise. As discussed, two measures of green bank proxies (broad and narrow measures) are considered in this analysis and are denoted as $Green\ bank_{b,t}$and $Green\ bank''_{b,t}$ respectively. Other specification details are largely similar to the loan-level regressions (1) and (2), except that the fixed effect term $FE_{i,b,\,t}$ additionally includes borrower and lead arranger fixed effects[22] while $Y_{b,t-1}$ includes each lead arranger b's profitability, Tier-1 capital ratio and size variables, to replace the corresponding average variables for the whole lending consortium in the loan. Here our variable of interest is the coefficient on the triple interaction term $High\_CO2_{i,t-1} * Green\ bank_{b,t} * Dum\_Paris_t$, which captures whether the loan spread on a brown firm by a green bank will exhibit a larger change relative to the same loan by a non-green bank after the Paris Agreement.

The left panel of Table 4 reports the results of equation (3) for all industries, emissions-intensive industries group and the other industry group respectively, using the broad green bank proxy $Green\ bank_{b,t}$, while the right panel of Table 3 reports the results using the narrow green bank proxy $Green\ bank''_{b,t}$.

First of all, our previous findings continue to hold after decomposing the loan-level observations into loan-lead arranger level observations. That is, banks on average charge a higher loan spread on brown firms from the emissions-intensive industries after the Paris Agreement, as indicated by the positive and significant coefficient on the $High\_CO2_{i,t-1} * Dum\_Paris_t$ in columns 2 and 5. Likewise, similar to the results in Table 2, the interaction term is not statistically significant when all industries and other industry group are considered. [23] Evidence for the additional transition risk premium on brown firms after the Paris Agreement

[22] As a result, state-ownership dummy, borrowing country- and borrower industry- fixed effects are being absorbed by including the borrower fixed effects.

[23] While the coefficient for $High\_CO2_{i,t-1}$ becomes statistically significant now, it may partly be driven here by the inclusions of borrower- and lead arranger- fixed effects.

is only present for borrowers from the emissions-intensive industries group. As a result, our attention is now mainly focused on loans for these groups of borrowers when discussing the potential impacts of the green status of a bank on the extent of transition risk premium in the loan pricing.

Our estimation results, in columns 2 and 5, suggest that the green status of banks does matter in determining the extent of transition risk premium in the loan pricing, as indicated by a positive and significant coefficient on the triple interaction term $High\_CO2_{i,t-1} * Green\ bank_{b,t} * Dum\_Paris_t$. This, together with the positive coefficients on the double interaction term $High\_CO2_{i,t-1} * Dum\_Paris_t$, indicate that there is a larger rise in the loan spread on brown firms on average after the Paris Agreement, but the change in the spread is larger if the brown firm borrows from a green bank compared with those borrowing from a non-green bank, after controlling for other key loan determinants. This finding is consistent with the view that green banks are more concerned about the associated transition risk in their loan portfolios after the Paris Agreement, thus leading them to charge an even larger rise in the loan spreads for highly emitting borrowers than would otherwise be the case for the non-green banks.

While the positive triple interaction term (i.e. $\widehat{\beta_6}$) points to a larger rise in the loan spread charged by a green bank towards a brown firm after the Paris Agreement, the cross-sectional difference in the level of loan spread between those charged by green banks and those by non-green banks during the post-Paris Agreement period is jointly determined by the sum of $\widehat{\beta_2} + \widehat{\beta_4} + \widehat{\beta_5} + \widehat{\beta_6}$.[24] The statistical tests for the cross-sectional difference in loan spread based on the two green bank proxies are separately reported in Table 5. It is interesting to note that the magnitude and statistical significance for the cross-sectional difference in loan spread varies depending on which of the two green bank proxies is considered. Based on the broad green bank proxy, the loan spread is around 5 bps higher if the loan to a brown firm is arranged by a green firm, but the result is not statistically significant (column 1). By contrast, the difference in loan spread is found to be larger (around 9.2 bps) and statistically significant if the narrow green bank proxy is employed for the classification of green banks (column 2). The magnitude of 9.2 bps is also economically significant, as it implies that green banks will require an additional 5.5% transition risk premium (as divided by the average lending spread of 166 bps for the sampled loans) in lending to the brown firm, compared with non-green banks. These results together suggest that the green attitude of banks plays a key role in determining the

[24] Based on equation (3), the cross-sectional difference in the loan spread between a brown firm borrowing from green bank and a brown firm borrowing from a non-green bank in the post-Paris Agreement period is determined by $Y[green\ bank = 1, brown\ firm = 1, post\ paris = 1] - Y[green\ bank = 0, brown\ firm = 1, post\ paris = 1] = \beta_2 + \beta_4 + \beta_5 + \beta_6$.

extent of transition risk premium and the effects would be more significant when these green banks are concurrently implementing and adhering to climate-related practices in their internal operations and business decisions.

IV. ROBUSTNESS CHECKS

In this section, we conduct several robustness tests to check if our results are sensitive to specification changes. The associated results are reported in Tables A2-A6 in the Appendix.

Firstly, we test whether the results are sensitive to alternative measures of firms' carbon emission intensity. Instead of using firms' scope emission intensity, we alternatively define brown firms based on the sum of scope 1 and 2 emission intensity. As shown in Table A2 and A3, the results remained quantitatively similar. This can be attributed to the fact that given the business nature of the emissions-intensive industries, scope 1 emission intensity of those corporates in the group usually dominate their scope 2 emission intensity. The results, therefore, are similar quantitatively even when we considered scope 1 and 2 emissions together.

