Corporate ESG Profiles and Banking Relationships*

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Abstract

In recent years, banks have faced increased internal and external pressure to be more accountable to their customers and to make more socially-responsible lending decisions. Recognizing these pressures, this paper examines if and when banking relationships act as a transmission mechanism for promoting corporate Environmental, Social and Governance (ESG) policies. We show that banks are more likely to grant loans to borrowers with similar ESG profiles, and positively influence the evolution of borrowers' ESG performance over time. Consistent with the theory of creditor control, this influence is more pronounced 1) when banks have relatively better ESG ratings than their borrowers, and 2) when borrowers are bank-dependent. As a disciplinary mechanism, we show that borrowers are more likely to experience costly disruptions in existing lending relationships following negative news coverage on their ESG-related issues. We exploit M&A in the banking industry as a quasi-exogenous shock to the lender's ESG standard to establish causality. Overall, our results suggest that banks have become an effective conduit promoting socially responsible activities among borrowers.

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1. Introduction

Beyond meeting their financial objectives, firms often strive to integrate a wide variety of Environmental, Social and Governance (ESG) goals into their business models (Bénabou and Tirole (2010), Hart and Zingales (2017)). Coincident with these efforts, they have faced growing internal and external pressures to improve performance along various non-financial dimensions including environmental impacts, social welfare, and fair labor practices. While these forces apply to a wide range of firms, banks in recent years have particularly faced increased pressure to be more accountable to their customers and to make more socially-responsible lending decisions. For example, in April 2019, a group promoting gun control released a well-publicized report card ranking banks on their ties to firearm manufacturers and organizations such as the National Rifle Association (NRA).[1] In another recent example, the head of Wells Fargo stepped down shortly after receiving intense criticism during Congressional hearings. This criticism stemmed primarily from the bank's well-documented fake accounts scandal, but Congressional leaders also heavily criticized the bank for making loans to firms operating private prisons and energy pipelines.[2] Despite the heightened interests in the social economic impact of bank lending practise, there is far from a consensus on whether banks could effectively discipline and shape borrowers' ESG activities.[3] Our study presents the first empirical evidence on the interplay between responsible lending and borrower ESG behavior, and informs policy makers regarding the efficacy and real ESG outcomes of bank lending regulation.

In this paper, we propose a novel economic mechanism to explain the propagation of ESG policies through lending relationships. We broadly examine the evolution of borrower ESG profiles for both public and private firms. While there is considerable evidence that bankers may affect their borrowers' policies and investments (Shleifer and Vishny (1997), Chava and Roberts (2008),

[1]See details of the news coverage at www.nytimes.com/2019/04/04/business/gun-control-banks.html

[2]See details of the news coverage at www.nytimes.com/2019/03/28/business/wells-fargo-timothy-sloan.html

[3]The literature on the causes and effects of firm ESG policies is long-standing. Earlier studies have largely focused on the determinants motivating cross-sectional differences in observed levels of ESG ratings, as well as the wealth effects of these policies, with a particular emphasis on the positive impact provided by institutional investors (Starks et al. (2017), Cao et al. (2019), He et al. (2018), Dimson et al. (2015), among others). Given this focus, most studies have concentrated on public firms. Nevertheless, data from RepRisk, a Zurich-based data science company that scans negative ESG news incidents, shows that the number of private firms involved in ESG incidents was six times higher than that of public firms between 2007 and 2018. In fact, the majority of firms that pose ESG risks to society are small, private firms that receive minimal level of public scrutiny from the equity market. In light of these facts, the roles played by critical stakeholders in shaping corporate ESG practice remain under-explored.

Nini et al. (2012)), it remains an open question whether lenders use this leverage to specifically influence borrower ESG policies. One view is that lenders focus primarily on their borrowers' financial performance, and consequently resist costly investments that chiefly benefit other non-bank stakeholders. Friedman (1970) argues that the only responsibility of a firm is to increase its profit. Brammer and Millington (2008) presents evidence consistent with the view that high social responsibility performers score the lowest in short term financial performance.

However, beyond this narrow view, lenders also have many compelling reasons to encourage their borrowers to be socially responsible. There are two mutually non-exclusive channels. The first channel emphasizes the financial exposures of the bank's relationship-specific investments in the existing loans. One obvious reason is that borrowers with high ESG-related risks are more likely to face financial consequences from these policies, which ultimately increase default risk and could theoretically subject the bank to lender liability risk. Consistent with this *financial channel*, some recent research has shown that promoting engagements in ESG issues can reduce firms' downside risk (Hoepner et al. (2018)), and has documented an association between measures of ESG ratings and loan pricing (Chava (2014), Goss and Roberts (2011), Hasan et al. (2017) ,Hauptmann (2017)).

