When Green Meets Green[§]

Hans Degryse[⋆,†] Roman Goncharenko[⋆] Carola Theunisz[⋆]

Tamas Vadasz[⋆]

September 11, 2021

ABSTRACT

We investigate whether and how the environmental consciousness (greenness for short) of firms and banks is reflected in the pricing of bank credit. Using a large international sample of syndicated loans over the period 2011-2019, we find that firms are indeed rewarded for being green in the form of cheaper loans—however, only when borrowing from a green consortium of lenders, and only after the ratification of the Paris Agreement in 2015. Thus, we find that environmental attitudes matter "*when green meets green*." We further construct a simple stylized theoretical model to show that the green-meets-green pattern emerges in equilibrium as the result of third-degree price discrimination with regard to firms' greenness.

Keywords: Paris Agreement, Green Firms, Green Banks, Bank Lending

JEL Classification: A13, G21, Q51, Q58

[§]For comments, we would like to thank Andrea Fabiani (discussant), Florian Hoffmann, Igor Lončarski (discussant), Mike Mariathasan, Steven Ongena, Tarik Roukny, Misa Tanaka (discussant) as well as the participants at the 2020 National Bank of Belgium (NBB) Colloquium about "Climate Change: Economic Impact and Challenges for Central Banks and the Financial System", the 2020 Annual Financial Market Liquidity (AFML) conference, the Belgian Environmental Economics Day 2021, the 28$^{\text{th}}$ Finance Forum 2021 (SANFI Award for the Best Paper on Banking), and KU Leuven seminar participants. We gratefully acknowledge the financial support from the Flemish Science Foundation and the National Bank of Belgium.

[⋆]All authors are affiliated with KU Leuven, Belgium; emails: hans.degryse@kuleuven.be, roman.goncharenko@kuleuven.be, carola.theunisz@kuleuven.be, tamas.vadasz@kuleuven.be

[†]CEPR

1 Introduction

Climate change might be threatening the future of the globe. Extreme weather conditions have attracted policymakers' interest and urged the need to take action. The UN Climate Change Paris conference in December 2015 put forward a limit of 1.5°C increase in average global temperatures relative to those prevailing before the Industrial Revolution, which can only be reached by drastically cutting the exhaust of carbon. This transition to a carbon-neutral economy requires environmental consciousness of firms and banks raising the question of how bank financing can contribute to reaching the global climate objectives.

In this paper, we investigate whether and how environmental consciousness (greenness for short) of firms and banks is reflected in the pricing of bank credit. Using a large international sample of syndicated loans, we find that firms are indeed rewarded for being green in the form of cheaper loans—however, only when borrowing from a green consortium of lenders and only after the ratification of the Paris Agreement. Hence, we find that environmental attitudes matter "*when green meets green*." We further develop a stylized theoretical model to provide a rational for why a robust green-meets-green pattern emerges after the Paris Agreement: we argue that heightened perception of the carbon transition risk—a consequence of the resounding commitment of world leaders to a carbon-neutral future—may have incentivized a subset of banks (i.e., green banks) to engage in third-degree price discrimination with regard to firms' greenness, resulting in an equilibrium in line with our estimated green-meets-green pricing patterns.

Our empirical analysis requires proxies for banks' and firms' greenness. We classify a firm as green if it voluntarily reports to the Carbon Disclosure Project (CDP), which is an investor-oriented non-profit initiative designed to facilitate and standardize disclosure of a firm's environmental impact. We expect firms that report to CDP to have better in-house capabilities in measuring and managing their exposure to the green transition of the economy, which can be viewed as evidence of their environmental consciousness. Our proxy for banks' green attitude is their membership in the United Nations' Environment Program Finance Initiative (UNEP FI), which aims to "*mobilize private sector finance for sustainable development*".[1] Since its creation in 1991 more than 160 banks have joined the Initiative. Fatica et al. (2019) find that signatory banks of UNEP FI are able to issue green bonds with a premium, because they are more clearly able to signal their environmental attitudes in lending. This provides external support to the use of UNEP FI membership as our proxy for green bank

Next, we employ these proxies to analyze the price information of syndicated loans using the LPC DealScan database. Our results suggest the presence of a statistically and economically significant green-meets-green (GMG) effect: we estimate that green firms enjoy an *additional* discount of 35-38 bps when borrowing from green banks rather than from non-green (brown) ones. These results are robust to the inclusion of several sets of fixed effects that help to alleviate concerns about omitted variables.

We further examine whether the Paris Agreement, which was reached on December 12, 2015, had affected the relationship between the banks' and firms' environmental attitude and loan credit spreads. By splitting our sample into before and after the Paris Agreement, we find that while the GMG effect is insignificant prior to the Paris Agreement, it is statistically and economically significant after the Paris Agreement. In particular, our estimation based on the sub-sample after the Paris Agreement shows that green banks offer a discount to green firms relative to brown firms of about 60-69 bps. This evidence indicates that the GMG effect is intimately linked to the changes brought forth by the Paris Agreement. We further confirm this employing a difference-in-difference-in-differences regression model.

Why would the Paris Agreement have such a big indirect impact on lending terms,

[1] https://www.unepfi.org

and why is this restricted to green banks only? Our proposed explanation interprets the Paris Agreement as a shift in the perception of climate transition risks, both by firms and by banks. Much of the difficulties in managing climate change-related risks are attributed to the highly uncertain real impacts of climate change, and to the endogenous nature of future policy shocks that affect the transition path to a low-carbon economy (e.g., Batten et al., 2016; Campiglio et al., 2018). For example, shifts in public views could lead to political pressure to strengthen environmental regulation, which could harm firms that do not anticipate the possibility of such shocks.[2] As the expectation of a regulatory shift, and so the probability of a negative shock, increases, so does the equilibrium environmental attitude of firms and banks. In such an uncertain environment—prone to sudden equilibrium shifts—there is a particularly strong emphasis on public events that anchor expectations and coordinate the behavior of economic agents. We hypothesize that the Paris Agreement, as the world's first comprehensive climate agreement, raised public awareness of climate-related risks and increased the soft commitment of policy-makers to a stricter enforcement of climate policy. This shifts the perception of climate transition risk by investors, therefore materially influencing equilibrium prices.

In order to illustrate the mechanism at play, we present a simple stylized theoretical model of credit market competition. A green bank has access to a superior but costly screening technology.[3] When put in use, screening borrowers regarding their true exposure to climate transition risk creates an informational advantage for the green bank. The green bank then uses this information and implements a climate risk-based price discrimination. However, the bank's screening technology heavily relies on information produced by the firms prior to establishing the lending relationship. This information

[2]For example, in May 2021 Royal Dutch Shell, a major player on the oil and gas market, was ordered by a Dutch court to cut its carbon emission faster, overruling the firm's own transition plans. This signals to the market an increased likelihood of the judiciary system's involvement in climate issues.

[3]This could stem, for example, from prior investment in expertise to understand the economic impact of climate change. This may be because of the management's commitment to, and awareness of climate considerations.

is generated in parallel with firms' attempts to change their business model in order to decrease their exposure to the climate transition risk. We show that the Paris Agreement, which is modelled as an exogenous shift in the probability of a climate transition shock (e.g., stricter climate regulation which negatively affects firms' business model), enables price discrimination on the credit market by inducing firms to attempt to address climate risk. The latter increases the quality of information and, in turn, the informativeness of the green bank's screening technology. From the green bank's perspective, the improvement of screening, heightened risk perception, and the increased heterogeneity in firms' exposure to climate change, all boost the economic rents from superior information. Resultingly, the green bank third-degree price discriminates between brown and green firms, and green-meets-green pricing arises.

Our findings, both empirically and theoretically, confirm that green attitudes are indeed reflected in pricing conditions in a significant way, and this was largely emanated following the adoption of the Paris Agreement. We consider this as a positive externality of the Paris Agreement; while improving access to debt was not an explicit aim of the Accord, the increased attention on environmental factors resulted in a measurable impact on the loan conditions for debt financing, and improved the allocative efficiency of financial markets.

Our paper contributes primarily to the literature on the relation between the environmental attitude of firms and their cost of funding. Investors factor in environmental risk either because of their specific preferences (Riedl and Smeets, 2017; Hartzmark and Sussman, 2019) or because of physical or transition costs that this risk entails (Krueger et al., 2020). There is empirical evidence that environmental risks are priced in equity markets (Ilhan et al., 2020; Bolton and Kacperczyk, 2021), bond markets (Fatica et al., 2019; Painter, 2020), and real estate markets (Bernstein et al., 2019; Baldauf et al., 2020). With regard to bank lending, Chava (2014) documents that firms with environmental risks pay a higher loan spread and receive loans granted by syndicates with fewer banks. Kleimeier and Viehs (2018) provide empirical evidence of a significant negative relation between voluntary disclosure of CO_2 emissions and loan spreads for informationally opaque borrowers. Ehlers et al. (2021) find that environmental risks related to firms' direct emissions are priced but do not find differential pricing of these risks by green banks. Javadi and Al Masum (2021) provide empirical evidence that firms in locations with higher exposure to climate change pay significantly higher spreads on their bank loans. Nguyen et al. (2021) show that banks charge higher interest rates for mortgages on properties exposed to a greater risk of sea-level rise. Our paper contributes to this literature by showing that environmental attitudes of firms and banks indeed matter for credit pricing but only when both contractual parties are green.

A closely related strand of the literature examines the effect of such a large-scale environmental policy as the Paris Agreement on bank lending. Examining the effect of the Paris Agreement on the pricing of "brown assets", Delis et al. (2021) find evidence of a significantly higher cost of bank credit for fossil fuel firms only after 2015. Reghezza et al. (2021) show that following the ratification of the Paris Agreement, banks reallocated credit away from polluting firms. They further show that in the aftermath of President Trump's 2017 announcement on the US withdrawal from the Paris Agreement European banks decreased lending to polluting firms in the United States. Our paper contributes to this literature by showing that our GMG effect manifests itself in the data only after the Paris agreement.

Another strand of the literature examines the role of bank financing in the green transition. De Haas and Popov (2019) examine the relationship between countries' financial systems and their CO2 emissions. They document that economies that rely relatively more on equity than debt (banking) financing pollute less suggesting that stock markets better reallocate investment to less polluting industries. Degryse et al. (2020) argue that banking can cause barriers to the green economy as the entry of innovative and green firms in polluting industries risks devaluating banks' legacy positions with incumbent clients. Our paper provides evidence that environmental consciousness of banks could play a positive role in the green transition by granting cheaper loans to firms exhibiting a similar attitude.

The green-meets-green discount in our paper is related to some recent studies emphasizing that similarity in "granters' and receivers' attitudes" are important for social and environmental responsibility efforts to have a material impact. For example, Houston and Shan (2020) document that similarity in environmental attitudes matters for lending decisions, as banks are more likely to lend to borrowers with similar (high) ESG-scores. Kim et al. (2014) find that lending conditions improve when there is a similarity in the ethical domain across borrower and lender. In Hauptmann (2017), a strong sustainability score leads to lower credit spreads but only when borrowing from a bank with a strong sustainability score. These findings are supportive of the idea that in-house expertise on the lender's side is a prerequisite to interpret the soft information in borrowers' disclosures about their environmental activity.

The remainder of our paper is organized as follows. Section 2 summarizes data and summary statistics. Section 3 presents the empirical analysis and results. Section 4 offers extensive robustness checks. Section 5 presents a simple stylized theoretical model of credit market competition. Finally, Section 6 concludes.

2 Data Description

2.1 Data Sources

To investigate our research question, we construct a comprehensive dataset by compiling data from the Carbon Disclosure Project (CDP) survey, the United Nations Environment

Programme Finance Initiative (UNEP FI), Thomson Reuters' LPC DealScan, Compustat, Orbis Global and Bank Focus.