Second, we also test the impact of replacing the brown firm dummy variable with the emission intensity deviation from the industry average level (i.e. a continuous variable) for the loan-level regression. This alternative specification aims to investigate whether the level of deviation above industry average level, among the group of "brown" firms, would also lead to a different lending term. The results in Table A4 show that the coefficient of Firm's CO_2e emission deviation from industry average level interacting with the Post Paris dummy, and the combination effect, are both positive and statistically significant at the 5% level. This suggests that firms with higher intensity levels above the industry average would be charged a higher premium following the Paris Agreement, which is consistent with the regression result in column (5) of Table 2.

Thirdly, we also considered the effect of replacing robust standard errors with clustered standard errors. For the loan-level regression in Table A5, when we use instead the clustered standard errors at borrower-level, the statistical significance for the combined effect, although weakened somehow, remained statistically significant at the 10% level. For the loan-lead arranger level regression, we considered both the clustered standard errors by borrower-level and by lender-level, respectively in Table A6. While the statistical significances of individual dummy variables have weakened for the first two columns, the linear combination test for our hypothesis in Section III.3 (i.e. compared with non-green banks, green banks charged higher terms on brown firms in the emissions-intensive industry after the Paris Agreement) remain valid at least at the 10% statistical significance level.

V. CONCLUSION

Based on a unique sample of syndicated loans originated in APAC, our analysis suggests that banks in the region have started to price-in climate transition risk for loans to emission-intensive sectors since the Paris Agreement. This probably reflects banks' increased awareness of climate change to borrowers that are more subject to transition risk. The extent of the transition risk premium is also found to be dependent on the environmental attitude of banks. Specifically, green banks are found to charge a higher loan spread than other banks, when lending to the same brown firm after the Paris Agreement. Such difference is found to be more pronounced if these green banks are concurrently taking actions to implement climate-related practice in their operations (such as regularly self-disclosing CO_2e emissions).

These findings together provide some important policy implications. Firstly, our analysis contributes to the policy debate on whether imposing climate-related regulatory requirements on banks, on top of the existing regulatory framework, could help them to manage climate-related risks. Our findings show that banks in the region started to price in climate-related risks since the Paris Agreement, probably reflecting that climate risks have been considered in the credit risk management of banks. The findings support the view that climate-related risks can be captured under the existing regulatory framework. This may suggest that the benefits of additional regulatory requirements on climate-related risks should be assessed carefully. Relatedly, there is an argument that climate-related capital requirement, if designed inappropriately, could unduly influence banks' lending behaviour and potentially lead to unintended consequences for financial stability (Bailey (2021)). As such, evaluating the trade-offs between additional climate-related capital requirements and the potential unintended consequences is highly warranted.

Secondly, despite the fact that banks in the region have started to incorporate climate risk into their existing risk management framework, managing climate risks will remain a key challenge for banks due to the different nature from the traditional risk types[25] and data gaps. Banks should therefore keep abreast of the latest developments in climate risk management practices to adjust their own risk management approach. Policymakers in the region should also proactively engage with the banking industry and help facilitate banks to incorporate climate risk management practices into their operations. In addition, it is important for policymakers to promote GHG emission disclosure by firms and urge them to follow common environmental reporting standards, such as those recommended by the Task Force on Climate Related

[25] Compared to the traditional risk types, climate risks are more susceptible to non-linearity and fat-tailed distributions.

Financial Disclosures (TCFD). Looking ahead, a broader coverage and higher quality of firms' environmental disclosure data would be highly desirable for banks to better assess the associated climate risk in their overall loan exposures.

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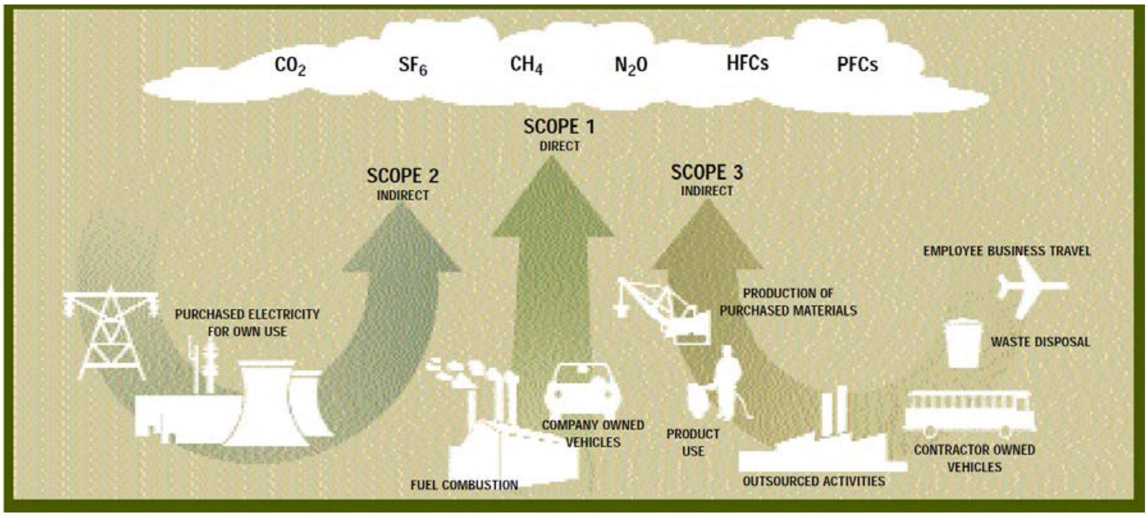
Figures and Tables

