When Green Meets Green[§]

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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 green banks indeed reward firms for being green in the form of cheaper loans—however, 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 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

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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 green banks indeed reward firms for being green in the form of cheaper loans but only after the ratification of the Paris Agreement. In particular, our estimation based on the period after the Paris Agreement shows that green consortia (i.e., consortia with only green lenders) offer a discount to green firms relative to brown firms of approximately 50-59 bps, whereas this is not significant in the pre-Paris Agreement period. This evidence indicates that the *green meets green* (GMG) effect is intimately linked to the changes brought forth by the Paris Agreement. We confirm this GMG-effect employing a difference-in-difference-in-differences regression model, and our identification strategy deals with concerns regarding omitted variables and endogenous matching, by the inclusion of different sets of fixed effects, and by employing several matching procedures and estimators, as well as an IV approach.

Why would the Paris Agreement have such a big indirect impact on lending terms, and why is this restricted to green banks only? Much of the difficulties in managing climate change-related risks are attributed to the uncertain and endogenous future policy shocks that eventually determine the transition path to a low-carbon economy (e.g., Batten et al., 2016; Campiglio et al., 2018). Shifts in public views lead to political pressure to strengthen environmental regulation, which could harm firms - and their lenders - that do not anticipate the possibility of such shocks. 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 policies.[1]

As the expectation of a regulatory shift, and in turn the level of transition risk increases, so does the environmental attitude of firms and banks, which changes equilibrium prices. We consider whether the resulting differential treatment between green and brown firms forms 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.

Although it is clear that the Paris Agreement has increased awareness, the mechanism how awareness transmits to the equilibrium price of credit is far from obvious. In order to illustrate the potential economic forces at play, we present a stylized theoretical model of credit market competition. A green bank has access to a superior, but costly screening technology.[2] 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 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 is generated in

[1] Various interventions, previously unprecedented, are now on the table. 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.

[2] 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, an aspect well captured by our empirical proxy which we discuss in detail in Section 2.

tandem 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, captured as an upward shift of the probability of a climate policy shock (e.g., stricter climate regulation which negatively affects firms' business model), enables price discrimination on the credit market by first inducing firms to attempt to address climate risk. The resulting observable actions increase the quality of public information and, in turn, the informativeness of the green bank's screening technology. From the green bank's perspective, more efficient screening, heightened perception of risk, and more heterogeneous population with respect to 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 in equilibrium.

We proxy for a firm's green awareness when it reports to the Carbon Disclosure Project (CDP) and for bank's green awareness when it is member of the United Nations' Environment Program Finance Initiative (UNEP FI).[3] We argue that our empirical proxies are the most suitable choices for a risk-based explanation. Costly commitment of banks to align their business model with climate objectives means that such banks are necessarily more equipped to understand - as well as to systematically reflect in their pricing decisions - borrowing firms' climate exposure. The link between climate awareness and costly investments in related technology, as a prerequisite of expertise, has also been recognized in the public discourse. For example, Euromoney, a magazine on financial markets, selected BNP Paribas, a member of UNEP FI, as winner of its "best bank for ESG data and technology 2021", and praises that "the French bank put data at the heart of its sustainable finance strategy and devoted substantial resources to developing its data collection and processing capabilities". Furthermore, there is evidence that such attitudes are not homogeneous in the banking sector: Bernad et al. (2022) report direct evidence for the

[3] More details on these proxies and initiatives in Section 2

heterogeneity in banks' revealed attitudes with regard to climate change, as well as a positive correlation between such attitudes and green performance. In addition, 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. These points provides external support to the use of UNEP FI membership as our proxy for green bank, and alleviate potential concerns of greenwashing.

It has also been recognized that to promote informed investment, disclosure of comparable and reliable climate-related data will be absolutely fundamental. Firms who are committed to disclose through CDP are likely to be more informed and in turn prepared to manage the realization of climate-related risks. While previous studies showed that environmental attitudes as proxied by environmental scores matter for lending decisions, we refrain from using such metrics as these are often inconsistent over time, across industries, and among different providers (Berg et al., 2019, 2021). As such, our employed metric for firm's greenness – which reflects a forward-looking measure of firm's management of the risks posed by the green transition – seems to be more adequate to steer clear of discretion in methodologies.

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 (2021) 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 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

[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).

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.

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

[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).

the UNEP FI database with DealScan. For the former merge, we are able to identify 1,246 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 94 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 16,500 non-financial companies.[9] In Table 1 we report the number of green and non-green firms by industry.

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. (2021).[10] Detailed definitions of all variables are provided in Table A1 in the Appendix. After obtaining borrower and lender controls, we are left with 10,071 loan facilities out of which 9,117 to non-financial firms. In our most restrictive specifications, including all control variables, approximately 1,973 facilities are granted to 594 green firms, 2,676 facilities are granted by green syndicates, resulting in 755 green-meets-green facilities. Figure 1 shows the distribution of green firms and green lenders by region. Figure 2 depicts our sample over time.

Figure 3 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.

[9] The summary statistics of this sample are reported in Table A2 in the Appendix.
[10] The generated database linking tables are available on request.

2.2 Summary Statistics

The summary statistics for our set of variables are provided in Table 2. 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 at the 1% level to deal with spurious outliers, falls within the range of 5 to 800 basis points with an average value of 238 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 1,973 loans are given to green firms and the mean AISD is 204 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 61% 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 331.69 bps.

Regarding the loan characteristics, we observe that loan facilities have at least 1 and a maximum of 54 lead arrangers, with an average of 2.84 lead banks. In fact, about 75% of the facilities have one single lead arranger. The table furthermore shows that 48% of the loans is classified as a relation loan, meaning 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 borrower controls, firm size is measured by the natural logarithm of total assets with a mean of 8.00, which is equivalent to 2,980M\$. 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 13.97, which is equivalent to 11,670B\$.

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. Thus, we estimate the following baseline regression:

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

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. $BGreen_{i,b,t}$ is the proxy for bank greenness, which measures the fraction of UNEP FI members among the lead arranger consortium at the time of the granting of the loan.[11] The interaction term $FGreen_{i,t-1} \times BGreen_{i,b,t}$ captures the GMG effect—that is, a discount a green bank offers when lending to a green firm. The interpretation of the coefficients is as follows: relative to brown banks, a green bank provides a discount β_3 to green firms as opposed to brown firms (when negative); when borrowing from a green bank, a green firm enjoys a net 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 net 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 arranger participation as well as loan type, loan purpose, secured, covenant and relationship lending dummies.[12] The borrower and lender controls are one-year lagged. At the

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

[12] We control for non-bank lead arranger participation as Lim et al. (2014) show that facilities originated

borrower-level, we control for industry type measured by the two-digit Standard Industrial Classification (SIC), profitability, leverage, firm size, the interest coverage ratio and whether the firm is listed or not.[13] At the lender-level, we control for profitability, capital ratio, business model (proxied by the net interest income to operating revenues 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, $FE_{i,b,t}$ 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.[14]

Table 4 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. To be specific, the estimated coefficient on the interaction term $FGreen \times BGreen$ is negative, yet statistically insignificant.

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

by non-bank institutional investors have higher spreads than otherwise identical bank-only facilities.

[13] Rather than including credit ratings which are only available for listed companies, we proxy a firm's creditworthiness using the interest coverage ratio which is available for both private and public firms.

[14] 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.

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 5 reports the result of estimating equation (1) for the two sub-samples: before and after the Paris Agreement. The results provide first evidence of a novel GMG effect: relative to brown banks, a green bank rewards a green firm as compared to non-green firms with an average discount of 49-58 bps (β_3). Given an economic increase in BGreen equal to 0.33, the GMG effect ranges between a discount of 16-19 bps. In contrast, a green bank charges a non-green firm, on average, a higher loan rate of about 51 bps (β_2) relative to the same firm borrowing from brown banks. 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. However, across all specifications, the estimation results consistently reveal that the GMG effect ($\beta_3 < 0$) is only prevalent 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 green banks set different prices based on firms' greenness.[15]

[15] To alleviate concerns w.r.t. changes in sample composition, we show in unreported regression results that our main findings based on the post-Paris period are robust to keeping the sample of borrowers constant to pre-Paris borrowers only. This suggests that our GMG-effect does not pick up compositional differences.