We use the Carbon Disclosure Project (CDP) survey to identify environmentally conscious firms that attempt to exert mitigating efforts, i.e., green firms.[4] In particular, a firm is identified as being green by its voluntary and costly participation in the survey. Since 2008, CDP annually collects self-reported information about firms' carbon emissions and other environmental information, such as governance and investments related to climate-related issues within the organization. Our CDP sample at hand covers the period between 2010-2018 during which the CDP collected environmental data on about 6000 firms worldwide. Respondents stand to benefit from disclosure for at least three reasons.[5] First, firms may decide to report their carbon footprint in order to enhance their Environmental, Social, and Governance (ESG) performance. Second, respondents may increase the likelihood of attracting investor funds since some investors, the so-called signatories, pay for CDP's corporate disclosure information to make sustainable investment decisions. Third, disclosing environmental performance in a structured way allows firms to identify environmental risks, keep track of opportunities and to prepare for the likely changes in regulation. Hence, we classify firms that respond to this survey as green since they measure, manage, and disclose their climate impact. Detailed information about the construction of the proxy is provided in Table A1 in the Appendix.

We identify a bank as being green if it is a member of the United Nations Environment Programme Finance Initiative (UNEP FI) (e.g., Delis et al., 2021). Data on the UNEP FI member banks and signature dates were hand-collected from the official website.[6] UNEP FI is a partnership between the United Nations Environment Programme and the global financial sector which was created to catalyze private sector finance towards

[4] Other studies that employ a similar approach include Kleimeier and Viehs (2018) and Ben-David et al. (2020)

[5] https://www.cdp.net/en/companies-discloser (accessed on November 15, 2019).

[6] http://www.unepfi.org/members/banking/ (accessed on September 6, 2019).

sustainable development. From 1991 onwards, about 160 leading banks have joined this initiative. By stating their adherence, banks align their business strategy to the United Nations' Principles of Responsible Banking and should adopt a framework for sustainable banking.[7] Hence, this membership proxies for a bank's attitude towards climate change and provides lenders with a superior screening technology.

Next, we collect loan-level data from Thomson Reuters' LPC DealScan database. DealScan contains data on bilateral and syndicated loans to firms worldwide, including loan amounts, interest rates, and non-price loan characteristics such as maturity and covenants, starting from 1988 to date. The detailed borrower information and broad country coverage provide an ideal setting to investigate loan terms in a cross-country setting. Syndicated lending is characterized by multiple lender types: lead arranger(s) and participant lenders. While the lead arranger establishes and maintains the relationship with the borrower, the participant lenders rely upon the information memorandum provided by the lead arranger and maintain an arm's length relationship with the borrower (Sufi, 2007). As such, the loan pricing decisions in syndicated loans are taken by the lead arranger. However, it is possible that a given loan facility consists of multiple lead arrangers. Therefore, it is important to note that in defining the green lender, we take into account the "greenness" of all lead arrangers in the loan syndicate. More specifically, we consider the fraction of UNEP FI members among the lead arrangers in the loan syndicate.[8] More information about the definition of lead arranger and the construction of the green lender proxy is provided in Table A1 in the Appendix.

[7] https://www.unepfi.org/membership/obligations/

[8] Rather than defining our green lender proxy at the individual lead arranger-level, we take into account the "greenness" of all lead arrangers in a given loan syndicate in order to ensure that our estimation exploits loan rate variation across loan facilities. This is important as there is no within-facility variation in loan spreads. Consider, for instance, a loan granted by a brown 'B' and a green 'G' lead arranger with spread x; hence, our green lender proxy, BGreen, equals 50%. Our estimation thus exploits variation in loan rates across facilities with different levels of BGreen. Contrarily, if we had considered the greenness of the individual lead arranger, then estimation would have been based on within-facility loan spread differences between lead banks B and G, which would naturally result in a misleading zero difference (i.e., the spread is x).

To examine whether green firms borrow at different terms than other firms and, in particular, when borrowing from green banks, we merge both the CDP database and the UNEP FI database with DealScan. For the former merge, we are able to identify 5,626 green firms active in DealScan using the ISINs reported in the CDP database. For the latter merge, we conduct a fuzzy name-matching algorithm in order to identify green lenders in DealScan. Specifically, we identify 120 green lenders active during the period 2011-2019. Since our focus is on loan pricing, we restrict our DealScan sample to consider only lead arrangers. Our sample is further restricted to loans with available data on loan spreads, the so-called all-in-spread-drawn (AISD). This variable constitutes our main outcome variable and measures the spread in basis points charged on a loan facility over the London Interbank Offering Rate (LIBOR) plus additional fees for each dollar drawn down. The remaining DealScan sample consists of approximately 71,000 loan facilities granted over the period 2011-2019 to 16,660 non-financial companies.

Finally, we obtain data on borrower and lender fundamentals from Compustat, Orbis Global and Orbis Bank Focus. To that end, we match the firms and lead arrangers in our DealScan sample to those in these various databases using the software package introduced by Cohen et al. (2018). Detailed definitions of all variables are provided in Table A1 in the Appendix. After obtaining borrower and lender controls, we are left with 13,620 loan facilities out of which 12,062 to non-financial firms. In our most restrictive specifications, including all control variables, approximately 1,650 facilities are granted to 366 green firms, 3,307 facilities are granted by green syndicates, resulting in 497 green-meets-green facilities. Figure 3 depicts our sample over time.

Figure 4 illustrates the mean spread over time (left) and the overall sample distribution (right) of our main dependent variable (all-in-spread-drawn) for the final matched sample. Both indicate a large unconditional green-effect, which we investigate further below.

2.2 Summary Statistics

The summary statistics for our set of variables are provided in Table 1. This table summarizes the variables defined at the facility-level, in which the unit of observation is the loan facility. Our left-hand side variable, the all-in-spread-drawn (AISD), which is right-winsorized by year at the 1% level to deal with spurious outliers, falls within the range of 1 to 875 basis points with an average value of 292 bps. This is in line with other studies such as Kleimeier and Viehs (2018) and Delis et al. (2021) that report average spreads of, respectively, 256.36 and 280.66 bps. $FGreen$ refers to our green borrower proxy that captures whether the firm disclosed information to CDP in the year before loan origination. The table reports that 5,224 loans are given to green firms and the mean AISD is 180 bps. Concerning our green lender proxy, $BGreen$, we construct a continuous variable which captures the fraction of green banks among the pool of lead arrangers in a specific loan syndicate. The table shows that green syndicates on average consists of 59% green lead banks. This shows that green lenders often tend to arrange loan facilities with other green lenders. If the lender consortium is 100% green, the average AISD is approximately 382 bps.

Regarding the loan characteristics, we observe that all loan facilities have at least 1 and a maximum of 54 lead arrangers, with an average of 2.60 lead banks. In fact, about 75% of the facilities have one single lead arranger. The table furthermore shows that 34% of the loans is classified as a relation loan, which means that the borrower has had a past relationship with one of the lead banks. The borrower and lender characteristics are annual, one-year lagged and winsorized. With regard to the borrower controls, firm size is measured by the natural logarithm of total assets with a mean of 7.05, which is equivalent to 1,153M$. With regard to lender controls, for our facility-level regressions the average is taken across the pool of lead arrangers in case the facility comprises multiple lead arrangers. The average size of the lead arrangers is 13.44, which is equivalent to 6,869B$.

3 Empirical Analysis: Green-Meets-Green Effect

To investigate the presence of the GMG effect—that is, whether green banks provide discounts when lending to green firms—we first consider our complete sample from 2011 to 2019. The GMG effect postulates that being green rewards a firm in terms of a lower rate when it borrows from a green bank. Thus, we estimate the following baseline regression:

$$\begin{aligned} AISD_{i,b,t} =& \alpha + FE_{i,b,t} + \beta_1 FGreen_{i,t-1} + \beta_2 BGreen_{i,b,t-1} \\ &+ \beta_3 FGreen_{i,t-1} \times BGreen_{i,b,t-1} + \gamma' X_{i,b,t-1} + \epsilon_{i,b,t} \end{aligned} \tag{1}$$

The dependent variable $AISD_{i,b,t}$ denotes the all-in-spread-drawn of loan facility i, issued by the syndicate's lead arranger(s) b in year t. $FGreen_{i,t-1}$ is the proxy for firm's greenness defined as a dummy variable equal to 1 if the loan is given to a firm that disclosed information to CDP the year before loan origination. $BGreen_{i,b,t-1}$ is the proxy for bank greenness, which measures the fraction of UNEP FI members among the lead arranger consortium.[9] The interaction term $FGreen_{i,t-1} \times BGreen_{i,b,t-1}$ captures the GMG effect—that is, a discount a green firm obtains when borrowing from a green bank. The interpretation of the coefficients is as follows: when borrowing from a green bank, being green rewards firms with an additional discount of β_3 (when negative); when borrowing from a green bank, a green firm enjoys a discount $\beta_1 + \beta_3$ relative to a brown firm; when borrowing from a green rather than a brown bank a green firm enjoys a discount of $\beta_2 + \beta_3$.

The vector $X_{i,b,t-1}$ denotes loan-, borrower-, and lender-level controls. Detailed definitions of all variables are provided in Table A1 in the Appendix. At the loan-level, we control for loan amount, loan maturity, syndicate concentration, non-bank lead ar-

[9]For brevity, the lender consortium is interchangeably referred to as "bank(s)", "lender(s)", or "syndicate".

ranger participation as well as loan type, loan purpose, secured, covenant and relationship lending dummies.[10] The borrower and lender controls are one-year lagged. At the borrower-level, we control for industry type measured by the two-digit Standard Industrial Classification (SIC), profitability, leverage, firm size and whether the firm is listed or not. At the lender-level, we control for profitability, capital ratio, and size. In the case of multiple lead arrangers, the average of the lender controls is taken across all lead arrangers of loan facility i. Depending on the specification, $FE_{i,t,b}$ may include various fixed effects such as time-, borrower country-, borrower x time-, and lender x time-fixed effects. By including year and borrower's country fixed effects we control for intertemporal differences between years and unobserved cross-sectional differences between countries which might affect the cost of debt. Replacing the year and country fixed effects by borrower $\times$ time fixed effects, for example, allows us to control for unobserved differences between borrowers by examining the loan spreads received by the same borrower in the same year obtaining a loan from both a green and a non-green syndicate.[11]

Table 2 reports the results of estimating equation (1) over the entire sample window 2011-2019. Our findings provide some weak evidence consistent with the GMG effect. The estimated coefficient on the interaction term $FGreen \times BGreen$ is negative and statistically significant in specifications in which we do not control for borrower $\times$ time fixed effects. This result provides first, albeit rather inconclusive, evidence of a novel GMG effect: when borrowing from a green bank, it rewards firms to be green with an additional discount of 35-38 bps (β_3). In contrast, a green bank charges a non-green firm, on average, a higher loan rate of about 45 bps (β_2) relative to the same firm borrowing

[10]We control for non-bank lead arranger participation as Lim et al. (2014) show that facilities originated by non-bank institutional investors have higher spreads than otherwise identical bank-only facilities.

[11]In order to be able to include lender fixed effects, we decompose our facility-level observations into lead arranger-level data in which the unit of observation is loan i and lead arranger b. To give an example, loan facilities with n lead arrangers are duplicated n number of times. Because 75% of the facilities have a single lead arranger, this is only the case for 25% of our sample. This data set allows us to control for unobserved cross-sectional differences between lenders by examining the loan spreads across green and non-green firms provided by the same bank in the same year.

from a brown bank. Thus, this analysis suggests that green lenders attach more value to disclosure and transparency of climate-related risk, and in turn have different priors regarding firms' exposure to such risk absent disclosure. Hence, green lenders ask (higher) lower loan rates from (non-)disclosing firms, as compared to non-green lenders.

So far, our results are not conclusive on whether green firms obtain cheaper credit when borrowing from green rather than brown banks. Recall, that the discount green firms obtain when borrowing from a green rather than a brown bank is captured by the sum of coefficients β_2 and β_3. While the analysis of the lead arranger-level data in Table 2 suggests that it is cheaper for a green firm to borrow from a green bank, the analysis of facility-level data indicates the opposite result. We address this issue below.