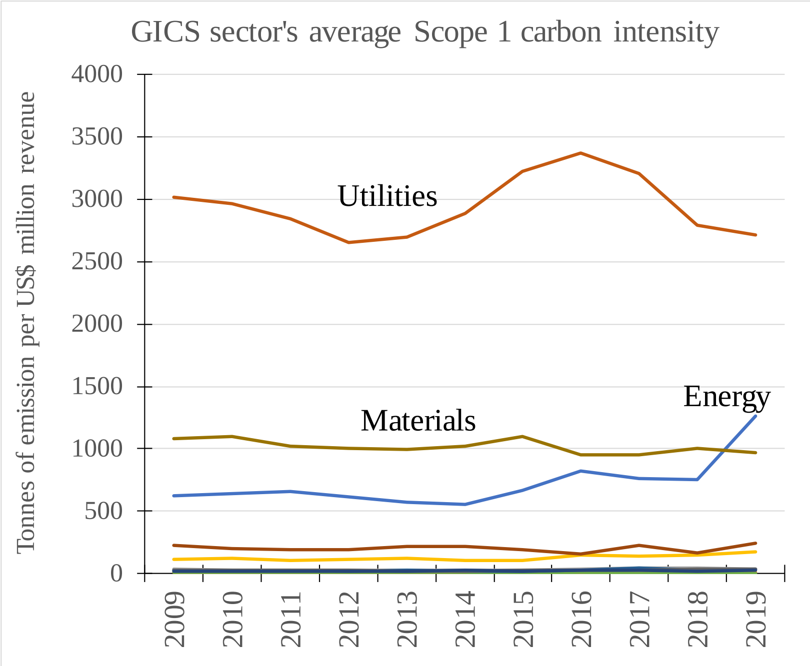
Figure 1: Overview of greenhouse gas emissions as defined in the Greenhouse Gas Protocol



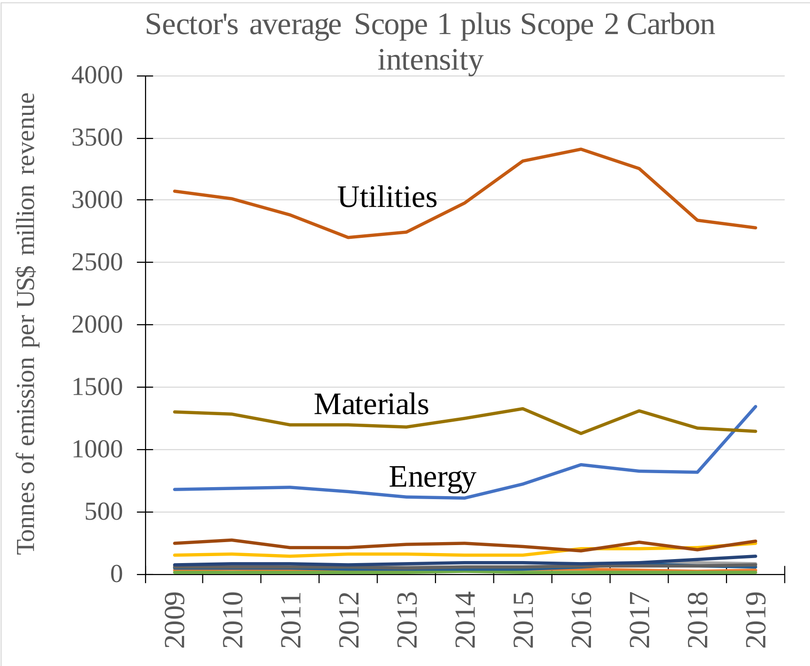
Source: Figure 3 in *The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard*, retrieved on 4 June 2021.

Figure 2: Average CO_2e emission intensity among GICS sectors

Panel A: GICS sector's average Scope 1 CO_2e emission intensity



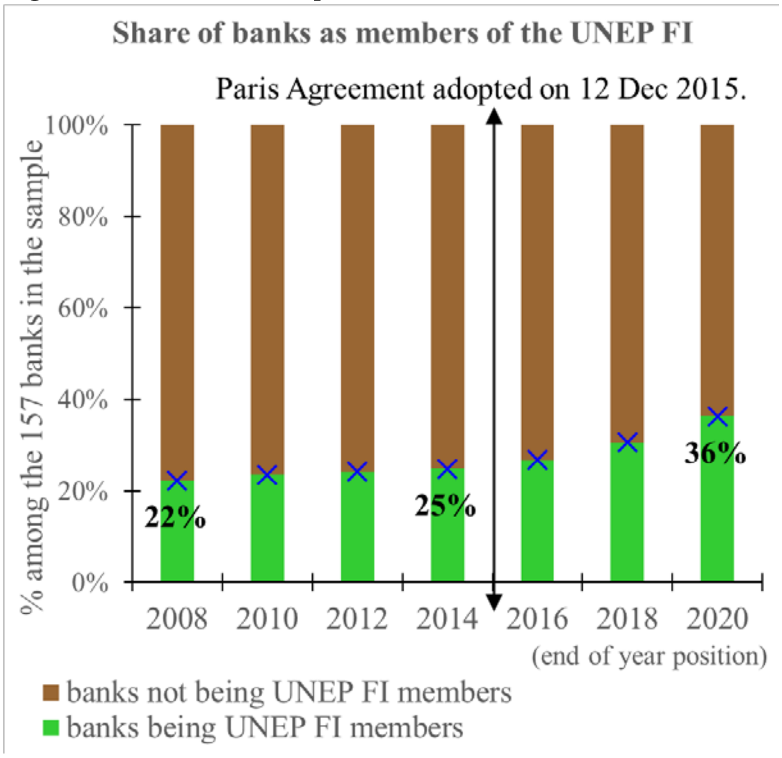
Panel B: GICS sector's average Scope 1 plus Scope 2 CO_2e emission intensity



Source: Authors' calculations based on data from S&P Trucost

Note: Panel A and B present the average firm emission intensity (in tonnes of CO_2e equivalent to revenues in US$ millions) by GICS economic sectors.