In fact, our analysis suggests that the magnitude of the GMG more than doubles 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 net discount green firms obtain when borrowing from green rather than brown banks—the sum of coefficients β_2 and β_3— is about 14 bps. It should be noted that a meaningful increase in BGreen equivalent to one standard deviation, which is equal to 0.33, translates to loan spreads that are, on average, 4.62 bps lower. These results are economically significant given that the mean all-in-spread-drawn is about 238 bps.

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, as 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 interaction of the following form:

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

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 6 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 ($FGreen \times BGreen \times Paris$).[16] The economic magnitudes are similar to the ones already discussed above. These correlations may be given a causal interpretation under the assumption that firm or bank unobservables do not correlate with our green proxies once fixed effects are included. Even if this assumption is not binding, our results present novel evidence for the importance of environmental attitudes in the pricing of bank credit. We examine the robustness of our findings with respect to endogeneity concerns in Section 4 below.

Finally, in Table 7, we show that green banks positively influence borrowers' subsequent CDP-disclosing performance. Specifically, we study the impact of obtaining green credit – as measured by the percentage of loans obtained from full green lender consortia in the year before CDP participation – on CDP scores.[17] CDP score is coded as 0 for non-disclosure and 5 for CDP disclosure that got awarded the highest A-score. Given the ordinal nature of the outcome variable, our preferred estimation relies on an ordered logit regression that controls for firm characteristics and borrower fixed effects.[18] Yet, we show that the obtained results are similar to those obtained using an OLS regression estimation. Estimation is, furthermore, achieved based on 196 firms since only firms who have variation in their scores, who were ex-ante active in the syndicated loan market

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

[17] The CDP scoring methodology is not only based on the level of detail and comprehensiveness of the disclosed content, but also on the company's awareness of climate change issues, management methods and progress towards action taken to address these issues.

[18] The employed command is feologit: A new command for fitting fixed-effects ordered logit models. Available from https://ideas.repec.org/a/tsj/stataj/v20y2019i2p253-275.html.

and for whom we have all necessary control variables are informative, resulting in 683 observations. We find that being served by green banks is positively related to borrower's subsequent CDP score performance at the 1% significance level. This suggests that having borrowed to a greater extent from green lender consortia significantly increases the probability of ending up into a higher score group, everything else equal. More specifically, we observe that the marginal probability effects at the average are negative for low categories (equal or lower than D) and positive for higher categories (C, B, and A). Quantitatively, the marginal effects for the average firm indicate that, after being served more extensively by green banks, borrowers are more likely to fall into the C, B and A score category with 0.6% points, 12% points and 13.3% points, respectively. It follows that green lending practices can foster a borrower's green decision-making and improve a company's progress in environmental stewardship.

4 Robustness

In this section, we confirm the validity of our results by subjecting them to various methods that aim to further strengthen the identification of our GMG effect. Firstly, using a matching approach, we document that our results are robust to accounting for covariates that potentially predict obtaining a green-meets-green loan. We secondly perform a sensitivity analysis to assess whether unobservable omitted variables spuriously drive our results. Thirdly, a control function approach is performed to deal with a potential selection bias which could arise due to CDP's survey design. An instrumental variable estimation is furthermore conducted to take into account potential endogenous matching between firms and lenders. 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 Matching Estimator

In this subsection, we examine the robustness of our results using a matching estimation approach. 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. Although we control for the *average* effect of these confounding covariates in the OLS regression model, we recognize that our point estimates might nevertheless be biased in case there is insufficient overlap among green and brown subjects (Heckman et al., 1998; Dehejia and Wahba, 1999). Table 3 shows that the mean difference between green and brown subjects are statistically significantly different. The average size of green borrowers and green lenders, for instance, is substantially larger than that of their respective brown control units, suggesting limited overlap on this dimension.

We address this issue using a matching estimator approach. In particular, we pair up green-meets-green loans with a sub-sample of matched controls that are extracted from the population of non green-meets-green loans (#57,360). To be precise, we employ the most restrictive definition of "green loan" and consider those issued by 100% green lender consortia to green firms (GMG, #359) as treated. Following the state-of-the-art in the matching estimator literature, we conduct our tests using both the multivariate-distance (MD) and the propensity score (PS) matching estimators with the bias-correction approach introduced by Abadie and Imbens (2011).[19] We select control units by first matching exactly on loan origination year, one-digit industry classification and borrower country. This means that we stratify our population into borrower industry-country-year

[19] 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.

groups. Within each stratum, we secondly require that the control units feature similar pre-treatment characteristics (i.e., similar firm and lender characteristics: size, profitability, leverage, credit worthiness and listing status) as well as similar loan characteristics (i.e., relation loan, loan amount, maturity and collateral) for which a significant lack in overlap was reported. Using a kernel epanechnikov weighting algorithm which uses a weighted average of all counterfactual loans with a distance or score smaller than the automatically determined bandwith and with larger weights given to controls with closer distances/scores, we impose common support. Abadie and Imbens (2011) bias-correction then removes any remaining imbalances between the continuous covariates from the estimates. Treated loans for which no control unit meets all these criteria are excluded from the analysis. This procedure allows us to compute the mean AISD difference between green-meets-green loans and other loans which are matched on each and all of the aforementioned covariates. Lastly, to examine how the green-meets-green effect changed after the ratification of the Paris Accord, the mean difference is computed separately for those loans granted before the Paris Climate Accord, and those after.

Evidence on the efficacy of the matching procedure in correcting for mean differences in observable covariates is provided in Figure 4. In particular, the figure shows the normalized mean difference for each covariate before and after constructing a matched sample in a MD- and PS-fashion. We observe that matching, either on the estimated propensity score or on the full set of covariates, successfully improves the balance. Whereas borrower size differed by 1.5 times a standard deviation (sd) in the raw sample, the normalized difference are less than 1 sd in the matched sample. Although for most covariates the normalized difference is reduced to one fourth of a sd, the remaining differences in borrower size and lender profitability displayed in Figure 4a are not negligible. We deal with this issue by additionally stratifying loans on borrower size and lender roa categories.[20] This

[20] Borrower size groups are defined as quartiles, and lender roa groups are based on a median split. We thus create strata for borrower size-industry-year-lender profitability and match controls within

gives us a second matching set allowing us to investigate the robustness of our results. Figure 4b provides evidence for the success of eliminating the remaining imbalances in borrower size and lender profitability. In particular, this matched sample is sufficiently well-balanced to maintain unconfoundedness as the normalized differences remain within the recommended threshold of one quarter (Imbens and Wooldridge, 2009). We secondly alleviate a potential identification concern regarding important omitted pair-level determinants in Figure 4c. One might be worried that our results are affected by established syndicated pricing determinants, such as the closeness of the lender and borrower (Giannetti and Yafeh, 2011; De Haas and Van Horen, 2012), and bank's specialisation (Giannetti and Saidi, 2019; De Jonghe et al., 2020), which might also affect treatment. To minimize the influence of these potential confounding factors, the log distance, bank's relative market share and sector specialization are added to the set of covariates.[21] While a higher market share is suggestive for more market power which might positively affect loan spreads, a high degree of specialization has been associated with lower monitoring costs and thus lower loan spreads (De Jonghe et al., 2020). As before, we enforce successful balancing by matching exactly on domestic loans with distance equal to zero, and bank's specialization categories (i.e., weak, medium, and strong sector specialization). The normalized mean differences are reported in Figure 4c.