In addition to these direct effects, there is a *reputation channel* which links the borrower ESG issues to the bank's ability to engage future business. In this channel, lending to low ESG borrowers increases the bank's costs dealing with regulatory scrutiny, tarnishes its reputation, and ultimately decreases its opportunity to engage future business. Given that banks are heavily regulated and are often the focus of public condemnation (as highlighted above), they have a strong incentive to reduce negative reputational incidents (both their own and that of their borrowers). For example, after the high school mass shooting in Parkland, Florida that claimed 17 deaths and 17 injures, Bank of America announced that it would stop lending money to gun manufacturers that choose to continue the production of military-inspired firearms for civilian use. Note that the bank's decision is unlikely based on considerations of the default and lender liability risks, given the lucrative nature and liquidity of its clients.[4] The event is hardly an isolated occurrence. Citibank and Wells Fargo have withdrawn their lending to oil firms that are involved in mountaintop removal, a legal and lucrative method of extracting oil but very harmful to environment. This anecdotal evidence collectively demonstrates the importance of expanding the focus beyond default and liability risks

[4] See New York Times, https://www.nytimes.com/2018/04/10/business/bank-of-america-guns.html

when attempting to understand the drivers of banks' lending decisions.[5]

In our analysis, we conduct three broad sets of tests that are designed to explore the extent to which lenders serve as important conduits influencing firm ESG policies. First, we consider whether lenders select borrowers based on their observed ESG profiles, and relatedly whether banks' own ESG standards affect the type of borrowers it works with. Second, we examine whether lenders systematically influence borrower ESG performance over time. Third, we investigate whether borrowers experience disruptions in existing lending relationships following a significant negative shock to their reputation. In each of our tests, we use the RepRisk database to obtain the negative news coverage and ESG ratings of both borrowers and lenders. The database is best suited for our study because its coverage on a wide range of both public and *private* borrowers, and its *outcome-driven* approach. The coverage on private firms is critical when we explore the corporate loan market, where the majority of borrowers are private firms which receive minimal level of scrutiny from the equity market. Also, RepRisk focuses on actual reported ESG related events, which incurred real costs. By contrast, other databases primarily assign ESG ratings based on whether the firm "claim" to enact certain policies that are more discretionary and subject to green-washing bias.[6] Notably, the rating system incorporates not just the number of incidents, but also the severity, reach and novelty of the events to evaluate the firm's reputation exposure to ESG and business conduct risks.

In our first set of results, we show that lenders tend to match with borrowers that have similar ESG profiles. Specifically, we find that a standard deviation decrease in the observed difference between the lender and borrower's RepRisk ratings translates into a 0.23% increase in the likelihood that the two will partner together.[7] This increase is both statistically and economically significant given that the unconditional likelihood of matching between a potential lender and borrower in our sample is only 3%. This finding is robust to the inclusion of a host of control variables including borrower's industry, lender, and year fixed effects, and measures of firm size (Stein (2002), Hubbard

[5]In one of our other projects on the same line of research, we examine how banks benefit from lower reputation risk exposures. We show that the level of bank reputation risk exposure is positively related to the risk-adjusted capital ratios, and cost of capital. See Appendix D and Houston, Shan and Tian (2019) for details.

[6]An increasing number of studies in ESG focus on the real outcomes, instead of discretionary disclosures which are often subject to Green-washing bias. For example, legal and litigation risks (Schiller (2018), and toxic and/or carbon emissions (Bartram et al. (2018), Shive and Forster (2019), Kim and Xu (2017), among others). In the same spirit, RepRisk focuses on real outcomes (externally reported ESG related incidents) which incorporate a broad range of ESG accidents that span across 28 issues. See WRDS RepRisk data manual for details.

[7]We construct both the adjusted and unadjusted difference between the borrower and lender's ESG ratings. Adjustments are made by subtracting the country-sector-month average from the raw ratings to account for comparability across industry, country and time. Our results are robust using both methods.

et al. (2002)), investment opportunities (Ongena and Smith (2001), Gopalan et al. (2011)), bank dependency (Sharpe (1990), Schwert (2018)), prior lending relationships (Bharath et al. (2007)), and debt overhang. Further, our sub-sample analysis on single-lead loans produce nearly identical results to those found in the broader sample. Altogether, our results show that lenders tend to associate with borrowers that share their attitudes regarding ESG-related policies, and/or have similar observed reputations related to ESG issues.