Figure 3: Share of the sampled banks which are members of the UNEP FI



Sources: Dealscan, UNEP FI and authors' calculations

Table 1: Summary statistics

Panel A (loan-level / loan-lead arranger level)								
Variable names	N	mean	sd	min	p25	p50	p75	max
AISD	2842	166.17	106.35	0	95	145	215	900
loan tenor	2842	50.34	26.50	7	36	48	60	180
ln(loan size)	2842	18.91	1.29	12.77	18.07	18.98	19.76	23.45
dummy(covenant)	2842	0.13	0.34	0	0	0	0	1
dummy(secured)	2842	0.21	0.41	0	0	0	0	1
No. of lead arrangers	2842	5.88	4.85	1	2	5	8	32
dummy(after Paris Agreement)	2842	0.54	0.50	0	0	1	1	1
dummy(green bank)	16161	0.45	0.50	0	0	0	1	1
Panel B (unique borrower-year level)								
Variable names	N	mean	sd	min	p25	p50	p75	max
borrower's ROA	1462	3.67	2.72	-1.19	1.84	3.24	5.08	9.60
borrower's debt-to-asset	1462	32.61	13.78	9.10	22.78	31.56	42.33	61.70
borrower's ln(total asset)	1462	22.62	1.51	17.77	21.55	22.61	23.69	27.59
dummy(state ownership)	1462	0.07	0.26	0	0	0	0	1
Scope 1 emission intensity	1462	508.97	1973.0	0.00	13.58	31.38	157.87	28702
Scope 2 emission intensity	1462	77.34	219.5	0.02	14.55	36.21	62.20	5294
Scope 1&2 emission intensity	1462	586.30	2001.9	0.02	42.84	82.25	286.81	28703
Panel C (unique lead arranger-year level)								
Variable names	N	mean	sd	min	p25	p50	p75	max
lead arranger's ROA	1095	0.70	0.40	0.02	0.35	0.71	1.01	1.37
lead arranger's log(total asset)	1095	26.41	1.41	24.45	25.00	26.54	27.57	28.63
lead arranger's t1-capital ratio	1095	12.09	2.57	8.21	9.93	11.90	13.80	16.80

Note: Panel A reports summary statistics for the full sample at the loan-level, except for dummy(green bank) which is reported at the loan-lead arranger level. Panel B reports the relevant statistics at unique borrower-year level for loan-level regression, while panel C reports related statistics at unique lead arranger-year level for the loan-lead arranger level regression.

Table 2: Estimation results for equation (1) and (2) with the loan level observations

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (Margin)	All industries	High CO_2e industries	all other industries	All industries	High CO_2e industries	all other industries
High CO_2 (β_1)	-0.988	-3.133	4.517	-4.016	-21.97**	7.055
	(3.102)	(6.864)	(3.512)	(4.500)	(9.006)	(5.365)
High CO_2 * Dum_Paris (β_2)				5.715	44.59***	-4.602
				(6.075)	(12.53)	(7.006)
Joint test: $H_0: \beta_1 + \beta_2 = 0$				1.699	22.61**	2.454
p-value				*0.685*	*0.0170*	*0.592*
Loan tenor	0.240***	0.504***	0.150	0.242***	0.514***	0.148
	(0.0767)	(0.127)	(0.0971)	(0.0768)	(0.124)	(0.0978)
Ln(Loan Amount)	-0.678	3.261	-2.002	-0.712	1.770	-2.024
	(1.711)	(3.747)	(1.948)	(1.707)	(3.670)	(1.951)
ROA (Borrower)	-1.459**	-1.578	-1.827**	-1.500**	-1.802	-1.798**
	(0.674)	(1.427)	(0.769)	(0.672)	(1.436)	(0.770)
Debt-to-asset (Borrower)	0.960***	0.857***	0.962***	0.965***	0.953***	0.958***
	(0.138)	(0.322)	(0.148)	(0.138)	(0.325)	(0.147)
Ln(Assets) (Borrower)	-4.330***	-12.06***	-1.604	-4.382***	-13.86***	-1.574
	(1.446)	(3.348)	(1.590)	(1.449)	(3.322)	(1.598)
Avg.ROA (Lender)	7.972	-21.64	18.18*	8.023	-23.92	18.04*
	(8.547)	(21.34)	(9.386)	(8.539)	(21.09)	(9.398)
Avg. ln(Assets) (Lender)	-8.462***	-5.484	-9.485***	-8.450***	-5.593	-9.475***
	(2.239)	(5.507)	(2.565)	(2.240)	(5.471)	(2.567)
Avg. Capital Ratio (Lender)	5.919***	5.688	5.578***	5.889***	6.480*	5.638***
	(1.558	(3.827)	(1.706)	(1.556)	(3.79)	(1.704)
Concentration	-3.050***	-3.468***	-2.532***	-3.037***	-3.332***	-2.538***
	(0.354)	(0.967)	(0.384)	(0.353)	(0.965)	(0.383)
Covenant	-7.986**	-16.28*	-3.231	-8.009**	-16.76*	-3.238
	(4.028)	(9.542)	(4.406)	(4.029)	(9.409)	(4.402)
State-owned dummy	-12.34*	-22.88	-12.23	-12.20*	-21.80	-12.32
	(6.978)	(14.12)	(8.956)	(6.981)	(14.10)	(8.935)
Observations	2,842	628	2,213	2,842	628	2,213
Adj. R-squared	0.531	0.510	0.560	0.531	0.519	0.560
Base rate dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country of syndication fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Currency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Collateral dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tranche type dummy	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors.