In the following, we investigate how the acceptance of the Paris Agreement shifted lenders' behaviour. In particular, we conjecture that the Paris Agreement, as the world's first comprehensive climate agreement, raised public awareness of climate-related risks and increased the soft commitment of policy-makers to a stricter enforcement of climate policy. We expect that this has shifted the perception of climate transition risks by investors, therefore materially changing the impact of climate-related disclosures. To test this hypothesis, we split our sample into a sample before and after the Paris Agreement. Specifically, we classify all loans with loan origination date preceding December 12, 2015, the agreement date of the Paris Accord, as "Before Paris"-sample, while all other loans constitute the "After Paris"-sample. We are again interested in β_3—the coefficient on the interaction term in equation (1).

Table 3 reports the result of estimating equation (1) for the two sub-samples: before and after the Paris Agreement. Across all specifications, the estimation results consistently reveal that the GMG effect ($\beta_3 < 0$) is statistically significant on loans granted *after* the Paris Climate Agreement. In contrast, the interaction term is never significant in the before-Paris sample indicating that the signaling value of climate-related disclosures changed after the event, and particularly so for green lenders. This finding supports our prior and underpins our key result that when green firms borrow from green banks they enjoy an additional discount. In fact, our analysis suggests that the magnitude of the GMG almost doubles—about 63-68 bps—when we split the sample. This suggests that our results in the overall sample were driven by the post-Paris Climate Agreement sample. Moreover, our results further show that the discount green firms obtain when borrowing from green rather than brown banks—the sum of coefficients β_2 and β_3— is about 30 bps. These results are economically significant given that the mean all-in-spread-drawn is about 290 bps.[12,13]

On balance, these findings indicate that only *after* the Paris Climate Agreement green lenders offer a discount to green firms and charge a premium from non-green firms, compared to non-green lenders' loan rates. To a certain extent, this provides evidence of the effectiveness of the Paris Accord in highlighting the importance of disclosing emissions-reducing strategies and increasing the role of climate change risk awareness in lending decisions, resulting in climate risk-based price discrimination by green lenders.

We further examine the effect of the event using an empirical model with three-way

[12]In unreported specifications we study whether the GMG-effect might differ across banks with different characteristics (capitalization, profitability, credit quality). We do not find statistically different results for banks above and below the median capitalization, profitability and credit quality. This suggests that our GMG-effect does not pick up other bank characteristics.

[13]Reghezza et al. (2021) show that after the announcement on the US withdrawal from the Paris Agreement European banks decreased lending to polluting firms in the United States. To study whether our results are picking up an impact of President's Trump announcement on 1 July 2017, we investigate whether the withdrawal affected GMG-pricing to US firms. In particular, in unreported results, we split the post-Paris sample into a pre-Trump and post-Trump period, and find that the GMG-effect is both quantitatively and qualitatively equivalent in both periods suggesting that the US withdrawal from the Paris Agreement is not materially affecting our results.

interaction of the following form:

$$\begin{aligned} AISD_{i,b,t} =& \alpha + FE_{i,b,t} + \beta_1 FGreen_{i,t-1} + \beta_2 BGreen_{i,b,t-1} + \beta_3 FGreen_{i,t-1} \times BGreen_{i,b,t-1} \\ &+ \beta_4 Paris_t + \beta_5 FGreen_{i,t-1} \times Paris_t + \beta_6 BGreen_{i,b,t-1} \times Paris_t \\ &+ \beta_7 FGreen_{i,t-1} \times BGreen_{i,b,t-1} \times Paris_t + \gamma' X_{i,b,t-1} + \epsilon_{i,b,t}, \end{aligned} \tag{2}$$

where in addition to previously defined variables, $Paris_t$ is a dummy variable which takes the value of 1 for loans originated after the Paris Agreement, i.e., after December 12, 2015, and 0 otherwise. The coefficient of particular interest is β_7, which captures the change in green firm borrowing conditions obtained from green banks following the adoption of the Paris Agreement.

Table 4 reports the result of estimating equation (2). These results are consistent with the previous ones using the sample splits. For example, examining the GMG effect, we find no statistically significant support of a spread difference before the Paris Agreement as is reflected by the insignificant coefficients on the interaction term, $FGreen \times BGreen$. However, consistent with our previous findings, the GMG effect is especially marked on loans granted by green lenders *after* the announcement of the Paris Climate Agreement as is shown by the significantly negative coefficients on the triple-interaction term ($FGreen \times BGreen \times Paris$). The economic magnitudes are similar to the ones already discussed above.[14]

4 Robustness

In this section, we confirm the validity of our results by subjecting them to various robustness checks. Firstly, a Heckman selection model is performed to deal with a potential

[14]The results obtained by employing lead arranger-level data remain robust to clustering the standard errors at the bank-level.

sample selection bias which could arise due to CDP's survey design. Secondly, using a propensity score matching technique, we document that our results are robust to accounting for covariates that potentially predict obtaining a green-meets-green loan. Thirdly, an instrumental variable estimation is conducted to take into account potential endogenous matching between firms and lenders. Next, we study whether the green-meets-green effect is also present on loans to financial companies by conducting a sample split. Finally, we provide a falsification test to strengthen confidence in the idea that loan spreads changed due to the ratification of the Paris Climate Agreement.

4.1 Heckman Selection Model

We examine the robustness of our results using a Heckman selection regression that takes into account a firm's decision to report to CDP and thus becoming "green". If this decision is nonrandom, then the estimated coefficients would be inconsistent. The Heckman selection model corrects for this potential selection bias by jointly estimating a selection model for participating to the CDP survey and a loan pricing regression model that corrects for the selection bias:

$$FGreen_{i,t} = \alpha + \beta_1 EPS_{i,t-1} + \beta_2 PeerPressure_{i,t-1} + \gamma' Y_{i,t-1} + \epsilon_{i,t}, \tag{3}$$

$$\begin{aligned} AISD_{i,b,t} =& \alpha + FE_{i,b,t} + \beta_1 FGreen_{i,t-1} + \beta_2 BGreen_{i,b,t-1} \\ & + \beta_3 FGreen_{i,t-1} \times BGreen_{i,b,t-1} + \lambda IMR_{i,t} + \gamma' X_{i,b,t-1} + \epsilon_{i,b,t} \end{aligned} \tag{4}$$

Equation (3) describes the selection model where next to previously defined firm characteristics, denoted by $Y_{i,t-1}$, two additional instrumental variables are included, namely the Environmental Policy Stringency (EPS) of a borrower's country of incorporation and a measure for a borrower's peer pressure from the same industry. Firstly, EPS is obtained from OECD statistics and measures a country's policy stringency with respect to climate change.[15] We posit that tightening environmental policy instruments, and thus increasing a country's EPS, would induce firms to report to CDP in order to signal their mitigating efforts. Hence, EPS proxies for exogenous pressure on firms to report to the CDP survey. Additionally, exogenous pressure to report might also be exerted by a firm's peers. Therefore, we secondly construct an instrumental variable, $Peer\ Pressure$, which represents the percentage of disclosing firms relative to the number of total firms in the borrower's industry group in the year of CDP participation. We expect that firms are more likely to report to CDP if they reside in countries and industries with higher exogenous pressure in terms of environmental policy stringency and industry peer pressure. Lastly, equation (4) is equivalent to our baseline regression in equation (1), except for the inclusion of the Inverse Mills ratio ($IMR_{i,t}$) which captures the potential selection bias and is obtained from the selection model.

The Heckman model is run on the full period and on sub-samples before and after the Paris Agreement, and the results are reported in Table 5. The negative $\hat{\lambda}$, which is sporadically significant at the 10% level, indicates that unobservables that decrease credit spreads tend to occur with unobservables that raise CDP membership. However, in most instances $\hat{\lambda}$ is insignificant. As significance would imply that a Heckman approach is essential to take account for the selection decision, we conclude that our main analyses do not suffer from sample selection bias caused by participation in the CDP survey. As such, comparing Panel A of Table 5 with the regression output displayed in Table 3, one can see that our main finding remains consistent, namely that the green-meets-green effect is largely prevalent on loans granted post-Paris resulting in an average spread difference

[15]Due to the limited time period coverage of this variable in the OECD statistics, namely up until 2015, we chose to extrapolate 2015 values to later years in order to avoid that our analysis would be confined to the same period.

between green firms and brown firms of about 69 bps relative to the same difference at brown banks.[16]

Panel B reports the result of the selection model and reveals that increased exogenous pressure exerted by both the firm's country and industry is associated with a higher likelihood to participate in the CDP survey, and larger so *after* the Paris Accord which is intuitively reasonable. With respect to firm characteristics, both larger-sized and publicly listed companies are associated with a higher participation rate, which is consistent with the fact that CDP targets primarily but not exclusively the largest companies as measured by market capitalization.

4.2 Propensity Score Matching (PSM)

We further examine the robustness of our results using a propensity score matching estimator. One might be worried that the decision to obtain a "green loan" may be endogenous. This because the firm's decision to disclose its environmental performance to CDP may not be random, nor might be the decision on whether or not to form a relationship with a green syndicate. In fact, these decisions are likely related to bank- and firm characteristics such as company size, ownership, industry, location, and previous banking relationships.

In order to study the difference in loan rates across firms and banks that are identical in these respects, we conduct a robustness check by employing the propensity score matching technique.[17] Using a logit model, we first compute the propensity score of obtaining a

[16] To test whether our main results suffer from selection on unobservables, we additionally perform the coefficient stability test proposed by Oster (2019). The test assesses omitted variable bias by using information from coefficient movements and the change in R^2 when more regressors are added to the model. This test is performed on the post-Paris specifications reported in Table 3 by computing δ, the coefficient of proportionality, when moving from uncontrolled to controlled regression. Across the different specifications, the estimates of δ are negative, implying that adding variables will continue to increase the magnitude of the estimates and that no amount of unobserved heterogeneity would negate the observed coefficients. This reveals that our point estimates might be conservative.

[17] The employed software is from: Jann, B. (2017). kmatch: Stata module for multivariate-distance and propensity-score matching. Available from https://ideas.repec.org/c/boc/bocode/s458346.html.

green-meets-green loan (= treatment) based on ex-ante lender- (i.e., log of total assets, return on assets- and capital ratio) and firm characteristics (i.e., log of total assets, return on assets ratio, leverage ratio, a public/private indicator, industry, location and a previous relationship indicator). We employ the most restrictive definition of "green loan" and consider those issued by 100% green lender consortia to green firms (GMG, #408) as treated. We then select the control units from the sample of all non green-meets-green loans in our DealScan sample (#57,433). To study particularly *green* lenders' pricing behavior in more detail, we secondly draw control units from a sub-sample that is limited to brown borrowers obtaining loans from 100% green lender consortia (BMG, #5,467). This approach allows us to compute the mean AISD difference between green loans to green firms and green loans to non-green firms that are matched using the propensity score.

We subsequently implement two different matching algorithms. First, we employ a nearest-neighbor matching with replacement to select both the 10 and the 50 nearest controls for each treated loan. Second, to study the robustness of the nearest-neighbor matching, we also apply a kernel epanechnikov matching algorithm with replacement. Lastly, to examine the impact of the Paris Agreement, the mean AISD difference is computed separately for those loans granted before the Paris Climate Accord, and those after.

The results for the different counterfactual definitions are reported, respectively, in Panel A and B of Table 6, and are broadly similar to previous findings. Across all matching specifications, we find that spreads on green-meets-green loans are significantly lower in the post-Paris Accord period while the difference is either positive or insignificant before the acceptance of the Paris Accord. Zooming in on green lenders' pricing behavior in particular, depicted in Panel B, the estimated differences in loan spreads show that the green-meets-green effect only arose after the Paris Accord raised the probability of stricter climate regulation, resulting in a spread difference between green firms and brown firms ranging from 50 to 69 bps.