The results for the different matched samples are reported, respectively, in Panel A, B and C of Table 8, and are broadly similar to previous findings. Across the matched samples, we find that spreads on green-meets-green loans are significantly lower in the

a stratum, after which the matching procedure is done on the full set of covariates. By dividing the stratum into finer strata, we ensure that treated and comparison units are close on the stratified dimension.

[21] Distance is calculated as the (average) geographical distance between the borrower's and lender's capital city using the great-circle distance formula. Following De Jonghe et al. (2020) bank's market share is computed as the total credit granted by a bank to a given sector relative to the total credit granted by all banks to the same sector over the previous 5 years. Bank specialization is defined as the total credit granted by a bank to a given sector relative to the bank's total credit granted over the previous 5 years. In case of multiple lenders, the highest value is taken.

post-Paris Accord period while the difference is either positive or insignificant before the acceptance of the Paris Accord.[22] Zooming in on Panel C, we observe that the estimated green-meets-green effect ranges between 43 and 47 bps.

4.2 Oster-test for Omitted Variable Bias

A caveat of the matching procedure conducted in the previous subsection is that we are limited to matching on observables. One remaining concern could be that *FGreen* x *BGreen* is spuriously correlated with important unobservable omitted variables. To test whether the estimated GMG effect suffers from selection on unobservables, we perform the coefficient stability test proposed by Oster (2019) which builds on the idea of Altonji et al. (2005).[23] The test assesses omitted variable bias by using information from coefficient movements and the change in R^2, before and after adjusting for observed confounding factors. Oster (2019) proposes two alternative approaches for implementation.[24] The bounding approach estimates an identified set of the true treatment effect $[\tilde{\beta}_{controlled}$, $\beta^*(R_{max}, \delta)]$ given a proportional degree of selection on unobservables relative to observables. As an alternative approach, one can estimate the coefficient of proportionality, δ, which provides an indication of how large the impact of unobservables would be necessary, relative to observables, to nullify the treatment effect.

Our goal is to assess whether unobservable omitted variables spuriously drive our estimates in our controlled specification, i.e., columns 2 in Table 5. Performing the first approach, we are able to bound the influence of omitted variables on the GMG effect

[22] In columns (1) - (3) of Panel A, the ATT should be interpreted with caution as large imbalances between borrower size and lender profitability remain present, for which the Abadie and Imbens (2011) procedure performs a bias-correction. Panel B improves upon these imbalances.

[23] Although our estimated coefficients remain robust to the inclusion of borrowerxtime and lenderxtime fixed effects as shown in Table 5, this test allows us to assess the extent to which any kind of unobserved heterogeneity would affect our β_3 coefficient.

[24] We perform the tests using the Stata program "psacalc": Stata module to calculate treatment effects and relative degree of selection under proportional selection of observables and unobservables. Available from `https://ideas.repec.org/c/boc/bocode/s457677.html`.

assuming that selection on unobservables is as strong as the selection on observable firm and lender characteristics.[25] Formally, we can calculate an approximation of the bias-adjusted treatment effect with:

$$\beta^* \approx \tilde{\beta} - \delta(\mathring{\beta} - \tilde{\beta})\frac{R_{max} - \tilde{R}}{\tilde{R} - \mathring{R}}$$

where δ captures the degree of proportionality of selection on observables relative to selection on unobservables; $\tilde{R}$ and $\mathring{R}$ denote the R^2 of the baseline (controlled) model and the simple parsimonious regression model, respectively;[26] and R_{max} denotes the highest possible value of the R^2, which we set to 0.9 for realism. Following Oster (2019), we compute the bound where the selection on unobservables is of equal importance as the selection on observables, i.e., we set δ to 1. The computed identified sets for column 2 is [-318.067; -49.702]. The identified set safely excludes zero, and hence rejects that the GMG effect is driven by omitted variables. Moreover, the identified set suggests that our estimated treatment effect is likely an upper bound of the true effect.

We further examine the sensitivity to omitted variable bias using the coefficient of proportionality approach which calculates the amount of selection bias necessary to invalidate the result. The test describes that selection on unobservables must be 54% as powerful as selection on ex-ante firm and lender characteristics in order to negate the estimated coefficients. This reveals that it is quite unlikely that unobserved omitted variables spuriously drive our estimates, and that our point estimates might be conservative.

[25] In our set of confounders, we consider the ex-ante borrower and lender characteristics: industry fixed effects, borrower country fixed effects, relation loan, borrower size, profitability, leverage, interest coverage ratio and listing status, lender size, profitability, capital ratio and net interest income to operating revenues.

[26] Our parsimonious regression model includes loan controls.

4.3 Control Function Approach: Selection into CDP

If the decision of firms to participate in CDP is nonrandom, FGreen might be endogenous and the estimated coefficients would be inconsistent. The two-stage residual inclusion (2SRI) estimator or control function approach corrects for this potential endogeneity by firstly capturing the variation in CDP participation that is not explained by observables and an instrumental variable, and including it as a control variable in the second stage loan pricing regression by means of correcting for the potential selection bias (Wooldridge, 2015):[27,28]

$$\begin{aligned} P(FGreen_{i,t} = 1|PeerPressure_{i,t-1}, Y_{i,t-1}) = \\ \Phi(\alpha + \beta_1 PeerPressure_{i,t-1} + \gamma' Y_{i,t-1}) \end{aligned} \tag{3}$$

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

Equation (3) describes the first stage probit model where next to previously defined firm characteristics, denoted by $Y_{i,t-1}$, an additional instrumental variable is included, namely a measure for a borrower's industry peer pressure. In particular, *Peer Pressure* represents the percentage of disclosing firms relative to the number of total firms in the borrower's industry group in the year before CDP participation. We expect that firms are more likely to report to CDP if they reside in industries with higher industry peer pressure. Lastly, equation (4) is equivalent to our baseline regression in equation (1), except for the inclusion of the generalized residuals ($GR_{i,t-1}$) which captures the

[27] Ioannidou et al. (2022), amongst others, apply a similar approach.

[28] An alternative to this approach is a 2SLS estimator. However, since our potentially endogenous variable appears both on its own and interacted with an exogenous variable (BGreen), the 2SLS would treat the interaction as a separate endogenous variable which "*can be quite inefficient relative to the more parsimonious control function approach*" (Wooldridge, 2015). This motivates the control function approach.

potential endogeneity of selection into CDP and is obtained from the first stage model.

The 2SRI model is run on the full period and on sub-samples before and after the Paris Agreement, and the results are reported in Table 9. The negative $\hat{\lambda}$, which appears to be significant at the 5% level in the post-Paris sub-sample, indicates that unobservables that decrease credit spreads tend to occur with unobservables that raise CDP membership. However, comparing Panel A of Table 9 with the regression output displayed in Table 5, 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 between green firms and brown firms of about 48-58 bps relative to the same difference at brown banks. This suggests that our prior conclusions remain qualitatively and quantitatively unchanged after controlling for selection bias into to CDP survey.

Panel B reports the result of the first stage model and reveals that increased exogenous pressure exerted by a firm's 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, creditworthy, 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.

4.4 IV Estimation: Endogenous Firm-Bank Matching

Another potential concern may be that our identification of green-meets-green after the Paris Agreement 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 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 (1) and (2) of Table 10 show that the instruments have a strong first stage. Columns (3) and (4) 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.[29] After including several different types of fixed effects, we find that the GMG effect survives this analysis and amounts to approximately 119 bps (β_3) in relative terms. It further follows that green firms enjoy an average net discount of 36 bps when borrowing from a green rather than a brown syndicate (i.e., $\beta_2 + \beta_3$).[30]

[29] 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.

[30] 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.

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 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 11 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. We are unable to produce similar results on our three-way interaction term employing fake Paris Accord ratification dates, providing 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. 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.

We now introduce and solve the model, and discuss implications of our 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.[31]

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 carbon transition risk: 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).