Table 3: Estimation results for equation (1) and (2) with the loan level observations (fixed borrowers sample)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (Margin)	All industries	High CO_2e industries	all other industries	All industries	High CO_2e industries	all other industries
High CO_2 (β_1)	5.358	18.78**	1.548	4.486	7.965	2.664
	(3.988)	(7.721)	(4.772)	(5.824)	(9.739)	(7.147)
High CO_2 * Dum_Paris (β_2)				1.553	26.98*	-1.927
				(6.454)	(14.26)	(7.647)
Joint test: $H_0: \beta_1 + \beta_2 = 0$				6.039	34.94***	0.737
p-value				(0.179)	(0.00161)	0.887
Loan tenor	0.338***	0.461**	0.194**	0.338***	0.454**	0.193**
	(0.0761)	(0.184)	(0.0788)	(0.0761)	(0.188)	(0.0787)
Ln(Loan Amount)	-3.887**	1.331	-5.066**	-3.867**	1.127	-5.094**
	(1.925)	(3.349)	(2.292)	(1.926)	(3.317)	(2.294)
ROA (Borrower)	-2.868***	-0.594	-3.517***	-2.863***	-0.706	-3.537***
	(0.934)	(1.594)	(1.197)	(0.935)	(1.531)	(1.205)
Debt-to-asset (Borrower)	0.265	0.541	-0.156	0.270	0.765	-0.160
	(0.269)	(0.577)	(0.318)	(0.271)	(0.587)	(0.318)
Ln(Assets) (Borrower)	-14.06***	-1.166	-19.07***	-14.07***	-2.009	-19.04***
	(4.913)	(12.70)	(5.302)	(4.912)	(12.15)	(5.318)
Avg.ROA (Lender)	17.27	12.46	21.01*	17.19	14.17	21.09*
	(10.62)	(20.04)	(12.33)	(10.59)	(20.10)	(12.29)
Avg. ln(Assets) (Lender)	-0.0226	7.613*	-1.053	-0.0108	8.006*	-1.065
	(2.191)	(4.309)	(2.604)	(2.19)	(4.202)	(2.603)
Avg. Capital Ratio (Lender)	1.745	-4.089	1.713	1.759	-4.027	1.7
	(1.535)	(4.092)	(1.685)	(1.532)	(3.987)	(1.683)
Concentration	-0.227	0.0237	-0.0654	-0.228	0.155	-0.0619
	(0.425)	(0.912)	(0.479)	(0.425)	(0.903)	(0.479)
Covenant	-17.96***	-34.37***	-16.14***	-17.94***	-34.29***	-16.15***
	(4.667)	(8.081)	(5.569)	(4.672)	(8.160)	(5.573)
Observations	1,747	1,747	332	332	1,414	1,414
Adj. R-squared	0.821	0.821	0.863	0.865	0.824	0.824
Base rate dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower industry fixed effect	No	No	No	No	No	No
Borrower country fixed effect	No	No	No	No	No	No
Country of syndication fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Currency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Collateral dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tranche type dummy	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors. As we have included the borrower fixed effect in this specification, borrower country, borrower industry group fixed effects, and also dummy for state-ownership would be absorbed.

Table 4: Estimation results for equation (3) with the loan-lead arranger level observations

	(1)	(2)	(3)	(4)	(5)	(6)
Green bank proxy	UNEPFI			UNEPFI + disclosure action		
VARIABLES (Margin)	All industry	High CO_2e industry	All other industries	All industry	High CO_2e industry	All other industries
High CO_2 (β_1)	8.543***	13.50***	5.634**	8.884***	13.77***	6.082***
	(1.954)	(3.520)	(2.281)	(1.959)	(3.537)	(2.284)
Green bank (β_2)	0.710	-1.530	2.394	1.570	3.123	1.421
	(2.522)	(4.188)	(2.745)	(2.379)	(4.078)	(2.613)
High CO_2 * Dum_Paris (β_3)	-3.066	19.73***	-5.487**	-3.241	20.27***	-5.888**
	(2.374)	(5.246)	(2.674)	(2.373)	(5.209)	(2.673)
High CO_2* Green bank (β_4)	-4.475**	-2.547	-3.990	-5.270**	-3.059	-5.093**
	(2.128)	(3.589)	(2.523)	(2.132)	(3.624)	(2.530)
Green bank * Dum_Paris (β_5)	-2.264	-1.593	-1.944	-2.192	-0.518	-1.837
	(1.900)	(3.789)	(2.102)	(1.902)	(3.731)	(2.115)
High CO_2 * Green bank *Dum_Paris (β_6)	2.886	10.55**	-1.801	3.225	9.606*	-0.984
	(2.881)	(5.154)	(3.451)	(2.875)	(5.131)	(3.442)
Loan tenor	0.552***	0.643***	0.475***	0.552***	0.642***	0.476***
	(0.0293)	(0.0556)	(0.0313)	(0.0293)	(0.0556)	(0.0313)
Ln(Loan Amount)	-3.187***	2.431***	-5.305***	-3.180***	2.459***	-5.308***
	(0.575)	(0.925)	(0.676)	(0.575)	(0.924)	(0.675)
ROA (Borrower)	-2.448***	-0.762	-3.091***	-2.450***	-0.742	-3.088***
	(0.319)	(0.616)	(0.372)	(0.319)	(0.617)	(0.372)
Debt-to-asset (Borrower)	0.134*	0.701***	-0.0255	0.133*	0.703***	-0.0259
	(0.0772)	(0.162)	(0.0868)	(0.0771)	(0.162)	(0.0867)
Ln(Assets) (Borrower)	-11.21***	-11.37**	-13.54***	-11.21***	-11.57**	-13.53***
	(1.920)	(4.491)	(2.008)	(1.920)	(4.493)	(2.008)
ROA (Lender)	10.12***	8.755*	8.117***	10.11***	8.617*	8.117***
	(2.107)	(4.531)	(2.345)	(2.113)	(4.540)	(2.359)
ln(Assets) (Lender)	-2.517	-6.665	-1.452	-2.338	-5.979	-1.325
	(2.671)	(5.438)	(2.993)	(2.666)	(5.450)	(3.000)
Capital Ratio (Lender)	-2.005***	-2.564***	-1.496***	-2.019***	-2.561***	-1.522***
	(0.343)	(0.715)	(0.384)	(0.343)	(0.714)	(0.384)
Concentration	-0.209	0.573**	-0.380***	-0.210*	0.582**	-0.382***
	(0.127)	(0.290)	(0.140)	(0.127)	(0.290)	(0.140)
Covenant	-16.37***	-27.28***	-13.54***	-16.39***	-27.40***	-13.57***
	(1.408)	(2.829)	(1.619)	(1.408)	(2.833)	(1.617)
Observation	16,161	3,828	12,313	16,161	3,828	12,313
Adj. R-Squared	0.857	0.864	0.868	0.857	0.864	0.868
Base rate dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country of syndication fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Currency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Collateral dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tranche type dummy	Yes	Yes	Yes	Yes	Yes	Yes
Lender fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors.