4.3 IV estimation

Another potential concern may be that our identification of green-meets-green after the Paris Climate Accord could be biased due to endogenous matching between the firm and a green bank. This source of endogeneity could arise when green firms strategically choose to match with a green bank in order to obtain an after-Paris discount. Similarly, non-green firms might potentially avoid to borrow from a green bank as to prevent penalty pricing. That is, instead of estimating a change in spreads caused by choosing to borrow from a green lender, it could be the other way around in that our estimation suffers from firms that anticipate a differential spread and therefore choose (not) to match with a green lender.

Notably, this source of reversed causation can only occur in the post-Paris period. If the borrowing firm already had a past relationship with a green lender in the pre-Paris period, however, this choice would not be made endogenously. We therefore deal with this endogeneity concern through an instrumental variable approach that uses pre-Paris green lender choice as an instrument for post-Paris green lender choice. The logic behind this instrumental variable is a simple one: although post-Paris green lender choices might be endogenous to loan rates, it is unlikely that pre-Paris green lender choices are subject to the same problem. We thus use the pre-Paris green lender choice ($L.BGreen$) to clean out the endogenous firm-bank matching in post-Paris green lender choice ($BGreen$) and link the exogenous firm-bank matching to actual variation in loan spreads, causing the bias to disappear.

Specifically, the instrumental variable $L.BGreen$ equals 1 if the firm borrowed from at least one green lead arranger in the pre-Paris Agreement period and zero otherwise.

Columns 3 and 4 of Table 7 report the results of estimating equation (1) where the endogenous regressor $BGreen$ and the interaction term $FGreen \times BGreen$ are instrumented by $L.BGreen$ and $FGreen \times L.BGreen$, respectively.[18] After including several different types of fixed effects, we find that the green-meets-green effect survives this analysis and amounts to approximately 80 bps.[19]

4.4 Financial Borrowers

In Table 8, we report the results of estimating the model in equation (1) on subsamples before and after the Paris Accord using a subset of financial borrowers. The table demonstrates that the interplay between CDP-disclosing banks and UNEP FI banks yields no green-meets-green discount, either before or after the Paris Accord. These findings suggest that the green-meets-green effect is only prevalent on loans between non-financial environmentally conscious borrowers and like-minded lenders.

4.5 Paris Falsification Test

Lastly, we conduct a falsification test to evaluate the soundness of our estimation on the impact of the Paris climate agreement. If the estimated change in the green-meets-green effect is not caused by the ratification of the Paris Accord, then we should be able to replicate similar findings using random signature dates. To verify this, we restrict the sample to the period before the accord effectively took place: 2011-2015. During this period, we should be unable to identify a reduction in loan rates when green-meets-green as there was no such event to align the green attitudes of market participants and increase

[18] Although the first-stage regression equations provide evidence that our IV's are correlated with the endogenous regressors, conducting the Hausman specification test on the difference between our baseline regression and the reduced-form regression reveals that our main analysis does not suffer from this kind of endogeneity. Nonetheless, we report the results of the instrumental variable estimation.

[19] Please note that due to collinearity with our IV's, which are constructed to be time-invariant at the borrower-level, we are unable to include borrower fixed effects in this analysis.

awareness towards transition risks. In particular, we do as if the Paris Accord acceptance date was in 2013 and 2014, respectively. That is, $Paris$ equals 1 after 2013 and 2014, respectively, and zero otherwise.

Table 9 reports the regression output of estimating equation (2) using fake signatory dates. Across the different specifications, there is no evidence of a green-meets-green discount neither before nor after the fake Paris Agreement signature dates as is reflected by the estimated coefficients on $FGreen \times BGreen$ and $FGreen \times BGreen \times Paris$, respectively. Since we are unable to produce similar results on our three-way interaction term employing fake Paris Accord ratification dates, this analysis offers confidence in our main result.

5 GMG as a result of price discrimination

We have argued that the robust GMG-effect could result from price discrimination by banks who are particularly concerned about climate change and the low-carbon transition of the economy. In this section, we present a stylized theoretical framework to highlight the mechanism which drives this effect, and in particular, to illustrate how the Paris agreement may have worked as a catalyst for such price discrimination to arise. In addition to emphasizing the potential channels behind our main results, we use the model to draw some conclusions and discuss possible implications of further policy changes.

Our model economy is populated with a continuum of firms, whose business activity is heterogeneously exposed to the risk of regulatory shocks addressing climate change. The firms initially are unaware of their exposure to such shocks, but can exert a costly effort to understand and (probabilistically) mitigate their exposure. For example, firms can hire external consultants to review their business model and identify threats and opportunities coming from future policy changes, or can decide to set-up an in-house team of sustainability experts. Crucially, we assume that the information created through such ventures is channeled towards investors in the form of increased transparency and information disclosure, such as CDP reporting. This is a natural assumption in the present context: as firms explore and implement various business strategies to speed up their transition to a low-carbon future, investors such as banks will have more publicly available information to rely on when judging the firm's exposure to such risks.

We model the loan market as a monopolistic competition between two banks, a "brown" and a "green" bank. The green bank, having previously accumulated the necessary knowledge to do so, can decide whether to price-discriminate against firms with high exposure to the carbon transition risk, i.e., to reflect such information in the pricing of loans. Doing so, it relies on information, the quality of which - and so the ability to profitably price-discriminate - depends on firms' prior effort, as explained above.

We argue that the first-order impact of the Paris-agreement was to shift the perception of the probability of future policy shocks which may negatively influence firms' business in the short term. Under quite general conditions this leads to higher equilibrium effort choices by the firms, and - as more and more firms become low-risk -, a more heterogeneous population of borrowers. On the loan market, the richer set of available information – a byproduct of firms' mitigation effort – increases the green bank's ability to tell apart high-risk from low-risk borrowers. Such improvement of the signal quality, the increased heterogeneity of population, as well as the higher probability of regulatory shock, all improve the relative profitability of price discrimination based on carbon risk. In particular, our model demonstrates that there is a state-transition in the equilibrium pricing pattern: GMG pricing arises if and only if the probability of such shock is sufficiently high.

In the next section we introduce the model set-up in detail. Then, we solve for equilibrium, and discuss some implications of the main result.

5.1 Set-up

We consider a model of differentiated credit market competition between a "green" bank, denoted by G, and a "brown" bank (B), which are endowed with a different screening technology. The banks compete for a unit measure of firms located uniformly on the interval $[0, 1]$ that have a fixed demand for one unit of loan. The two banks are located at the two endpoints, Bank G located at 0 and Bank B located at 1. When borrowing from any of the two banks, a firm located at $\gamma \in [0, 1]$ incurs a transportation cost of $\tau\delta$ where δ is its distance from the bank.[20]

There is a systematic risk component in the economy (i.e., carbon transition risk) captured by a random variable $z \in \{0, 1\}$, which is the only aggregate source of risk. The variable takes the value of 1 (risk-event) with probability p, and 0 with complementary probability $1 - p$. Nature draws the probability p before, but the realization of z only after the lending relationships are established.

Firms are heterogeneously exposed to the carbon transition risk, and their exposure can take two values, β_L with probability $q < 1/2$ and $\beta_H > \beta_L$ with probability $(1 - q)$. When the risk-event materializes (i.e., $z = 1$), a firm with exposure β suffers a monetary loss of β, which may be (partially) transferred to the lending bank. In particular, a bank's expected loss from lending to a firm with exposure β is a function $c(\beta, p)$ which is increasing in p and β and has increasing differences (i.e., the difference $c(\beta_H) - c(\beta_L)$ is increasing in p).

Firms can exert an effort $e \in [0, 1]$ for a cost of $c_F(e)$ to learn their true exposure, and, if they turn out to be a high-exposure type, mitigate it with some probability. In particular, exerting effort e decreases a firm's exposure from β_H to β_L with probability e. The cost function $c_F(e)$ is increasing and convex in e. The firm maximizes the following

[20] A similar setup is used in Thanassoulis and Vadasz (2021) to study the joint pricing of current accounts and customer credit.

"profit" function:

$$\pi_F(e) = \mathbb{E}[-z\tilde{\beta}(e) - c_F(e)] \tag{5}$$

where $\tilde{\beta}(e)$ is the random realization of the firm's exposure after the mitigation effort. That is, maximizing profit is equivalent with minimizing the expected shock adjusted with the cost of effort. Suppose that the functions are such that with $p = 1$ the firm exerts maximum effort $e = 1$, so all high-exposure firms become low-exposure.[21]

The two banks have different endowment technology. The type G bank has access to a screening technology which may be activated for a fixed cost of F.[22] The technology, if applied, delivers a signal $s \in \{l, h\}$ on the firm's exposure to the green transition risk, and the bank can condition the loan prices on this signal. In particular, let us denote by r_l the loan price when l is observed and r_h when h is observed. The signal has the following conditional distribution:

$$Pr[l\ |L] = q + (1-q)x(e) \quad \text{and} \quad Pr[h\ |L] = (1-x(e))(1-q)$$
$$Pr[h\ |H] = 1 - q(1-x(e)) \quad \text{and} \quad Pr[l\ |H] = q(1-x(e))$$

where the function $x(e) \in [0, 1]$ parameterizes the informativeness of the signal. We assume that the informativeness increases in the firm's effort, so $\partial x/\partial e > 0$. We will suppress the argument e where it can be done without confusion. Note that with $x = 0$ the signal's distribution equals to the prior, so the signal is uninformative. With $x = 1$ the signal is fully informative. The timing of the model is summarized in Figure 1.

[21] This normalization is not critical, but it allows us to study extreme cases, where climate transition becomes so important that all firms mitigate. Notice that we specify firms' utility in a way which does not depend on the banks' equilibrium loan offer. We justify this by arguing that, although a firm can gain by strategically becoming green just to obtain the cheaper loan from a green bank, this benefit is of second order compared to the potential losses from actual shocks. So the effort decision is not primarily driven by the potential savings on loan. Alternatively, one could assume formally that firms' location on the loan market is not known at the time of the effort choice.

[22] For example, the risk management division may have to initiate a costly revision and board approval process of their existing internal risk assessment methodologies before it is eventually put in use.

5.2 Analysis

First, we establish a result regarding the firm's optimal effort choice $e^\star$.

Lemma 1 *The firm's optimal effort $e^\star$ is increasing in the expected exposure difference $p(\beta_H - \beta_L)$.*[23]

The firm trades off the marginal benefits of exerting extra effort with the associated marginal costs. As the potential benefit of mitigating the exposure increases with the probability of shock p, so does the optimal effort choice of the firm.

Next, we analyze both banks' pricing game. Notice that when bank G does not apply the screening technology, it cannot price-discriminate and $r_l = r_h := r_G$. In this case the results follow the standard Hotelling duopoly benchmark. In contrast, if bank G chooses to apply the screening technology, the loan rates will be conditioned on the signal. Bank B cannot condition on the signal and thus sets one loan rate. The solution is a vector of loan rates $\mathbf{r} := \{r_l, r_h, r_B\}$. Proposition 1 below establishes equilibrium prices and profits.

Proposition 1 *When bank G applies the screening technology and conditions the rates on the signal, the equilibrium loan rates will be as follows:*

$$\begin{aligned} r_B^\star &= \tau + \bar{c} \\ r_l^\star &= \tau + \bar{c} - \frac{1}{2}x(1-q)\Delta c \\ r_h^\star &= \tau + \bar{c} + \frac{1}{2}xq\Delta c \end{aligned}$$

This generates the following profits for the two banks in equilibrium:

$$\begin{aligned} \pi_G^\star &= \frac{\tau}{2} + \frac{(1-q)qx^2[\Delta c]^2}{8\tau} - F \\ \pi_B^\star &= \frac{\tau}{2} - \frac{(1-q)qx^2[\Delta c]^2}{4\tau} \end{aligned}$$

[23] All proofs can be found in Appendix A.

where $\Delta c := c(\beta_H, p) - c(\beta_L, p)$.