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

Firms can exert an effort $e \in [0,1]$ at 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. 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 "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.[32]

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.[33] 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:

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

where the function $x(e) \in [0,1]$ parameterizes the informativeness of the signal. We

[32] 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.

[33] 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.

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 5.

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 $p(\beta_H - \beta_L)$.*[34]

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:*

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

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

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

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

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

The no-discrimination benchmark is 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.[35]

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

[35] 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.

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 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 6, 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.[36] In particular, when carbon transition risk

[36] 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

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 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.[37] 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, GMG pricing could be 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

population more heterogeneous and price discrimination less profitable for banks.

[37] 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.

loan rates to firms exhibiting (or not) environmental consciousness.

Employing data on syndicated loans over the period 2011-2019, we find that firms showing environmental consciousness (i.e., green firms) enjoy more favorable terms of about 50-59bps 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 banking-competition model to show 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 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 relying 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.

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Tables

Table 1

CDP respondents by sector.

SIC	Industry Classification - Description	N Green Firm	%	N Brown Firm	%
1	Agricultural Production - Crops	0	0.00	22	0.26
2	Agricultural Production - Livestock and Animal Specialties	0	0.00	8	0.09
7	Agricultural Services	1	0.15	24	0.28
8	Forestry	1	0.15	5	0.06
9	Fishing, Hunting and Trapping	0	0.00	2	0.02
10	Metal Mining	21	3.05	88	1.02
12	Coal Mining	2	0.29	39	0.45
13	Oil and Gas Extraction	43	6.25	496	5.75
14	Mining and Quarrying of Nonmetallic Minerals, Except Fuels	2	0.29	38	0.44
15	Construction - General Contractors & Operative Builders	5	0.73	123	1.43
16	Heamy Construction, Except Building Construction, Contractor	7	1.02	109	1.26
17	Construction - Special Trade Contractors	0	0.00	44	0.51
20	Food and Kindred Products	36	5.23	255	2.96
21	Tobacco Products	3	0.44	6	0.07
22	Textile Mill Products	1	0.15	47	0.55
23	Apparel, Finished Products from Fabrics & Similar Materials	4	0.58	66	0.77
24	Lumber and Wood Products, Except Furniture	0	0.00	30	0.35
25	Furniture and Fixtures	6	0.87	28	0.32
26	Paper and Allied Products	13	1.89	102	1.18
27	Printing, Publishing and Allied Industries	4	0.58	99	1.15
28	Chemicals and Allied Products	51	7.41	406	4.71
29	Petroleum Refining and Related Industries	7	1.02	54	0.63
30	Rubber and Miscellaneous Plastic Products	6	0.87	109	1.26
31	Leather and Leather Products	2	0.29	23	0.27
32	Stone, Clay, Glass, and Concrete Products	7	1.02	72	0.84
33	Primary Metal Industries	11	1.60	190	2.20
34	Fabricated Metal Products	8	1.16	140	1.62
35	Industrial and Commercial Machinery and Computer Equipment	27	3.92	284	3.29
36	Electronic & Other Electrical Equipment & Components	56	8.14	326	3.78
37	Transportation Equipment	24	3.49	245	2.84
38	Measuring, Photographic, Medical, & Optical Goods, & Clocks	19	2.76	174	2.02
39	Miscellaneous Manufacturing Industries	3	0.44	76	0.88
40	Railroad Transportation	4	0.58	23	0.27
41	Local & Suburban Transit & Interurban Highway Transportation	0	0.00	25	0.29
42	Motor Freight Transportation	4	0.58	84	0.97
44	Water Transportation	3	0.44	165	1.91
45	Transportation by Air	10	1.45	78	0.90
46	Pipelines, Except Natural Gas	1	0.15	56	0.65
47	Transportation Services	6	0.87	84	0.97
48	Communications	36	5.23	303	3.52
49	Electric, Gas and Sanitary Services	73	10.61	687	7.97
50	Wholesale Trade - Durable Goods	12	1.74	333	3.86
51	Wholesale Trade - Nondurable Goods	12	1.74	235	2.73
52	Building Materials, Hardware, Garden Supplies & Mobile Homes	3	0.44	12	0.14
53	General Merchandise Stores	7	1.02	57	0.66
54	Food Stores	11	1.60	60	0.70
55	Automotive Dealers and Gasoline Service Stations	0	0.00	50	0.58
56	Apparel and Accessory Stores	5	0.73	71	0.82
57	Home Furniture, Furnishings and Equipment Stores	2	0.29	32	0.37
58	Eating and Drinking Places	6	0.87	120	1.39
59	Miscellaneous Retail	18	2.62	169	1.96
70	Hotels, Rooming Houses, Camps, and Other Lodging Places	14	2.03	127	1.47
72	Personal Services	2	0.29	37	0.43
73	Business Services	51	7.41	981	11.38
75	Automotive Repair, Services and Parking	6	0.87	52	0.60
76	Miscellaneous Repair Services	1	0.15	22	0.26
78	Motion Pictures	4	0.58	44	0.51
79	Amusement and Recreation Services	1	0.15	132	1.53
80	Health Services	5	0.73	390	4.52
81	Legal Services	0	0.00	5	0.06
82	Educational Services	0	0.00	69	0.80
83	Social Services	0	0.00	31	0.36
84	Museums, Art Galleries and Botanical and Zoological Gardens	0	0.00	1	0.01
86	Membership Organizations	0	0.00	9	0.10
87	Engineering, Accounting, Research, and Management Services	15	2.18	296	3.43
89	Services, Not Elsewhere Classified	6	0.87	48	0.56
99	Nonclassifiable Establishments	0	0.00	2	0.02
	Total:	688	100.00	8620	100.00

Table 2

Summary Statistics.

	Min	Max	Mean	Std.Dev.	Obs
Loan characteristics:					
All-in-Spread-Drawn (AISD)	5.00	800.00	237.78	142.71	9,117
AISD $\mid FGreen = 1$			204.26	145.44	1,973
AISD $\mid BGreen = 1$			331.69	162.47	1,028
Log Loan Amount	7.97	24.51	19.45	1.79	9,117
Maturity (months)	1.00	432.00	59.03	21.75	9,117
Concentration (N leads)	1.00	54.00	2.84	4.76	9,117
Secured	0.00	1.00	0.71	0.46	9,117
Covenant	0.00	1.00	0.53	0.50	9,117
Nonbank	0.00	1.00	0.01	0.10	9,117
Relation loan	0.00	1.00	0.48	0.50	9,117
$BGreen \neq 0$	0.05	1.00	0.61	0.33	2,677
Borrower characteristics:					
Log Total Assets	0.01	14.74	8.00	1.82	9,117
Leverage	0.12	103.31	3.85	8.64	9,117
ROA	-18.63	22.47	3.04	6.60	9,117
Interest Coverage Ratio	-99.20	233.00	14.71	35.76	9,117
Listed	0.00	1.00	0.52	0.50	9,117
Lender characteristics:					
(Avg) Total Assets	6.26	14.86	13.97	1.03	9,117
(Avg) Capital ratio	9.06	25.80	15.67	1.83	9,117
(Avg) ROA	-0.66	3.48	0.63	0.44	9,117
(Avg) NII/OR	4.67	90.48	46.60	9.12	9,117

Table 3

Difference-in-Means Test.