Table 5: Joint hypothesis testing results on equation (3) for emissions-intensive industries

	(2)	(5)
Green bank proxy	UNEPFI	UNEPFI + disclosure action
VARIABLES (Margin)	High CO_2e industry	High CO_2e industry
High CO_2 (β_1)	13.50***	13.77***
	(3.520)	(2.965)
Green bank (β_2)	-1.530	3.123
	(4.188)	(4.078)
High CO_2 * Dum_Paris (β_3)	19.73***	20.27***
	(5.246)	(6.517)
High CO_2* Green bank (β_4)	-2.547	-3.059
	(3.589)	(3.071)
Green bank * Dum_Paris (β_5)	-1.593	-0.518
	(3.789)	(4.326)
High CO_2 * Green bank * Dum_Paris (β_6)	10.55**	9.606*
	(5.154)	(4.789)
Joint test: $H_0: \beta_2 + \beta_4 + \beta_5 + \beta_6 = 0$	4.875	9.152**
p-value	*0.299*	*0.0384*
Observation	3,828	3,828
Adj. R-Squared	0.864	0.864
Base rate dummy	Yes	Yes
Year fixed effect	Yes	Yes
Country of syndication fixed effect	Yes	Yes
Currency fixed effect	Yes	Yes
Collateral dummy	Yes	Yes
Tranche type dummy	Yes	Yes
Lender fixed effect	Yes	Yes
Borrower fixed effect	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors.

Table A1: Variable definitions and sources

Variable	Description	Source
loan-level variables		
Loan spread	All-in-spread-drawn, defined as loan spread over reference rates in basis points.	Dealscan
Loan size	The loan amount in US dollar with natural logarithm transformation.	Dealscan
Tenor	The maturity of the loan in months.	Dealscan
Dummy(collateral)	Dummy equal to 1 if the loan is secured with collaterals.	Dealscan
Dummy(covenant)	Dummy equal to 1 if the financial covenant is present in the loan contract.	Dealscan
Number of lead arrangers	The number of lead arrangers in the loan syndicate.	Dealscan
Loan type	In line with Degryse et al.(2020), three broad categories are considered: 1. credit line; 2. term loans; 3. Other loan types.	Dealscan
Country of syndication	The location of the loan syndication.	Dealscan
Dummy after Paris Agreement	Dummy taking value of 1 if the loan active day is after 1 January 2016.	Dealscan
borrower-level variables		
Firm size	Logarithm of total assets in US dollar, one-year lagged.	S&P Capital IQ
Firm profitability	The return on asset, one-year lagged.	S&P Capital IQ
Firm leverage	The ratio of total debt to total asset, one-year lagged.	S&P Capital IQ
Dummy(state ownership)	This variable is for capturing the risk mitigating effect for lending to borrower which are backed by the state government. Specifically, dummy takes the value of 1 if the borrower/ultimate parent of the borrower is controlled by state/ having significant ownership shares (i.e. 20%) by the state government/SOEs.	S&P Capital IQ
CO_2e scope 1 emission intensity	Borrower's tonnes of scope 1 CO_2e emissions per US$ million, one-year lagged.	S&P Trucost
CO_2e scope 2 emission intensity	Borrower's tonnes of scope 2 CO_2e emissions per US$ million, one-year lagged.	S&P Trucost
Global industry average level of emission intensity	The global industry (GICS sub-industry) group average scope 1 (scope2) emission intensity level for each calendar year. The data is available at S&P Trucost E-board platform.	S&P Trucost
Dummy(High CO_2)	Dummy variable taking value of 1 if the borrower's CO_2e scope 1 (Scope1&2) intensity is higher than its respective industry-average level at year t-1.	S&P Trucost and authors' calculation.
lead arranger-level variables		
lender profitability	The return on asset, one-year lagged.	S&P Capital IQ
lender tier-1 capital ratio	T1 Capital ratio, one-year lagged (or the latest quarterly available data before the loan origination date up to one-year lagged period, whichever is available).	S&P Capital IQ
lender size	Logarithm of total assets in US dollar, one-year lagged.	S&P Capital IQ
Dummy(Green bank)	Green lender proxy. This is a dummy taking value of 1 if the lead arranger has become a member of UNEP FI as of the loan origination date.	Website of UNEP FI
Dummy(Green bank")	A more restrictive green lender proxy. This is a dummy taking value of 1 if as of the loan origination date, i.) the lead arranger has become a member of UNEP FI and ii.) the lead arranger (or its parent holding company) is also regularly self-disclosing GHG footprint.	Website of UNEP FI & S&P Trucost