The no-discrimination benchmark can be obtained by substituting $x = 0$ (i.e., completely uninformative signal) and $F = 0$. Indeed, one can easily verify that in that case all prices and profits are equal, and coincide with the well-known Hotelling duopoly solution.[24]

Finally, we establish conditions for price discrimination to emerge as equilibrium. Intuitively, bank G decides to price-discriminate, if the extra profit from this (the second term of $\pi_G^\star$) compensates for the fixed cost of the technology (F).

Proposition 2 *Bank G applies the screening technology and price discriminates if and only if $p \in (\underline{p}, \overline{p})$ with some $\underline{p} > 0$ and $\overline{p} < 1$. The price discrimination interval shrinks with F and disappears for sufficiently high F.*

5.3 Discussion

Our main result in Proposition 2 says that there is price discrimination by the green bank if the probability of the shock is sufficiently high, but not too high to induce the vast majority of firms to exert very high effort to mitigate climate risk. Intuitively, an increase of the probability of the carbon transition shock (p) from low to medium increases the potential loss from being highly exposed to the shock ($p \cdot (\beta_H - \beta_L)$) and in turn the expected loss transmitted from firms to banks (Δc). As a response, firms exert more effort in order to probabilistically mitigate their exposure (Lemma 1). This has two effects. First, assuming that initially most firms are highly exposed, the heterogeneity of population increases, i.e., there is more prior uncertainty regarding the type of the borrower on the bank's side. In turn, it becomes more profitable for the bank to identify

[24]Notice that bank B's equilibrium price ($r_B^\star$) is independent of x. This implies that bank B's prices are the same whether or not bank G applies the technology. So, the equilibrium selection is entirely in bank G's hand and there are no strategic considerations.

those who successfully decreased their exposure. Second, the effort exerted by firms increases the precision of bank's signals, which also increases profitability.

To sum up, according to our model, after Paris a green bank observes higher probability of a shock, higher uncertainty about firms' exposure, and an improvement of its technology. All these effects increase the profit from price discrimination. In particular, there is a threshold value $\underline{p}$ when this profit just compensates for the cost of applying the screening technology.

The model's main empirical prediction with regard to the loan rates is illustrated in the left panel of Figure 2, which uses a quadratic cost function ($c_F(e)$) and a linear expected loss function ($c(p, \beta)$). Before the Paris Agreement (i.e., for low p values) we expect that the green bank will not distinguish green firms and brown firms. When p jumps up to the intermediate region, we would expect that the green bank offers a discount for green firms and a penalty to brown firms relative to the brown bank's pricing. The magnitude of this green-meets-green effect can change with the shock probability. For example, the US' withdrawal from the Paris Agreement would lead to a decrease of the effect, if that would be interpreted as a permanent softening of climate transition commitment. The right panel illustrates the model's prediction with regard to the equilibrium profits.

Proposition 2 also reveals the limits of this argument, as it highlights that after endogenous responses by firms and banks to higher risk are taken into account, GMG is non-monotonous in the underlying risk.[25] In particular, when carbon transition risk becomes 'extreme' (with very high probability all firms will be affected, unless they change their business model), most firms would exert maximum effort to mitigate and become low-risk. The lack of the resulting heterogeneity renders climate risk-based price

[25] With alternative assumptions on the functional forms, when high effort is prohibitively costly, one would get a result when profit from price discrimination always increases in p. We believe that our assumptions better reflect our optimism: eventually the increasing business risks from climate change would force the vast majority of firms to confront the changing environment - which would make the population more heterogeneous and price discrimination less profitable for banks.

discrimination non-profitable - banks would rather price the aggregate risk for all loans.

Using our framework one could speculate what would happen if measurement of climate business risk and the necessary information disclosure becomes highly standardized.[26] We do not model explicitly how and why exactly a bank becomes green at the first place, however, we postulate that (1) such expertise accumulates over time as a result of unmodeled decisions or factors (i.e., CEO / board affinity), and on the short term can be regarded as fixed; (2) even with on-board expertise, it is costly to apply such screening technology. If - hypothetically - climate risk information becomes standardized, easy-to-understand and readily available, our framework suggest that such dichotomy of "green" and "brown" banks would cease to exist, and all banks would consider our z-factor simply as part of their regular and standard risk-assessment procedures, which, again, would eliminate the GMG pricing pattern.

In conclusion, it is possible that such GMG pricing is part of a transitory phase towards a future low-carbon economy. As it punishes brown firms, while subsidizes green firms, GMG can improve the allocation of resources in the banking sector towards a low-carbon economy.

6 Conclusion

The Paris Agreement of December 2015 put climate change high on the political agenda. It increased public awareness of climate-related risks and increased the soft commitment of policy-makers to a stricter enforcement of climate policy. In this paper, we study whether the augmented perception of climate transition risk by banks gets reflected into loan rates to firms exhibiting (or not) environmental consciousness.

Employing data on syndicated loans over the period 2011-2019, we find that firms

[26] Given the endogenous nature of policy shock, precise and standardized measurement of such risks is at the moment highly unlikely, but it is a goal of policy makers nevertheless.

showing environmental consciousness (i.e., green firms) enjoy more favorable terms of about 35bps compared to brown firms when borrowing from a green bank. The green-meets-green effect kicks in after the Paris Agreement, consistent with green banks price discriminating between green firms and brown firms.

We present a stylized theoretical framework of banking competition to illustrate how the Paris agreement may have worked as a catalyst for such price discrimination to arise. Green banks have incentives to pursue third-degree price discrimination between green firms and brown firms when public awareness of climate transition risk is sufficiently high. Green firms compared to brown firms then enjoy a discount when borrowing from green banks.

De Haas and Popov (2019) show that countries that rely more on capital markets compared to banks are more forthcoming in dealing with climate change. Our results show that (parts of) the banking systems may also be conducive to the transition as they are favorably pricing loans to green firms relative to brown firms. This holds when banks also have a similar environmental consciousness, i.e., our green-meets-green effect. Putting climate change on the agenda through the Paris Agreement has fostered this attitude.

References

Baldauf, M., L. Garlappi, and C. Yannelis (2020). Does Climate Change Affect Real Estate Prices? Only If You Believe In It. *The Review of Financial Studies 33*(3), 1256–1295.

Batten, S., R. Sowerbutts, and M. Tanaka (2016). Let's Talk about the Weather: the Impact of Climate Change on Central Banks. *Bank of England Staff Working Paper No . 603*.

Ben-David, I., S. Kleimeier, and M. Viehs (2020). Exporting Pollution: Where Do Multinational Firms Emit CO2? *NBER Working Paper* (No. 25063).

Berg, T., A. Saunders, and S. Steffen (2016). The Total Cost of Corporate Borrowing in the Loan Market: Don't Ignore the Fees. *Journal of Finance 71*(3), 1357–1392.

Bernstein, A., M. T. Gustafson, and R. Lewis (2019). Disaster on the Horizon: The Price Effect of Sea Level Rise. *Journal of Financial Economics 134*(2), 253–272.

Bharath, S., S. Dahiya, A. Saunders, and A. Srinivasan (2011). Lending Relationships and Loan Contract Terms. *The Review of Financial Studies 24*(4), 1141–1203.

Bolton, P. and M. Kacperczyk (2021). Do Investors Care About Carbon Risk? *Journal of Financial Economics*.

Campiglio, E., Y. Dafermos, P. Monnin, J. Ryan-Collins, G. Schotten, and M. Tanaka (2018). Climate Change Challenges for Central Banks and Financial Regulators. *Nature Climate Change 8*(6), 462–468.

Chava, S. (2014). Environmental Externalities and Cost of Capital. *Management Science 60*(9), 2223–2247.

Cohen, G. J., M. Friedrichs, K. Gupta, W. Hayes, S. J. Lee, W. B. Marsh, N. Mislang, M. Shaton, and M. Sicilian (2018). The U.S. Syndicated Loan Market: Matching Data. Finance and Economics Discussion Series 2018-085. Washington: Board of Governors of the Federal Reserve System.

De Haas, R. and A. Popov (2019). Finance and Carbon Emissions. SSRN Working Paper.

Degryse, H., T. Roukny, and J. Tielens (2020). Banking Barriers to the Green Economy. National Bank of Belgium Working Paper Research 391.

Delis, M., K. de Greiff, M. Iosifidi, and S. Ongena (2021). Being Stranded with Fossil Fuel Reserves? Climate Policy Risk and the Pricing of Bank Loans. Swiss Finance Institute Research Paper Series No 18-10.

Ehlers, T., F. Packer, and K. de Greiff (2021). The Pricing of Carbon Risk in Syndicated Loans: Which Risks are Priced and Why? *Journal of Banking and Finance forthcoming*.

Fatica, S., R. Panzica, and M. Rancan (2019). The Pricing of Green Bonds: Are Financial Institutions Special? *JRC Working Papers in Economics and Finance*.

Hartzmark, S. M. and A. B. Sussman (2019). Do Investors Value Sustainability? A Natural Experiment Examining Ranking and Fund Flows. *The Journal of Finance 74*(6), 2789–2837.

Hauptmann, C. (2017). Corporate Sustainability Performance and Bank Loan Pricing: It Pays to Be Good, but Only When Banks Are Too. SSRN Working Paper.

Houston, J. F. and H. Shan (2020). Corporate ESG Profiles and Banking Relationships. SSRN Working Paper.

Ilhan, E., Z. Sautner, and G. Vilkov (2020). Carbon Tail Risk. *The Review of Financial Studies 34*(3), 1540–1571.

Ivashina, V. (2009). Asymmetric Information Effects on Loan Spreads. *Journal of Financial Economics 92*(2), 300–319.

Javadi, S. and A. Al Masum (2021). The Impact of Climate Change on the Cost of Bank Loans. *Journal of Corporate Finance*, 102019.

Kim, M., J. Surroca, and J. A. Tribó (2014). Impact of Ethical Behavior on Syndicated Loan Rates. *Journal of Banking & Finance 38*, 122 – 144.

Kleimeier, S. and M. Viehs (2018). Carbon Disclosure, Emission Levels, and the Cost of Debt. SSRN Working Paper.

Krueger, P., Z. Sautner, and L. T. Starks (2020). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies 33*(3), 1067–1111.

Lim, J., B. A. Minton, and M. S. Weisbach (2014). Syndicated loan spreads and the composition of the syndicate. *Journal of Financial Economics 111*(1), 45–69.

Nguyen, D. D., S. R. G. Ongena, S. Qi, and V. Sila (2021). Climate Change Risk and the Cost of Mortgage Credit. *Swiss Finance Institute Research Paper No. 20-97*.

Oster, E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics 37*(2), 187–204.

Painter, M. (2020). An Inconvenient Cost: The Effects of Climate Change on Municipal Bonds. *Journal of Financial Economics 135*(2), 468–482.

Reghezza, A., Y. Altunbas, D. Marques-Ibanez, C. R. d'Acri, and M. Spaggiari (2021, May). Do Banks Fuel Climate Change? *ECB Working Paper Series No 2550*.

Riedl, A. and P. Smeets (2017). Why Do Investors Hold Socially Responsible Mutual Funds? *The Journal of Finance 72*(6), 2505–2550.

Sufi, A. (2007). Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans. *Journal of Finance 62*(2), 629–668.

Thanassoulis, J. E. and T. Vadasz (2021). Free banking and credit market competition. *Available at SSRN 3859667*.