	Green		Brown		
	Mean	Std.Dev.	Mean	Std.Dev.	Δ
Panel A: Borrower characteristics (firm-year observations)					
Log Total Assets	9.65	1.49	7.52	1.55	-2.14***
ROA	4.21	6.54	2.93	6.89	-1.28***
Leverage	3.09	5.37	3.57	8.77	0.47**
Interest Coverage Ratio	14.20	27.27	16.88	40.43	2.68***
Listed	0.67	0.47	0.53	0.50	-0.14***
Observations	1,122		4,073		5,195
Panel B: Loan characteristics by borrower type (facility-level data)					
AISD	204.26	145.44	247.03	140.56	42.78***
Log Loan Amount	20.22	1.66	19.23	1.77	-0.98***
Maturity	55.59	23.60	59.98	21.11	4.39***
Secured	0.48	0.50	0.77	0.42	0.29***
Covenant	0.43	0.50	0.55	0.50	0.13***
Concentration (N leads)	4.60	7.06	2.35	3.75	-2.25***
Nonbank	0.01	0.11	0.01	0.10	-0.00
Relation loan	0.50	0.50	0.47	0.50	-0.04***
Credit line	0.57	0.50	0.54	0.50	-0.03***
Term loan	0.38	0.48	0.43	0.50	0.05***
Observations	1,973		7,144		9,117
Panel C: Lender characteristics (bank-year observations)					
Log Total Assets	13.45	1.14	12.24	2.04	-1.21***
ROA	0.54	0.52	0.62	0.59	0.09
Capital Ratio	15.29	2.64	15.63	3.44	0.34
NII/OR	50.98	14.96	53.08	17.09	2.10
Observations	79		595		674
Panel D: Loan characteristics by lender type (lead arranger-level data)					
AISD	244.63	167.88	200.90	135.84	-43.73***
Log Loan Amount	20.22	1.58	19.47	2.20	-0.75***
Maturity	60.92	27.42	58.06	24.37	-2.86***
Secured	0.61	0.49	0.62	0.49	0.01
Covenant	0.16	0.37	0.40	0.49	0.23***
Concentration (N leads)	11.97	10.98	8.59	10.32	-3.38***
Nonbank	0.00	0.00	0.01	0.09	0.01***
Relation loan	0.61	0.49	0.56	0.50	-0.05***
Credit line	0.48	0.50	0.57	0.50	0.09***
Term loan	0.46	0.50	0.39	0.49	-0.07***
Observations	5,018		13,593		18,611

Table 4

Green-Meets-Green and Loan Spreads: 2011-2019.

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 $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t}$ 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, $\text{BGreen}_{i,b,t}$ 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	5.196		1.659	
	(4.407)		(3.763)	
BGreen	40.346***	49.244***	16.730*	58.914***
	(6.919)	(13.188)	(9.816)	(9.871)
FGreen x BGreen	-17.878	-35.885	-9.829	-17.274
	(12.018)	(29.346)	(9.260)	(23.382)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	No	Yes	No
Lender characteristics	Yes	Yes	No	No
Year fixed effects	Yes	No	No	No
Borrower country fixed effects	Yes	No	Yes	No
Borrower x time fixed effects	No	Yes	No	Yes
Lender x time fixed effects	No	No	Yes	Yes
Adj. R^2	.565	.736	.674	.879
Observations	9,117	17,012	26,906	68,305
Mean AISD	237.777	330.384	220.612	291.281
SD. AISD	142.712	172.031	152.448	171.232
Mean BGreen	.180	.259	.239	.247
SD. BGreen	.331	.378	.254	.265

Table 5

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 $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t}$ 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, whereas $\text{BGreen}_{i,b,t}$ 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	1.420	11.798*			-9.852	8.092		
	(5.705)	(6.398)			(8.359)	(7.159)		
BGreen	40.096***	35.991***	62.045***	11.951	18.169*	30.656***	68.698***	51.218***
	(7.939)	(12.410)	(17.232)	(19.603)	(10.273)	(11.863)	(13.250)	(14.187)
FGreen x BGreen	5.031	-50.045***	3.339	-70.915*	19.464	-61.611***	8.912	-58.086**
	(18.081)	(14.188)	(37.027)	(37.419)	(19.259)	(18.069)	(31.607)	(26.984)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	No	No	Yes	Yes	No	No
Lender characteristics	Yes	Yes	Yes	Yes	No	No	No	No
Year fixed effects	Yes	Yes	No	No	No	No	No	No
Borrower country fixed effects	Yes	Yes	No	No	Yes	Yes	No	No
Borrower x time fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Lender x time fixed effects	No	No	No	No	Yes	Yes	Yes	Yes
Adj. R^2	.586	.563	.732	.742	.695	.699	.892	.860
Observations	5,524	3,584	9,606	7,394	17,076	9,797	39,827	28,443
Mean AISD	245.714	225.626	339.722	318.269	223.109	216.270	289.780	293.407
SD. AISD	146.264	136.289	171.194	172.392	155.940	146.118	170.865	171.757
Mean BGreen	.179	.181	.263	.254	.250	.221	.253	.239
SD. BGreen	.327	.338	.378	.378	.249	.262	.258	.274

Table 6

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 $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t} \times \text{Paris}_t$, 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. $\text{BGreen}_{i,b,t}$ 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. Please note that we also control for all other individual and pairwise interaction terms that are not absorbed by the fixed effects, but exclude them from the table for brevity. 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 x BGreen	6.999	-6.898	11.603	8.210
	(17.262)	(38.812)	(13.331)	(23.868)
FGreen x BGreen x Paris	-52.909**	-72.862	-57.575***	-66.072*
	(22.160)	(55.649)	(16.007)	(36.077)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	No	Yes	No
Lender characteristics	Yes	Yes	No	No
Year fixed effects	Yes	No	No	No
Borrower country fixed effects	Yes	No	Yes	No
Borrower x time fixed effects	No	Yes	No	Yes
Lender x time fixed effects	No	No	Yes	Yes
Adj. R^2	.567	.733	.675	.880
Observations	9,117	16,921	26,906	68,128
Mean AISD	237.777	329.740	220.612	290.945
SD. AISD	142.712	171.703	152.448	171.075
Mean BGreen	.180	.258	.239	.247
SD. BGreen	.331	.377	.254	.264

Table 7

Green Banks and CDP Scoring Improvement

This table reports the results of estimating an OLS regression and an Ordered Logit regression. The dependent variable is CDP Score$_{i,t}$ of company i in year t which equals 0 for non-disclosure and 5 for CDP disclosure with an A-score. The main variable of interest is Green Credit$_{i,t-1}$ which reflects the percentage of loans obtained from full green lenders consortia in the year before CDP participation. In parentheses, we report the standard errors which are clustered at the firm level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	CDP Score	
	OLS Regression	*Ordered Logit*
	(1)	(2)
Panel A: Coefficients		
Green Credit$_{t-1}$ (%)	.744**	1.073***
	(.338)	(.416)
Log Total Assets	.278	.412
	(.244)	(.442)
ROA	.007	.015
	(.014)	(.024)
Leverage	.006	.007
	(.013)	(.018)
Interest Coverage Ratio	.002	.003
	(.005)	(.011)
Borrower fixed effects	Yes	Yes
Observations	683	683
Adj./Pseudo R^2	.469	0.019
No. Firms	196	196
SD. Green Credit$_{t-1}$	.269	.269
Panel B: Marginal Effect at the Average		
No CDP respondent		-.155***
		(.060)
Respondent w/o score		-.054***
		(.021)
D score		-.0486***
		(.019)
C score		.006***
		(.002)
B score		.120***
		(.046)
A score		.133***
		(.052)

Table 8

Green-Meets-Green, Loan Spreads: Matching Estimator.