Table A2: Estimation results for equation (1) and (2) with the loan level observations (Scope 1 and 2 emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable (Margin)	All industries	High CO_2e industries	all other industries	All industries	High CO_2e industries	all other industries
High CO_2 (β_1)	-8.332***	-10.26	-4.354	-10.65**	-30.29***	-0.821
	(3.091)	(7.171)	(3.546)	(4.616)	(9.202)	(5.413)
High CO_2 * Dum_Paris (β_2)				4.164	46.09***	-5.978
				(6.058)	(12.29)	(6.893)
Joint test: $H_0: \beta_1 + \beta_2 = 0$				-6.485	15.80*	-6.799
p-value				*0.110*	*0.0977*	*0.132*
Loan tenor	0.241***	0.507***	0.151	0.243***	0.506***	0.148
	(0.0765)	(0.128)	(0.0962)	(0.0765)	(0.125)	(0.0968)
Ln(Loan Amount)	-0.638	3.244	-1.971	-0.677	1.703	-1.958
	(1.710)	(3.718)	(1.954)	(1.707)	(3.631)	(1.953)
ROA (Borrower)	-1.460**	-1.701	-1.758**	-1.486**	-1.973	-1.729**
	(0.670)	(1.412)	(0.766)	(0.669)	(1.409)	(0.767)
Debt-to-asset (Borrower)	0.953***	0.839***	0.968***	0.958***	0.944***	0.961***
	(0.137)	(0.321)	(0.146)	(0.137)	(0.323)	(0.146)
Ln(Assets) (Borrower)	-4.007***	-11.23***	-1.477	-4.009***	-13.09***	-1.499
	(1.435)	(3.347)	(1.588)	(1.435)	(3.337)	(1.589)
Avg.ROA (Lender)	6.809	-21.28	16.03*	6.671	-23.98	16.26*
	(8.516)	(21.24)	(9.409)	(8.515)	(20.97)	(9.417)
Avg. ln(Assets) (Lender)	-8.468***	-5.235	-9.714***	-8.452***	-5.458	-9.734***
	(2.235)	(5.52)	(2.551)	(2.235)	(5.463)	(2.548)
Avg. Capital Ratio (Lender)	5.965***	5.861	5.561***	5.999***	6.793*	5.541***
	(1.556)	(3.827)	(1.703)	(1.557)	(3.786)	(1.705)
Concentration	-3.093***	-3.516***	-2.614***	-3.097***	-3.468***	-2.604***
	(0.353)	(0.970)	(0.381)	(0.353)	(0.966)	(0.382)
Covenant	-8.098**	-15.32	-3.621	-8.054**	-15.69*	-3.683
	(4.018)	(9.527)	(4.418)	(4.024)	(9.422)	(4.417)
State-owned dummy	-11.89*	-24.24*	-11.22	-11.65*	-21.49	-11.68
	(7.043)	(14.21)	(9.192)	(7.034)	(14.19)	(9.190)
Observations	2,842	628	2,213	2,842	628	2,213
R-squared	0.549	0.570	0.578	0.549	0.579	0.579
Base rate dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower country fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country of synd. fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Currency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Collateral dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tranche type dummy	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors.

Table A3: Estimation results for equation (3) with the loan-lead arranger level observations (Scope 1 and 2 emissions)

	(1)	(2)	(3)	(4)	(5)	(6)
Green bank proxy	UNEPFI			UNEPFI + Trucost dislcosure		
VARIABLES (Margin)	All industry	High CO_2e industry	All other industries	All industry	High CO_2e industry	All other industries
High CO_2 (β_1)	-1.565	2.247	3.561	-1.584	2.546	3.512
	(2.080)	(3.899)	(2.449)	(2.080)	(3.899)	(2.451)
Green bank (β_2)	1.020	-0.356	2.048	1.835	4.428	0.813
	(2.508)	(4.138)	(2.741)	(2.377)	(4.025)	(2.629)
High CO_2 * Dum_Paris (β_3)	-0.283	28.71***	-8.563***	-0.0699	29.21***	-8.552***
	(2.520)	(5.631)	(2.778)	(2.520)	(5.593)	(2.779)
High CO_2* Green bank (β_4)	-5.365**	-6.586*	-2.620	-5.430**	-7.222*	-2.602
	(2.123)	(3.949)	(2.417)	(2.136)	(3.971)	(2.436)
Green bank * Dum_Paris (β_5)	-2.191	-2.959	-1.315	-1.848	-1.793	-0.900
	(1.956)	(3.778)	(2.185)	(1.960)	(3.713)	(2.202)
High CO_2 * Green bank *	3.133	13.78**	-3.557	2.693	12.97**	-3.663
Dum_Paris (β_6)	(2.790)	(5.358)	(3.201)	(2.786)	(5.325)	(3.197)
Loan tenor	0.559***	0.659***	0.470***	0.558***	0.658***	0.470***
	(0.0294)	(0.0560)	(0.0313)	(0.0294)	(0.0559)	(0.0313)
Ln(Loan Amount)	-3.184***	2.431***	-5.217***	-3.176***	2.464***	-5.217***
	(0.575)	(0.920)	(0.676)	(0.575)	(0.919)	(0.676)
ROA (Borrower)	-2.476***	-0.893	-3.042***	-2.479***	-0.879	-3.043***
	(0.319)	(0.612)	(0.371)	(0.318)	(0.613)	(0.371)
Debt-to-asset (Borrower)	0.129*	0.739***	-0.0403	0.129*	0.740***	-0.0402
	(0.0772)	(0.162)	(0.0874)	(0.0772)	(0.162)	(0.0873)
Ln(Assets) (Borrower)	-11.86***	-13.81***	-13.23***	-11.86***	-14.01***	-13.23***
	(1.946)	(4.456)	(2.023)	(1.946)	(4.457)	(2.025)
ROA (Lender)	10.61***	9.048**	8.647***	10.61***	8.872*	8.668***
	(2.103)	(4.531)	(2.342)	(2.111)	(4.535)	(2.359)
ln(Assets) (Lender)	-3.189	-6.928	-1.855	-3.050	-6.167	-1.774
	(2.670)	(5.404)	(2.989)	(2.668)	(5.423)	(2.998)
Capital Ratio (Lender)	-2.052***	-2.517***	-1.539***	-2.065***	-2.517***	-1.567***
	(0.341)	(0.717)	(0.384)	(0.342)	(0.715)	(0.384)
Concentration	-0.253**	0.462	-0.377***	-0.254**	0.472	-0.378***
	(0.129)	(0.291)	(0.142)	(0.129)	(0.292)	(0.142)
Covenant	-15.86***	-26.07***	-13.99***	-15.86***	-26.19***	-14.01***
	(1.436)	(2.917)	(1.636)	(1.436)	(2.921)	(1.635)
Observation	16,161	3,828	12,313	16,161	3,828	12,313
R-Squared	0.865	0.875	0.876	0.865	0.876	0.876
Base rate dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Country of syndication fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Currency fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Collateral dummy	Yes	Yes	Yes	Yes	Yes	Yes
Tranche type dummy	Yes	Yes	Yes	Yes	Yes	Yes
Lender fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Borrower fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors.