Tables

Table 1

Summary Statistics

	Min	Max	Mean	Std.Dev.	Obs
Loan characteristics:					
All-in-Spread-Drawn (AISD)	1.00	875.00	292.94	171.55	71,191
AISD $\mid FGreen = 1$			180.00	131.37	5,224
AISD $\mid BGreen = 1$			381.87	180.05	6,526
Log Loan Amount	2.88	24.69	18.41	2.00	71,187
Maturity (months)	1.00	725.00	57.63	29.86	70,440
Concentration	1.00	54.00	2.60	4.27	71,191
Secured	0.00	1.00	0.85	0.35	38,137
Covenant	0.00	1.00	0.19	0.39	71,191
Nonbank indicator	0.00	1.00	0.08	0.27	71,191
Relation loan	0.00	1.00	0.34	0.47	71,191
$BGreen \neq 0$	0.02	1.00	0.59	0.34	17,441
Borrower characteristics:					
Log Total Assets	0.00	14.48	7.05	2.41	28,170
Leverage	0.17	103.09	4.34	11.79	24,695
ROA	-29.58	27.58	2.90	8.13	27,598
Listed	0.00	1.00	0.24	0.42	70,502
Lender characteristics:					
(Avg) Total Assets	1.25	15.08	13.44	1.50	63,428
(Avg) Capital ratio	6.08	98.86	15.93	3.67	61,325
(Avg) ROA	-0.72	31.43	0.70	0.58	63,421

Table 2

Green-Meets-Green and Loan Spreads.

This table reports the results of estimating the model in equation (1). The dependent variable is the all-in-spread-drawn of loan facility i, issued by the syndicate's lead arranger(s) b in year t. The main variable of interest is the interaction term $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t-1}$ which captures the green-meet-green effect on loan spread. $\text{FGreen}_{i,t-1}$ is the dummy variable equal to 1 for loans given to green firms, $\text{BGreen}_{i,b,t-1}$ describes the fraction of UNEP FI members among the lead arranger consortium. Loan, borrower and lender characteristics are defined in Table A1. In parentheses, we report the standard errors which are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	All-in-Spread-Drawn			
	(facility-level data)		*(lead arranger-level data)*	
	(1)	(2)	(3)	(4)
FGreen	1.062	-	-3.511	-
	(4.266)		(3.527)	
BGreen	43.725***	45.833***	28.854***	58.610***
	(6.295)	(11.221)	(8.947)	(9.977)
FGreen x BGreen	-38.244***	-31.396	-35.649***	-21.845
	(12.234)	(24.408)	(10.027)	(22.992)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	-	Yes	-
Lender characteristics	Yes	Yes	-	-
Year fixed effects	Yes	-	-	-
Borrower country fixed effects	Yes	-	Yes	-
Borrower x time fixed effects	No	Yes	No	Yes
Lender x time fixed effects			Yes	Yes
Adj. R^2	.5560	.7187	.6760	.8771
Observations	12,062	19,133	31,854	68,569

Table 3

Green-Meets-Green and Loan Spreads: Paris Sample Split.

This table reports the results of estimating the model in equation (1) from sub-samples before and after the Paris Agreement. The dependent variable is the all-in-spread-drawn of loan facility i, issued by the syndicate's lead arranger(s) b in year t. The main variable of interest is the interaction term FGreen$_{i,t-1}$ $\times$ BGreen$_{i,b,t-1}$ which captures the green-meet-green effect on loan spread. FGreen$_{i,t-1}$ is the dummy variable equal to 1 for loans given to green firms, whereas BGreen$_{i,b,t-1}$ describes the fraction of UNEP FI members among the lead arranger consortium. Loan, borrower and lender characteristics are defined in Table A1. In parentheses, we report the standard errors which are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	All-in-Spread-Drawn							
	(facility-level data)				*(lead arranger-level data)*			
	(1) Before Paris	(2) After Paris	(3) Before Paris	(4) After Paris	(5) Before Paris	(6) After Paris	(7) Before Paris	(8) After Paris
FGreen	-6.271	11.511*	-	-	-21.337***	14.149***	-	-
	(5.214)	(6.287)			(5.642)	(4.891)		
BGreen	50.890***	32.699***	57.045***	21.354	31.241***	32.742***	69.673***	53.549***
	(7.459)	(10.368)	(14.878)	(17.227)	(11.554)	(10.793)	(13.308)	(14.146)
FGreen x BGreen	-22.428	-63.762***	-1.588	-67.034***	-13.063	-54.580***	8.728	-68.907***
	(14.012)	(17.086)	(33.831)	(25.584)	(14.690)	(12.578)	(31.731)	(25.680)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	-	-	Yes	Yes	-	-
Lender characteristics	Yes	Yes	Yes	Yes	-	-	-	-
Year fixed effects	Yes	Yes	-	-	-	-	-	-
Borrower country fixed effects	Yes	Yes	-	-	Yes	Yes	-	-
Borrower x time fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Lender x time fixed effects					Yes	Yes	Yes	Yes
Adj. R^2	.5753	.5573	.7189	.7194	.6970	.6931	.8900	.8594
Observations	7,076	4,974	10,616	8,503	18,964	12,857	39,940	28,594

Table 4

Green-Meets-Green and the Impact of the Paris Agreement.
This table reports the results of estimating the model in equation (2). The dependent variable is the all-in-spread-drawn of loan facility i, issued by the syndicate's lead arranger(s) b in year t. The main variable of interest is the triple interaction term $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t-1} \times \text{Paris}_t$, which captures the change in the green-meet-green effect with the adoption of the Paris Agreement. $\text{FGreen}_{i,t-1}$ is the dummy variable equal to 1 for loans given to green firms. $\text{BGreen}_{i,b,t-1}$ describes the fraction of UNEP FI members among the lead arranger consortium. Paris_t is a dummy variable which takes the value of 1 for loans originated after the Paris Agreement, i.e. after December 12, 2015. Loan, borrower and lender characteristics are defined in Table A1. In parentheses, we report the standard errors which are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	All-in-Spread-Drawn			
	(facility-level data)		*(lead arranger-level data)*	
	(1)	(2)	(3)	(4)
FGreen	-1.040	-	-13.231***	-
	(5.115)		(4.730)	
BGreen	55.836***	53.406***	28.068**	65.261***
	(7.206)	(14.054)	(11.595)	(13.205)
FGreen x BGreen	-20.839	2.804	-15.016	12.867
	(14.519)	(34.698)	(13.538)	(32.123)
Paris	-10.083	49.584	-22.067***	75.834*
	(11.604)	(36.991)	(8.032)	(42.312)
FGreen x Paris	4.506	-84.401**	22.100***	-113.994***
	(7.138)	(37.020)	(5.871)	(42.329)
BGreen x Paris	-31.188***	-16.688	1.867	-14.158
	(9.778)	(20.403)	(13.920)	(18.693)
FGreen x BGreen x Paris	-46.552**	-75.099*	-48.871***	-81.040**
	(21.706)	(42.906)	(17.552)	(41.335)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	-	Yes	-
Lender characteristics	Yes	Yes	-	-
Year fixed effects	Yes	-	-	-
Borrower country fixed effects	Yes	-	Yes	-
Borrower x time fixed effects	No	Yes	No	Yes
Lender x time fixed effects			Yes	Yes
Adj. R^2	.5574	.7172	.6762	.8780
Observations	12,062	18,870	31,854	67,936

Table 5

Green-Meets-Green and Loan Spreads: Heckman selection correction.
This table reports the results of estimating the Heckman selection model using a two-step OLS procedure. The Heckman model is run on the full period and on sub-samples before and after the Paris Agreement. Panel A presents the regression model in Equation (4); Panel B the selection model in Equation (3) estimated using a probit model; and Panel C the key statistics. All regressions include loan purpose, loan type, time, borrower country and industry fixed effects, on top of the standard set of loan, borrower and lender controls defined in Table A1. In columns 4-6, borrower and lender fixed effects are included as well. $\hat{\lambda}$ represents the estimated coefficient on the Inverse Mills ratio and reflects the covariance between the residuals of the regression and selection model; significance would imply that the null hypothesis of independent equations (i.e. $\hat{\lambda}$ equal to 0) or no self-selection can be rejected. In parentheses, we report bootstrapped standard errors with sub-samples drawn from borrower-clusters. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(facility-level data)			*(lead arranger-level data)*		
	(1) 2011-2019	(2) Before Paris	(3) After Paris	(4) 2011-2019	(5) Before Paris	(6) After Paris
Panel A: Regression Equation (*dep. var: All-in-Spread-Drawn*)						
FGreen	.791	-6.008	9.721	20.500**	19.471	13.362
	(4.268)	(4.524)	(6.948)	(10.168)	(16.370)	(12.836)
BGreen	42.926***	49.191***	34.610***	22.887**	33.741***	49.021***
	(5.472)	(7.809)	(10.503)	(9.118)	(12.966)	(16.201)
FGreen × BGreen	-35.771***	-21.552*	-61.434***	-20.229	-13.621	-69.543**
	(11.844)	(13.015)	(19.881)	(22.631)	(35.645)	(34.664)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Lender characteristics	Yes	Yes	Yes	-	-	-
Year fixed effects	Yes	Yes	Yes	-	-	-
Borrower country fixed effects	Yes	Yes	Yes	-	-	-
Borrower fixed effects	No	No	No	Yes	Yes	Yes
Lender x time fixed effects	No	No	No	Yes	Yes	Yes
Panel B: Selection Equation (*dep. var: FGreen*)						
Environmental Policy Stringency	.408***	.351***	.522***	.484***	.411***	.610***
	(.077)	(.083)	(.109)	(.093)	(.093)	(.136)
Peer Pressure	.050***	.049***	.052***	.059***	.058***	.062***
	(.005)	(.006)	(.007)	(.008)	(.011)	(.012)
Log Total Assets	.330***	.333***	.330***	.291***	.325***	.253***
	(.029)	(.029)	(.042)	(.040)	(.048)	(.060)
ROA	.007	.007	.007	.004	.008	.000
	(.006)	(.006)	(.009)	(.008)	(.009)	(.012)
Leverage	-.004	-.007**	-.001	-.003	-.007	.002
	(.003)	(.003)	(.005)	(.005)	(.005)	(.006)
Listed	.435***	.401***	.477***	.541***	.507***	.600***
	(.068)	(.077)	(.091)	(.109)	(.143)	(.139)
Panel C: Statistics						
$\hat{\lambda}$	8.768	18.438	15.948	-28.566*	-15.527	-8.622
	(12.823)	(17.442)	(18.816)	(14.862)	(18.563)	(19.173)
Adj. R^2	.5366	.5557	.5392	.8308	.8611	.8408
Observations	11,006	6,528	4,471	25,870	15,569	9,727

Table 6

Green-Meets-Green, Loan Spreads and Paris Sample Split: PSM.

For sub-samples before and after the Paris Agreement, this table reports the average difference in AISD between "green-meets-green" loans and (Panel A) matched non-GMG loans, or (Panel B) matched loans granted to brown firms by green banks. For each loan, we estimated the propensity score of being a green-meets-green loan conditional on ex-ante borrower and lender characteristics using a logit model. The borrower characteristics include firm size, profitability, leverage, listed status, industry, country and a relation loan indicator. The lender characteristics include size, profitability- and capital ratios. We then matched each green-meets-green loan to other sets of loans which have similar propensity scores using two matching approaches. In columns 1-4, we employed a nearest neighbor (NN) matching approach thereby choosing the n loans with closest propensity scores. In columns 5-6, we report the results of performing a kernel epanechnikov matching approach which uses a weighted average of all loans with a score smaller than the automatically determined bandwidth and with larger weights given to controls with closer propensity scores. The reported standard errors are computed by bootstrapping with 50 replications. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	NN (n=10)		NN (n=50)		Kernel	
	(1) Before Paris	(2) After Paris	(3) Before Paris	(4) After Paris	(5) Before Paris	(6) After Paris
Panel A: GMG vs. other loans						
Δ AISD	15.600	-40.085**	26.138*	-33.099***	22.369	-51.012**
	(20.675)	(16.663)	(15.405)	(9.394)	(16.045)	(20.168)
Observations	12,170	8,940	12,170	8,940	12,170	8,940
Panel B: GMG vs. BMG loans						
Δ AISD	28.426	-51.840*	-6.560	-69.446***	42.710	-52.258**
	(29.111)	(26.717)	(19.012)	(20.153)	(26.840)	(26.409)
Observations	979	723	979	723	979	723

Table 7

Green-Meets-Green and Loan Spreads: IV estimation.