For sub-samples before and after the Paris Agreement, this table reports the average difference in AISD between "green-meets-green" loans and matched non-GMG loans computed using a multivariate-distance (MD) matching estimator as well as a propensity-score (PS) matching estimator. The MD-estimator matches on the Mahalanobis metric, which is based on the inverse of the full covariance matrix of the covariates. The PS-estimator matches on the estimated propensity-score of being a green-meets-green loan conditional on a set of covariates using a logit model. The employed covariates include ex-ante borrower and lender characteristics as well as loan amount, maturity and collateral. The borrower characteristics include firm size, profitability, leverage, interest coverage ratio, listed status, and a relation loan indicator. The lender characteristics include size and profitability. Exact matching is performed on year, borrower industry and country. In Panel B & C, we relax the exact country match otherwise insufficient treated units are matched. Control units are selected using kernel epanechnikov weighting 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 scores. Remaining imbalances are accounted for using the Abadie and Imbens (2011) bias-correction. The balancing statistics are reported in Figure 4. ΔAISD denotes the average treatment effect on the treated (ATT). The reported standard errors are computed by bootstrapping with 50 replications. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	Multivariate-distance		Propensity-score	
	(1) Before Paris	(2) After Paris	(3) Before Paris	(4) After Paris
Panel A: Matched across loan, firm & bank characteristics				
Δ AISD	37.015*	-6.241	32.182*	-27.372**
	(21.005)	(11.763)	(19.210)	(10.983)
N treated	121	94	114	87
N control	2,920	2,096	3,089	1,394
Panel B: Additionally matched on size and roa groups				
Δ AISD	57.720***	-21.230*	67.769***	-28.476**
	(17.275)	(11.756)	(17.674)	(13.919)
N treated	126	101	118	94
N control	1,101	747	1,266	660
Panel C: Additionally matched on pair-level determinants				
Δ AISD	28.278	-43.557**	27.755	-46.725**
	(18.986)	(19.109)	(23.571)	(21.654)
N treated	107	77	101	74
N control	333	312	335	316

Table 9

Green-Meets-Green and Loan Spreads: Control Function Approach.

This table reports the results of estimating a control function model using a 2SRI procedure. The two-step procedure is executed using 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 first stage 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 generalized residuals and reflects the covariance between the residuals of the regression and first stage 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: Second Stage Regression Equation (*dep. var: All-in-Spread-Drawn*)						
FGreen	28.263	19.260	66.257**	83.366**	68.608	70.369**
	(18.035)	(21.692)	(31.573)	(32.995)	(52.608)	(32.570)
BGreen	40.275***	40.014***	35.739***	21.419*	37.197**	29.509**
	(7.192)	(8.016)	(12.559)	(11.652)	(17.012)	(12.521)
FGreen × BGreen	-17.484	5.103	-48.107***	-9.911	-21.857	-58.218***
	(12.770)	(16.484)	(14.881)	(17.950)	(32.568)	(19.286)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Lender characteristics	Yes	Yes	Yes	No	No	No
Year fixed effects	Yes	Yes	Yes	No	No	No
Borrower country fixed effects	Yes	Yes	Yes	No	No	No
Borrower fixed effects	No	No	No	Yes	Yes	Yes
Lender x time fixed effects	No	No	No	Yes	Yes	Yes
Panel B: First Stage Probit Model (*dep. var: FGreen*)						
Peer Pressure	.021***	.017***	.025***	.037***	.034**	.046***
	(.005)	(.006)	(.008)	(.010)	(.014)	(.015)
Log Total Assets	.517***	.527***	.505***	.456***	.430***	.543***
	(.033)	(.042)	(.044)	(.043)	(.059)	(.064)
ROA	.012*	.019**	.005	-.000	.010	-.015
	(.006)	(.008)	(.008)	(.010)	(.014)	(.011)
Leverage	-.009*	-.011*	-.006	-.011*	-.012	-.012
	(.005)	(.007)	(.007)	(.006)	(.009)	(.011)
Interest Coverage Ratio	.002**	.001	.003**	.004***	.004**	.005**
	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)
Listed	.222***	.243**	.183	.337***	.405***	.208
	(.082)	(.095)	(.113)	(.122)	(.150)	(.182)
Panel C: Statistics						
$\hat{\lambda}$	-14.068	-10.916	-32.867*	-34.307*	-25.650	-38.274**
	(9.957)	(11.906)	(18.367)	(17.795)	(28.425)	(19.136)
Adj. R^2	.5651	.5858	.5638	.8550	.8802	.7002
Observations	9,117	5,524	3,584	26,380	16,522	9,797

Table 10

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) *BGreen*	(2) *FGreen x BGreen*	(3) *AISD*	(4) *AISD*
L.BGreen	.156***	-.013***		
	(.011)	(.003)		
FGreen		.112***	19.156***	25.463***
		(.008)	(6.579)	(7.367)
FGreen x L.BGreen		.283***		
		(.014)		
BGreen			82.568***	78.962
			(29.009)	(68.378)
FGreen x BGreen			-119.071***	-140.580***
			(24.670)	(31.163)
Loan characteristics	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	Yes	Yes	Yes
Lender characteristics	Yes	Yes	Yes	No
Year fixed effects	Yes	Yes	Yes	No
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	.4950	.6835	.2030	.1002
Observations	7,160	7,160	7,160	9,797

Table 11

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 $\text{FGreen}_{i,t-1} \times \text{BGreen}_{i,b,t} \times \text{Paris}_t$, 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. $\text{BGreen}_{i,b,t}$ 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	.931		-8.313		3.058		-12.762	
	(8.797)		(12.732)		(7.601)		(10.525)	
BGreen	53.705***	96.686***	24.667	65.019**	42.167***	52.287**	18.341	54.836***
	(12.483)	(31.565)	(16.410)	(28.912)	(9.200)	(20.955)	(12.108)	(17.407)
FGreen x BGreen	-4.796	44.735	-1.101	98.817	20.207	36.751	31.248	42.774
	(27.817)	(88.174)	(31.538)	(96.217)	(21.396)	(65.176)	(26.135)	(55.534)
FGreen x Paris	1.856		.786		-2.980		9.869	
	(9.616)		(12.872)		(9.073)		(11.989)	
BGreen x Paris	-21.794	-47.744	-10.928	.503	-6.376	19.200	-1.733	22.185
	(14.166)	(34.400)	(19.384)	(32.061)	(13.148)	(29.052)	(19.139)	(24.686)
FGreen x BGreen x Paris	18.561	-42.076	30.468	-105.099	-24.123	-58.532	-23.907	-55.377
	(34.301)	(97.861)	(35.788)	(101.143)	(27.851)	(76.469)	(34.165)	(63.408)
Loan characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower characteristics	Yes	No	Yes	No	Yes	No	Yes	No
Lender characteristics	Yes	Yes	No	No	Yes	Yes	No	No
Year fixed effects	Yes	No	No	No	Yes	No	No	No
Borrower country fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
Borrower x time fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Lender x time fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Adj. R^2	.5869	.7308	.6943	.8924	.5868	.7306	.6941	.8924
Observations	5,584	9,624	17,260	40,105	5,584	9,624	17,260	40,105

Figures

Figure 1: Green Firms and Green Banks by Region

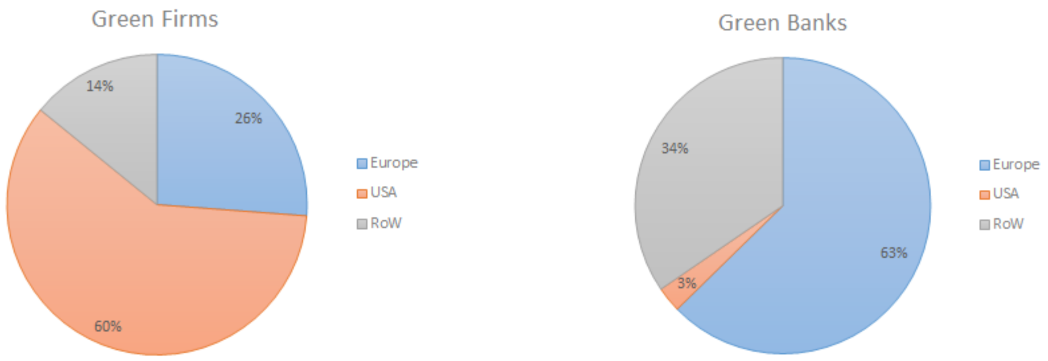
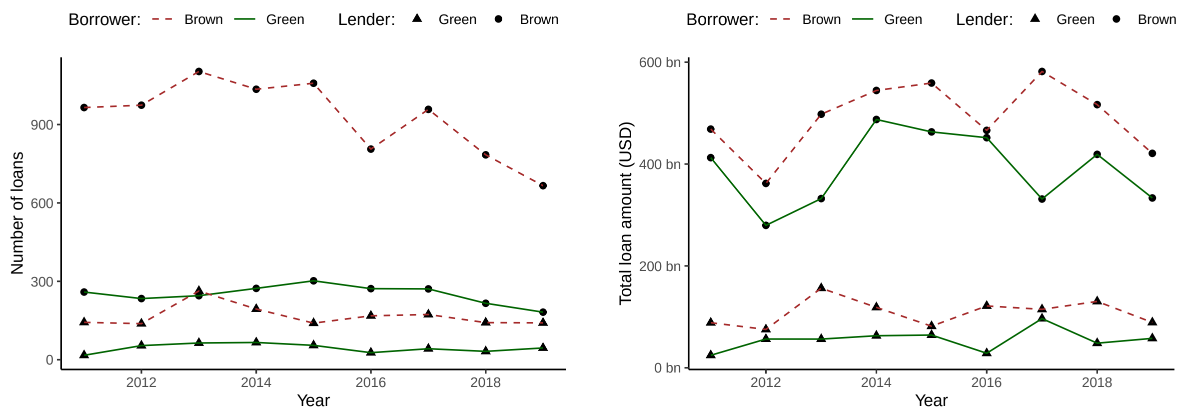