Table A4: Estimation results for equation (1) and (2) with continuous GHG emission intensity deviation as interaction term (emissions-intensive industries only).

	(1)	(2)
Dependent variable (Margin)	High CO_2e industries	High CO_2e industries
Firm's CO_2e emission deviation from industry benchmark (β_1)	-0.198	-2.850
	(1.628)	(1.885)
Firm's CO_2e emission deviation from industry benchmark * Post_Paris (β_2)		6.431**
		(2.530)
Joint test: $H_0: \beta_1 + \beta_2 = 0$		3.582**
p-value		*0.0433*
Loan tenor	0.508***	0.488***
	(0.128)	(0.128)
Ln(Loan Amount)	3.221	2.946
	(3.740)	(3.715)
ROA (Borrower)	-1.564	-1.344
	(1.435)	(1.457)
Debt-to-asset (Borrower)	0.866***	0.939***
	(0.322)	(0.328)
Ln(Assets) (Borrower)	-12.37***	-12.69***
	(3.314)	(3.291)
Avg.ROA (Lender)	-21.78	-21.78
	(21.35)	(21.25)
Avg. ln(Assets) (Lender)	-5.526	-6.056
	(5.508)	(5.464)
Avg. Capital Ratio (Lender)	5.667	5.434
	(3.849)	(3.845)
Concentration	-3.481***	-3.445***
	(0.966)	(0.966)
Covenant	-16.52*	-18.30*
	(9.547)	(9.582)
State-owned dummy	-22.19	-19.91
	(13.99)	(14.17)
Observations	628	628
R-squared	0.568	0.572
Base rate dummy	Yes	Yes
Year fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Borrower country fixed effect	Yes	Yes
Country of syndication fixed effect	Yes	Yes
Currency fixed effect	Yes	Yes
Collateral dummy	Yes	Yes
Tranche type dummy	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the (robust) standard errors.

Table A5: Estimation results for equation (1) and (2) for interested variables only using clustered by borrower standard error

	(2)	(5)
Dependent variable (Margin)	High CO_2e industries	High CO_2e industries
High CO_2 (β_1)	-3.133	-21.97*
	(9.287)	(11.80)
High CO_2 * Dum_Paris (β_2)		44.59***
		(15.37)
Joint test $H_0: \beta_1 + \beta_2 = 0$		22.61*
p-value		*0.0677*
Observations	628	628
R-squared	0.570	0.579
Base rate dummy	Yes	Yes
Year fixed effect	Yes	Yes
Industry fixed effect	Yes	Yes
Borrower country fixed effect	Yes	Yes
Country of synd. fixed effect	Yes	Yes
Currency fixed effect	Yes	Yes
Collateral dummy	Yes	Yes
Tranche type dummy	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the clustered-(by-borrower) standard errors.

Table A6: Estimation results for equation (3) for emissions-intensive industries only using clustered-by-borrower and clustered-by-lead arranger standard errors

	(2)	(5)	(2)	(5)
Clustered standard errors	By-borrower		By-Lead arranger	
Green bank proxy	UNEPFI	UNEPFI + disclosure action	UNEPFI	UNEPFI + disclosure action
VARIABLES (Margin)	High CO_2e industry	High CO_2e industry	High CO_2e industry	High CO_2e industry
High CO_2 (β_1)	13.50*	13.77*	13.50***	13.77***
	(8.046)	(8.007)	(2.855)	(2.965)
Green bank (β_2)	-1.530	3.123	-1.530	3.123
	(4.294)	(4.532)	(3.303)	(4.078)
High CO_2 * Dum_Paris (β_3)	19.73	20.27	19.73***	20.27***
	(13.54)	(13.47)	(6.396)	(6.517)
High CO_2 * Green bank (β_4)	-2.547	-3.059	-2.547	-3.059
	(4.307)	(4.442)	(3.066)	(3.071)
Green bank * Dum_Paris (β_5)	-1.593	-0.518	-1.593	-0.518
	(7.539)	(7.621)	(4.465)	(4.326)
High CO_2 *Green bank *Dum_Paris	10.55**	9.606	10.55**	9.606*
(β_6)	(7.799)	(7.794)	(5.147)	(4.789)
Joint test: $H_0: \beta_2 + \beta_4 + \beta_5 + \beta_6 = 0$	4.875	9.152*	4.875	9.152**
p-value	*0.317*	*0.0615*	*0.285*	*0.043*
Observation	3,828	3,828	3,828	3,828
Adj. R-Squared	0.864	0.864	0.864	0.864
Base rate dummy	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Country of syndication fixed effect	Yes	Yes	Yes	Yes
Currency fixed effect	Yes	Yes	Yes	Yes
Collateral dummy	Yes	Yes	Yes	Yes
Tranche type dummy	Yes	Yes	Yes	Yes
Lender fixed effect	Yes	Yes	Yes	Yes
Borrower fixed effect	Yes	Yes	Yes	Yes

Note: ***, **, and * indicate significance at the 1%, 5% and 10% levels respectively. Figures in parentheses are the clustered-(by-borrower) standard errors for the first two columns and the clustered-(by-lead arranger) standard errors for the last two columns.