This table reports the results of the instrumental variable estimation on the sub-sample of post-Paris Accord loans. The IV's used are $L.BGreen$ and $FGreen \times L.BGreen$, where $L.BGreen$ represents a pre-Paris Accord green lender choice indicator. Column 1 & 2 display the first-stage regression equations. In column 3 & 4, $BGreen$ and $FGreen \times BGreen$ are instrumented using the IV's. All regressions include loan purpose, loan type, time, borrower country and industry fixed effects, on top of the standard set of loan, borrower and lender controls defined in Table A1. In column 4, lender x time fixed effects are additionally included. In parentheses, we report robust standard errors clustered at the borrower-level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(lead arranger-level data)			
	First Stage		Second Stage	
	(1)	(2)	(3)	(4)
	BGreen	*FGreen x BGreen*	*AISD*	*AISD*
L.BGreen	.109***	-.004**		
	(.008)	(.002)		
FGreen x L.BGreen		.255***		
		(.011)		
FGreen		.082***	20.608***	19.568***
		(.006)	(5.823)	(6.270)
BGreen			90.121***	-.416
			(33.606)	(72.145)
FGreen x BGreen			-90.992***	-80.808***
			(26.912)	(30.245)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Lender characteristics	Yes	Yes	Yes	-
Year fixed effects	Yes	Yes	Yes	-
Borrower country fixed effects	Yes	Yes	Yes	Yes
Borrower x time fixed effects	No	No	No	No
Lender x time fixed effects	No	No	No	Yes
Adj. R^2	.4435	.7206	.1966	.1041
Observations	11,274	11,274	11,274	12,857

Table 8

Green-Meets-Green and Loan Spreads: Financial Borrowers.
This table reports the results of estimating the model in equation (1) from sub-samples before and after the Paris Agreement using a subset of financial borrowers. The dependent variable is the all-in-spread-drawn of loan facility i, issued by the syndicate's lead arranger(s) b in year t. The main variable of interest is the interaction term $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t-1}$ which captures the green-meet-green effect on loan spread. $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t-1}$ which captures the green-meet-green effect on loan spread. $\text{FGreen}_{i,t-1}$ is the dummy variable equal to 1 for loans given to green financial borrowers, whereas $\text{BGreen}_{i,b,t-1}$ describes the fraction of UNEP FI members among the lead arranger consortium. Loan, borrower and lender characteristics are defined in Table A1. In parentheses, we report the standard errors which are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	All-in-Spread-Drawn							
	(facility-level data)				*(lead arranger-level data)*			
	(1) Before Paris	(2) After Paris	(3) Before Paris	(4) After Paris	(5) Before Paris	(6) After Paris	(7) Before Paris	(8) After Paris
FGreen	-15.545	-31.005**	-	-	-19.624*	-23.002*	-	-
	(12.222)	(12.836)			(11.017)	(13.131)		
BGreen	50.884	21.771	45.802	14.715	-2.677	46.261	41.274	-29.676
	(31.973)	(26.249)	(40.027)	(31.801)	(30.111)	(35.029)	(25.737)	(38.662)
FGreen x BGreen	59.637	-43.217	-41.715	80.094	-91.130*	-44.002	-108.779	38.330
	(105.764)	(31.022)	(43.369)	(299.414)	(48.133)	(36.526)	(68.880)	(88.222)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	-	-	Yes	Yes	-	-
Lender characteristics	Yes	Yes	Yes	Yes	-	-	-	-
Year fixed effects	Yes	Yes	-	-	-	-	-	-
Borrower country fixed effects	Yes	Yes	-	-	Yes	Yes	-	-
Borrower x time fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Lender x time fixed effects					Yes	Yes	Yes	Yes
Adj. R^2	.5909	.5600	.8291	.8331	.7652	.6923	.9365	.9237
Observations	849	692	1,392	1,439	1,303	1,322	6,303	7,876

Table 9

Green-Meets-Green and the Impact of the Paris Agreement: Falsification test. This table reports the results of estimating the model in equation (2) using fake Paris Agreement dates. The sample period consists of the period before the official Paris Climate Agreement i.e. 2011-2015. The dependent variable is the all-in-spread-drawn of loan facility i, issued by the syndicate's lead arranger(s) b in year t. The main variable of interest is the triple interaction term $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t-1} \times \text{Paris}_t$, which captures the change in the green-meet-green effect with the adoption of the Paris Agreement. $\text{FGreen}_{i,t-1}$ is the dummy variable equal to 1 for loans given to green firms. $\text{BGreen}_{i,b,t-1}$ describes the fraction of UNEP FI members among the lead arranger consortium. Paris_t is a dummy variable which takes the value of 1 for loans originated after 2013 (in columns 1-4), or after 2014 (in columns 5-8). In parentheses, we report the standard errors which are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. Loan, firm and lender controls are defined in Table A1.

	All-in-Spread-Drawn							
	(facility-level data)		*(lead arranger-level data)*		*(facility-level data)*		*(lead arranger-level data)*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Paris Accord date: 2013				Paris Accord date: 2014			
FGreen	-11.226	-	-34.256**	-	-8.849	-	-29.430**	-
	(8.611)		(15.548)		(6.790)		(11.958)	
BGreen	73.257***	65.546**	40.074***	68.641**	57.120***	39.546**	30.380***	54.598***
	(11.905)	(28.151)	(15.353)	(28.938)	(8.650)	(17.742)	(11.536)	(17.429)
FGreen x BGreen	-27.099	40.765	-8.422	97.332	-6.105	41.818	11.659	43.287
	(27.989)	(73.105)	(39.734)	(96.428)	(19.664)	(62.409)	(29.429)	(55.422)
FGreen x Paris	8.149	-	23.320	-	5.394	-	19.993	-
	(9.395)		(16.269)		(7.984)		(13.075)	
BGreen x Paris	-35.623***	-18.290	-17.894	-11.931	-19.052	27.633	-3.255	10.809
	(12.985)	(31.843)	(17.862)	(32.534)	(11.947)	(26.279)	(16.174)	(26.132)
FGreen x BGreen x Paris	10.070	-40.070	-5.194	-95.726	-27.271	-62.027	-48.531	-44.867
	(30.692)	(81.946)	(42.863)	(101.389)	(26.572)	(72.351)	(37.867)	(63.831)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	-	Yes	-	Yes	-	Yes	-
Lender characteristics	Yes	Yes	-	-	Yes	Yes	-	-
Year fixed effects	Yes	-	-	-	Yes	-	-	-
Borrower country fixed effects	Yes	-	Yes	-	Yes	-	Yes	-
Borrower x time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Lender x time fixed effects			Yes	Yes			Yes	Yes
Adj. R^2	.5768	.7177	.6959	.8905	.5762	.7178	.6955	.8905
Observations	7,149	10,548	19,174	40,098	7,149	10,548	19,174	40,098

Figures

Figure 1: The Timing of the Model

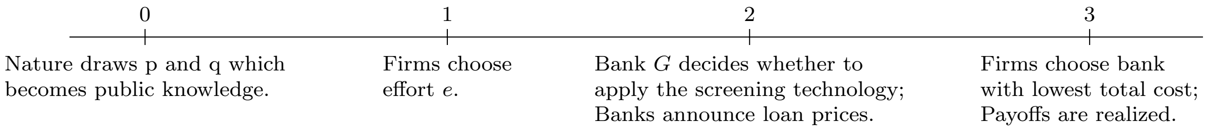
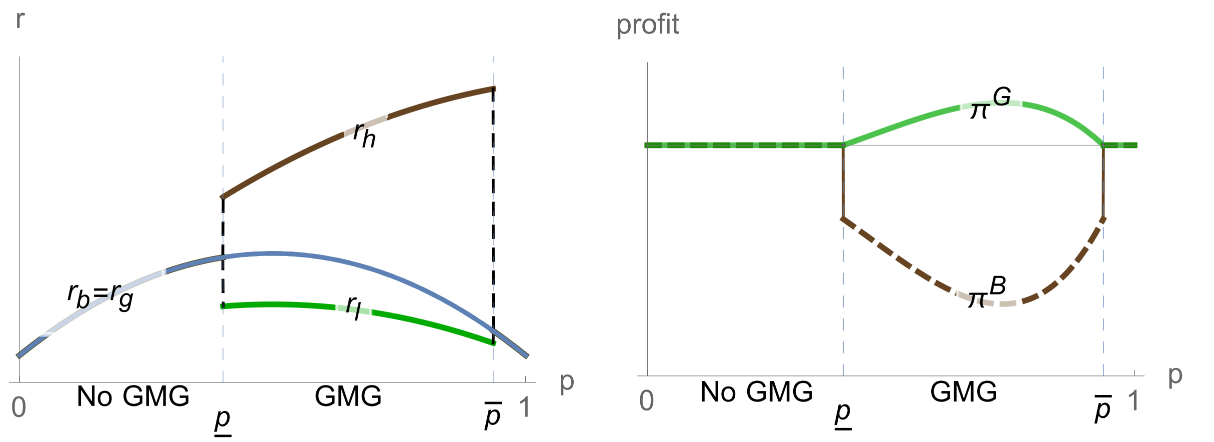
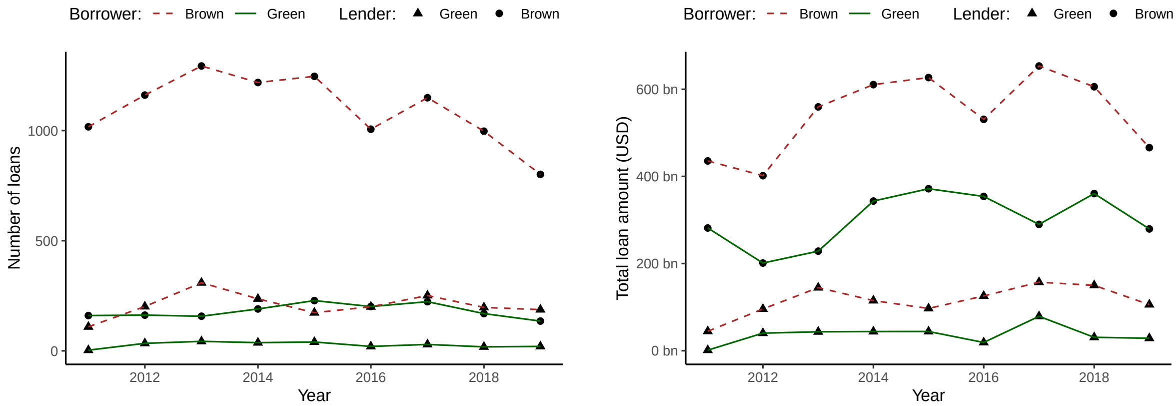


Figure 2: Equilibrium illustration



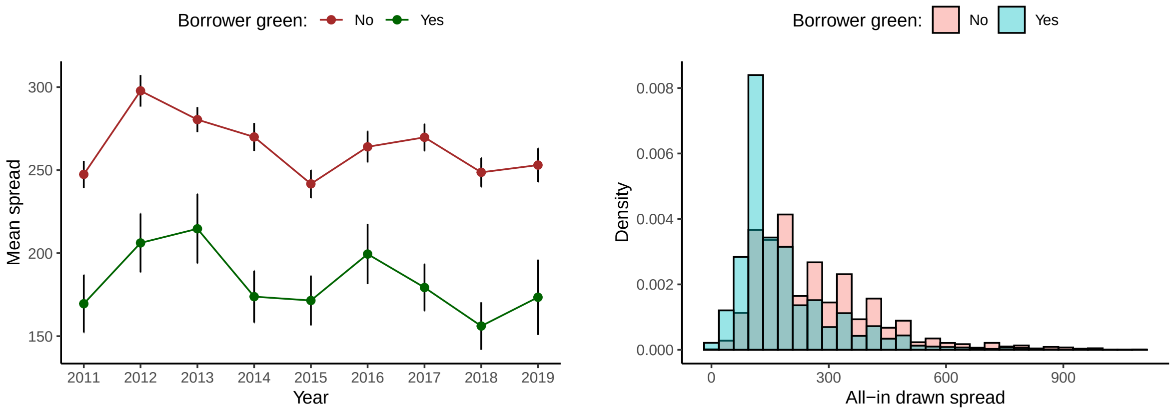
GMG-pricing arises as equilibrium when the probability of shock is high, but not too high (left panel). In this region the green bank obtains economic rent, while the brown bank's profit is diminished due to adverse selection (right panel).