Figure 2: Loans to green firms by green banks over time.



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

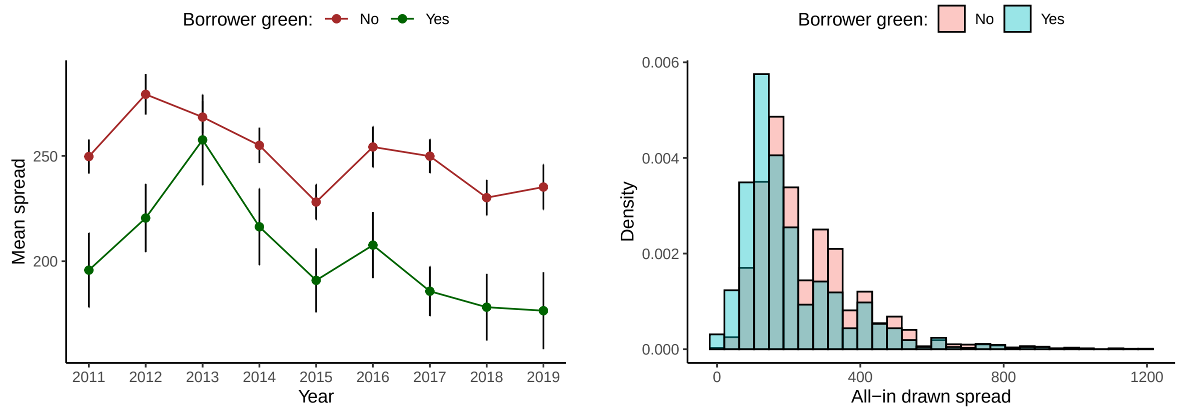
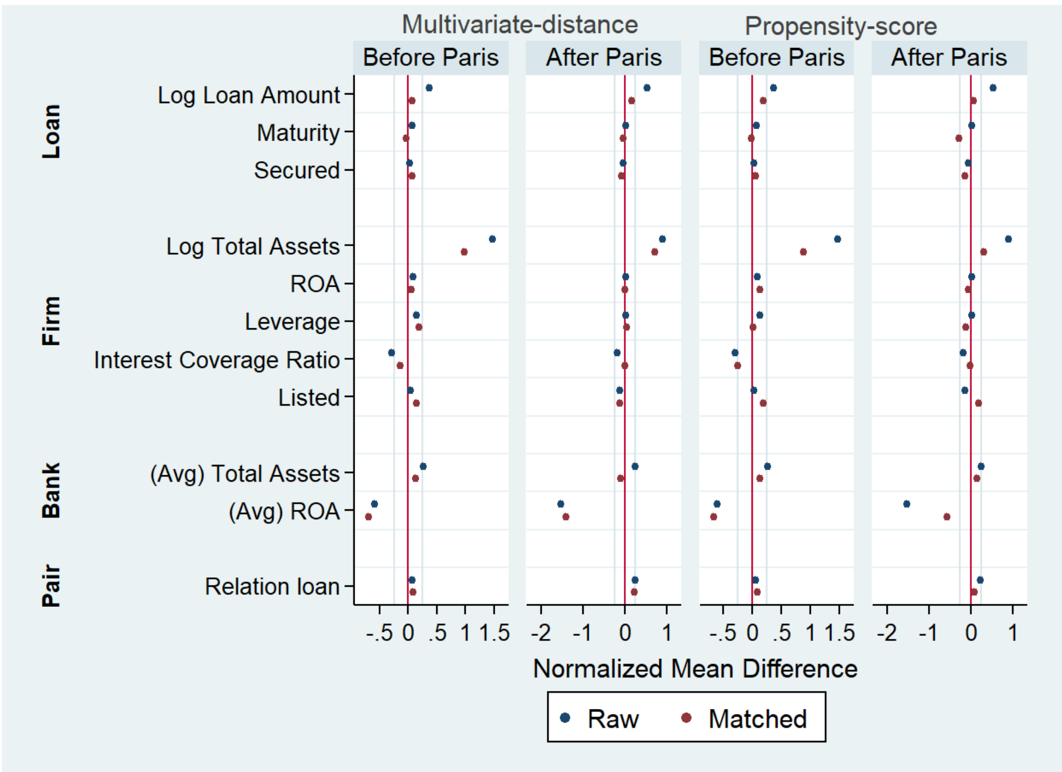
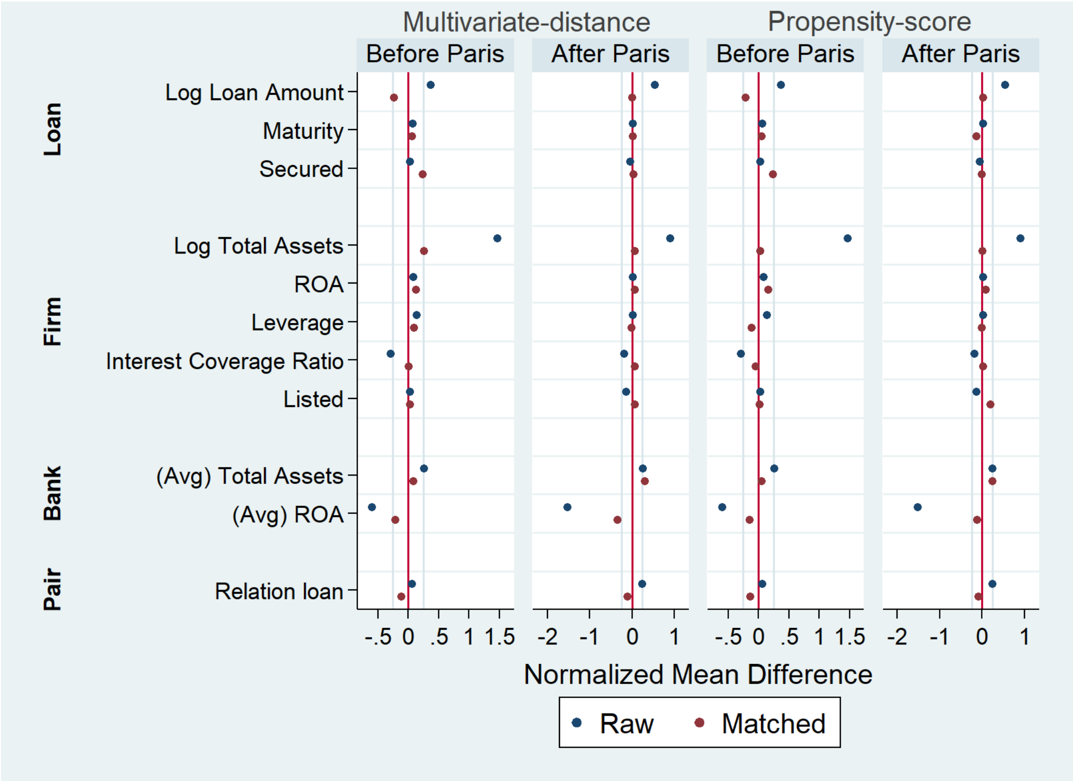


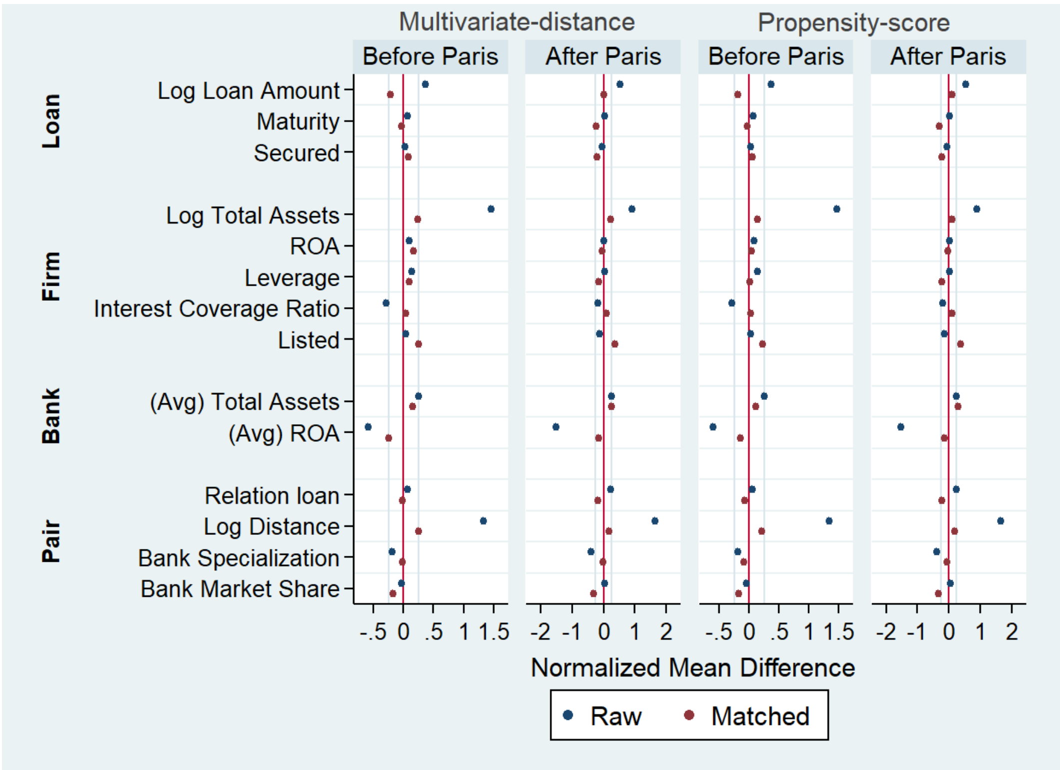
Figure 4: Balancing Statistics of the Matching Estimators.



(a) Matched across loan, firm and bank characteristics



(b) Additionally matched on size and roa groups.



(c) Additionally matched on pair-level determinants

Figure 5: The Timing of the Model

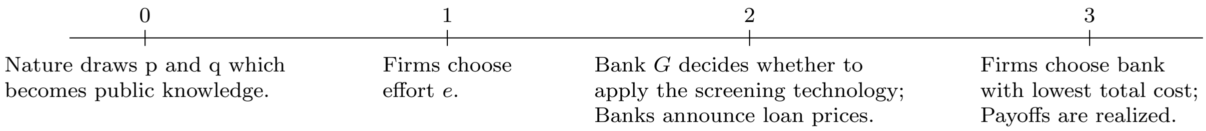
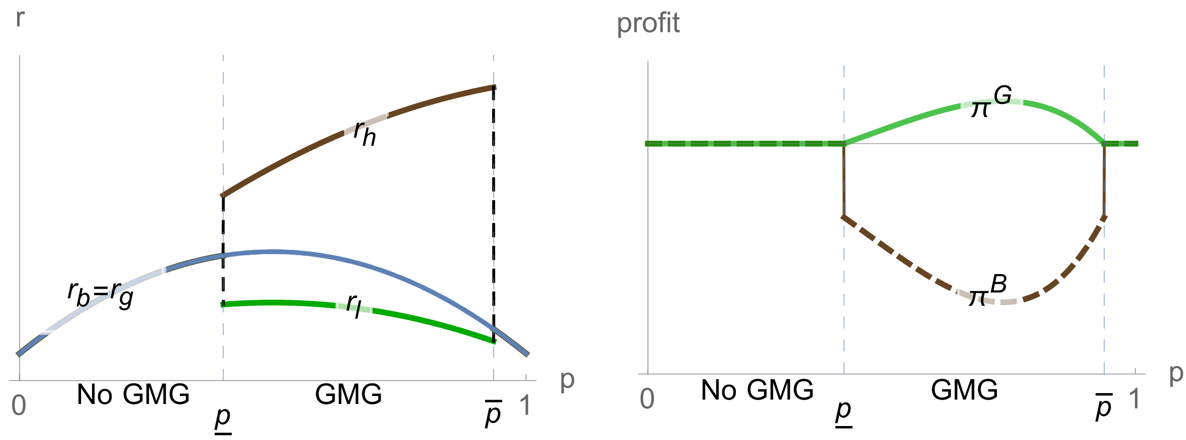


Figure 6: Equilibrium illustration



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).

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 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
Interest Coverage	Interest coverage ratio.	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
Net Interest Income	Net interest income to operating revenues	idem

Table A2: **Summary Statistics: Complete DealScan Sample.**

	Min	Max	Mean	Std.Dev.	Obs
Loan characteristics:					
All-in-Spread-Drawn (AISD)	1.00	800.00	293.07	171.42	71,362
AISD | $FGreen = 1$			179.76	131.33	5,219
AISD | $BGreen = 1$			381.46	178.91	6,527
Log Loan Amount	2.88	24.69	18.41	2.00	71,358
Maturity	1.00	725.00	57.61	29.87	70,620
Concentration (N leads)	1.00	54.00	2.60	4.27	71,362
Secured	0.00	1.00	0.85	0.35	38,285
Covenant indicator	0.00	1.00	0.19	0.39	71,362
Nonbank indicator	0.00	1.00	0.08	0.28	71,362
Relation loan	0.00	1.00	0.34	0.47	71,362
$BGreen \neq 0$	0.02	1.00	0.59	0.34	17,468
Borrower characteristics:					
Log Total Assets	0.00	14.74	7.80	2.13	25,031
Leverage	0.12	103.31	4.02	9.82	21,493
ROA	-18.63	22.47	3.22	6.58	24,740
Interest Coverage Ratio	-99.20	233.00	14.45	34.57	21,347
Listed	0.00	1.00	0.23	0.42	70,761
Lender characteristics:					
(Avg) Total Assets	2.08	15.21	13.50	1.35	63,364
(Avg) Capital ratio	7.80	86.67	15.64	2.15	62,307
(Avg) ROA	-0.66	9.58	0.72	0.59	63,023
(Avg) NII/OR	4.67	90.48	49.45	11.09	57,625

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 $\{\underline{\gamma}, \overline{\gamma}\}$.

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

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:

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

Notice that

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

With this simplification, the first-order conditions are:

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

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

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

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:

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

Bank G's profit then follows from including the fixed cost of screening technology. □

A.3 Proof of Proposition 2

From the green bank's profit $\pi_G^\star$, it follows 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 for $p = 0$ the optimal effort is $e = 0$. For small p therefore the profit is increasing in p. Since 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.