Figure 3: Loans to green firms by green banks over time.



The figure shows the evolution of green firms and green lenders over time in our final sample, with the number of loan facilities on the left and the total amount on the right. We use our dummy proxy to identify green banks (i.e. the syndicate is classified as green when the majority of participants is green).

Figure 4: All-in-Spread-Drawn, green vs. brown loans.



Appendix

Table A1: Variable definitions and data sources

Variable Name	Definition	Source
All-in-Spread-Drawn	The amount the borrower pays in basis points over LIBOR for each dollar drawn down plus any annual or facility fee paid.	DealScan
FGreen	Green firm proxy; dummy variable indicating that the borrowing firm disclosed information to CDP one year before loan origination.	Carbon Disclosure Project
BGreen	Green lender proxy; continuous variable describing the fraction of UNEP FI members among the lead arrangers of the syndicate.	UNEP FI
Lead arranger	Following Ivashina (2009), we define lead arrangers as (1) the administrative agent of the syndicate, if not available (2) all lenders that act as agent, (mandated or coordinating) arranger, bookrunner, (mandated) lead arranger, lead bank or manager.	DealScan
Loan characteristics:		
Loan type	Following Berg et al. (2016), we lump together following loan types: (i) credit lines (i.e. revolver lines, 364-day facilities and limited lines); (ii) term loans (i.e. term loans and delay draw term loan) and (iii) other loan types (e.g. leases, bonds etc.).	DealScan
Loan purpose	Primary purpose of the facility.	DealScan
Facility amount	Natural logarithm of the loan amount in USD committed by the pool of lenders.	DealScan
Maturity	The maturity of the facility in months.	DealScan
Secured	Dummy variable equal to 1 if the loan facility is secured.	DealScan
Covenant	Dummy variable equal to 1 if the loan facility has any type of covenant attached.	DealScan
Concentration	The number of lead arrangers in the loan syndicate.	DealScan
Nonbank indicator	Following Lim et al. (2014), we define as bank: commercial and investment banks, and as non-banks (all other financial lenders): insurance agents, mutual funds, hedge funds, private equity and other. The indicator is equal to 1 if at least one of the lead arrangers is a nonbank, and 0 otherwise.	Dealscan

Table A1: Variable definitions and data sources – *Continued*

Variable Name	Definition	Source
Relation loan	Following Bharath et al. (2011), relation loan equals 1 if the borrower had received a loan of at least one of the lead banks over the previous five-year window.	Dealscan
Borrower characteristics:		
Industry type	Two-digit primary Standard Industrial Classifications (SIC) code.	DealScan
ROA	Net income (loss) to total assets (%).	Compustat/ Orbis Global
Leverage	Total liabilities to total equity (%).	idem
Total Assets	Natural logarithm of total assets in USD.	idem
Listed	Dummy equal to 1 if the borrower is publicly listed.	idem
Lender characteristics:		
ROA	Net income (loss) to total assets (%).	Compustat/ BankFocus
Capital Ratio	Tier 1 capital to RWAs.	idem
Total Assets	Natural logarithm of total assets in USD.	idem

A Proofs

A.1 Proof of Lemma 1

We can rewrite the profit function as

$$\pi_F(e) = -p((q + (1-q)e)\beta_L + (1-\tilde{q})(1-e)\beta_H) - c_F(e)$$

where $\tilde{q}(e)$ is the realized exposure after exerting effort e. The first-order condition is:

$$\frac{\partial \pi_F}{\partial e} = p(1-q)(\beta_H - \beta_L) - \frac{\partial c_F}{\partial e} = 0$$

which implies that the optimal effort is implicitly defined through

$$\frac{\partial c_F}{\partial e} = p(1-q)(\beta_H - \beta_L)$$

Convexity of c_F is sufficient to guarantee that the optimal effort $e^\star$ is increasing in p. Formally,

$$\frac{\partial e}{\partial p} = \left(\frac{\partial c_F}{\partial e}^{-1}\right)' \cdot (1-q)(\beta_H - \beta_L)$$

which is positive if and only if the second derivative of c_F is positive (i.e. convexity). □

A.2 Proof of Proposition 1

A firm located at $\gamma \in [0,1]$ would choose bank G when offered r_h (resp. r_l) by bank G while r_B by bank B if the following conditions are respectively satisfied. The two conditions define two threshold firms who are just indifferent between the two banks given the choice r_h (resp. r_l), which we denote by $\{\underline{\gamma}, \overline{\gamma}\}$.

$$r_h + \gamma\tau \leq r_B + (1-\gamma)\tau \qquad \Rightarrow \qquad \underline{\gamma} = \frac{\tau + r_B - r_h}{2\tau}$$
$$r_l + \gamma\tau \leq r_B + (1-\gamma)\tau \qquad \Rightarrow \qquad \overline{\gamma} = \frac{\tau + r_B - r_l}{2\tau}$$

This means firms with $\gamma < \underline{\gamma}$ choose bank G irrespective of the price, while firms with $\gamma > \overline{\gamma}$ choose Bank B irrespective of the price. For simplicity we always maintain as an assumption that τ is sufficiently high so that $0 < \underline{\gamma} < \overline{\gamma} < 1$. The choice of firms $\gamma \in (\underline{\gamma}, \overline{\gamma})$ is indeterminate and depends on the (random) signal realization. To simplify notation, let $Pr[l\,|L] := x_l$ and $Pr[h|H] := x_h$ denote the probability that a firm of low (high) exposure is correctly revealed by the signal.

The profits of bank G and B are:

$$\pi^G = \left[\tilde{q}(r_l - c_L) + (1-\tilde{q})(r_h - c_H)\right]\underline{\gamma} + \left(\tilde{q}x_l(r_l - c_L) + (1-\tilde{q})(1-x_h)(r_l - c_H)\right)\left(\overline{\gamma} - \underline{\gamma}\right)$$
$$\pi^B = \left[r_B - qc_L - (1-q)c_H\right](1-\overline{\gamma}) + \left[q(1-x_l)(r_B - c_L) + (1-q)x_h(r_B - c_H)\right]\left(\overline{\gamma} - \underline{\gamma}\right)$$

Notice that

$$qx_l + (1-q)(1-x_h) = q \qquad \text{and} \qquad q(1-x_l) + (1-q)x_h = 1-q$$
$$\left(\tilde{q}x_l(r_l - c_L) + (1-\tilde{q})(1-x_h)(r_l - c_H)\right) = q\left[(r_l - c_H) + x_l(c_H - c_L)\right]$$

With this simplification, the first-order conditions are:

$$\frac{\partial \pi^G}{\partial r_l} = \frac{q}{2\tau}\left((\tau + r_b - r_h) + (r_h - r_l) - ((r_l - c_H) + x_l(c_H - c_L))\right) = 0$$
$$\frac{\partial \pi^G}{\partial r_h} = (1-q)\underline{\gamma} - \frac{1}{2\tau}\left[\tilde{q}(r_l - c_L) + (1-\tilde{q})(r_h - c_H)\right] - \frac{1}{2\tau}\left(q\left[(r_l - c_H) + x_l(c_H - c_L)\right]\right) = 0$$

and, for the B-bank:

$$\frac{\partial \pi^B}{\partial r_b} = (1-\overline{\gamma}) - \frac{1}{2\tau}\left(r_b - qc_L - (1-q)c_H\right) + \frac{r_h - r_l}{2\tau}(1-q) = 0$$
$$\therefore \frac{1}{2\tau}\left(\tau - r_b + r_l - r_b + qc_L + (1-q)c_H + (1-q)(r_h - r_l)\right) = 0$$

The best-response functions are respectively:

$$r_l = \frac{1}{2}\left(\tau + r_b + c_H(1-q)(1-x) + c_L(q + x - qx)\right)$$
$$r_h = \frac{1}{2}\left(\tau + r_b + c_H - qc_H(1-x) + qc_L(1-x)\right)$$
$$r_b = \frac{1}{2}\left(\tau + \overline{c} + (1-q)r_h + qr_l\right)$$

Notice that $qr_l + (1-q)r_h = \frac{1}{2}\left(\tau + r_b + qc_L + (1-q)c_H\right)$. Substituting this to $r_b(r_l, r_h)$ gives

$$r_b = \frac{1}{2}\left(\frac{3}{2}\tau + \frac{3}{2}\overline{c} + \frac{1}{2}r_b\right)$$

which implies the equilibrium price for the B-bank:

$$r_b^\star = \tau + \overline{c} \tag{A1}$$

where $\overline{c}$ is the (weighted) average cost. This can be substituted back to $r_l(\cdot)$ and $r_h(\cdot)$.

$$r_l^\star = \tau + \overline{c} - \frac{1}{2}x(1-q)(c_H - c_L)$$
$$r_h^\star = \tau + \overline{c} + \frac{1}{2}xq(c_H - c_L)$$

It is immediate that

$$r_h^\star - r_l^\star = \frac{x}{2}(c_H - c_L)$$

Substituting back to the profit functions we obtain:

$$\pi_G^\star = \frac{\tau}{2} + \frac{(1-q)qx^2(c_H - c_L)^2}{8\tau} \tag{A2}$$
$$\pi_B^\star = \frac{\tau}{2} - \frac{(1-q)qx^2(c_H - c_L)^2}{4\tau} \tag{A3}$$

The profit of bank G in the Proposition follows by including the fixed cost of screening technology. □

A.3 Proof of Proposition 2

It is obvious from the green bank's profit $\pi_G^\star$ that the bank applies the screening technology if and only if

$$\frac{q(1-q)x^2[\Delta c]^2}{8\tau} > F \tag{A4}$$

where $\Delta c = c(\beta_H, p) - c(\beta_L, p)$. Parameters q and x depend on e, which depends on p. The term Δc depends directly on p.

$$\frac{\partial \pi_G}{\partial e} = \frac{\partial \pi_G}{\partial x}\frac{\partial x}{\partial e}\frac{\partial e}{\partial p} + \frac{\partial \pi_G}{\partial \Delta c}\frac{\partial \Delta c}{\partial e}\frac{\partial e}{\partial p} + \frac{\partial \pi_G}{\partial \tilde{q}}\frac{\partial \tilde{q}}{\partial e}\frac{\partial e}{\partial p} \tag{A5}$$

All partial derivatives in the equation are positive either by definition or following straightforward algebra from (A2), except the term $\frac{\partial \pi_G}{\partial \tilde{q}}$ which is positive for $\tilde{q} < 1/2$ only. With straightforward algebra and recalling that $\tilde{q} = q + (1-q)e$ by definition, we can bring this to a more compact form:

$$\Delta c \frac{\partial e}{\partial p}\left[1 - 2\tilde{q} + 2\tilde{q}\frac{\partial x}{\partial e}\right] + 2\tilde{q}\frac{\partial \Delta c}{\partial p} > 0$$

which is a necessary and sufficient condition for profit increasing in p.

We know that before exerting effort in the population $q < 1/2$, and by construction for $p = 0$ the optimal effort is $e = 0$. For small p therefore the profit is increasing in p. Because of the assumption that at $p = 1$ the optimal effort choice is $e = 1$ and therefore $\tilde{q} = 1$ which brings down the profit to zero, so for large enough p the profit is decreasing. The derivative of extra profit changes sign only once, due to it's dependence on q which is quadratic. Due to continuity, there exists some $\underline{p}(F)$ and $\overline{p}(F)$ such that inequality A4 is satisfied.