Next, we provide evidence that lenders also influence the evolution of their borrower's ESG profiles. Specifically, borrowers that have lenders with relatively better ESG standard are more likely to realize improved ESG ratings over time. Here we find that a one standard deviation increase in the difference between the borrower and lender(s)' ESG ratings is associated with a 0.70 increase in the borrower's RepRisk rating over a two year window centered on the loan initiation date, which is equivalent to 37% of the standard deviation of the change in ESG for all firms during the same two year window. These results confirm that banks can impact the borrowers' ESG performance in a significant and dynamic manner.

While the demonstrated associations appear to be economically significant and robust to a variety of specifications, establishing direct causation is notoriously challenging. The biggest identification concern relates to disentangling treatment from selection effects. While we believe that banks have a positive impact on the evolution of borrower's ESG performance (*treatment*), a reasonable alternative explanation is that borrowers who expect to improve their ESG standard choose to borrow money from ESG focused banks (*selection*). To alleviate concerns on the potential selection problem and other omitted variable bias, we follow the literature to exploit M&A in the banking industry as a quasi-exogenous shock to the lender's ESG standard (Asker and Ljungqvist (2010), Hong and Kacperczyk (2010), Chen et al. (2015)).[8] In a Diff-in-Diff setting, we examine if the exogenous variation transmits through the *established* lending relationship to affect the evolution of borrower's ESG ratings post the M&A. We apply a wide range of fixed effects on the lender, borrower, industry, and year levels to absorb the remaining unobservable time-invariant heterogeneities across lenders, borrowers and industries, and to preclude the effects of common time trends. In short, we set a high bar to refute conclusion that banks can effectively discipline

[8] We believe that the timing and the decision of bank M&A activities are arguably exogenous to the borrowers' firm-level unobservable characteristics that determine ESG ratings. As noted by prior studies, the bank merger waves were largely driven by regulatory, technological, and competitive changes (Pilloff (2004)).

borrowers' ESG activities.

We also construct a variety of conditional tests to further explore the specific channels in which banks may influence the borrower's ESG evolution. First, we find that lenders have a more profound influence if the borrower is bank dependent (as proxied by whether the firm is unrated, and the intensity of covenants). We also show that bank's influence critically hinges on secured loans where the transfer of control rights and liability exposures is triggered under a significant adverse shock. Second, we find that there is an important asymmetry – banks that have better ESG-related ratings relative to the borrower are more likely to induce borrowers to improve their ESG levels over time. On the other hand, lender's impact on borrower's ESG evolution is indistinguishable from zero if the lender's ESG rating is worse relative to that of the borrower. Finally, we disaggregate the overall ESG rating into its three sub-components (environmental (E), social (S) and governance (G)). Similar to findings in Dimson et al. (2015), we find that banks are more likely to induce their borrowers to improve along the environmental (E) and social (S) dimension. Their influence on their borrower's governance (G) appears to be negligible.

In a third set of results, we document a novel disciplinary mechanism. In the process of lending to a firm, a bank acquires proprietary firm-specific information that is unavailable to non-lenders (Schenone (2009)). Switching lenders is costly for borrowers and is often accompanied by reduction in the availability of credit (Petersen and Rajan (1994)). If the borrower continues to engage in risky ESG practices and are exposed to a greater number of negative news incidents, does it lead to interruptions in the existing lending relationship? We find that borrowers are significantly more likely to observe a shift in lead lender(s) following a negative shock to their ESG-related reputation. More specifically, conditional on obtaining new loan financing within the 12 months period after the end date of the original loan, we find that borrowers are 3-4% less likely to initiate a new loan with the same lead lender(s) if there was a negative ESG-related news incident. Furthermore, we find that these borrowers exposed to negative ESG related news are more likely to shift to lenders with worse RepRisk ratings. We control for both the level, and the change in the borrower's financials including ROA, assets, leverage, and Tobin's Q to make sure that the switch in lending relationship is not driven by fundamental changes in credit and liability risk. To alleviate concerns of omitted variable bias, we utilize *negative* news coverage initiated by *outsiders*, whose timing relative to the loan expiration date is arguably quasi-exogenous and out of the control of corporate insiders.

On balance, our findings clearly demonstrate that the banking system has an important systematic effect on corporate ESG policies. In this regard, we believe our findings make an important contribution to the growing literature on the role of key stakeholders in shaping corporate ESG policies (Shive and Forster (2019), Lins et al. (2017), Starks et al. (2017), Chava (2014), Dimson et al. (2015), Bartram et al. (2018)). Most notably, recent papers by Schiller (2018) and Dai et al. (2018) document that socially conscious customers have taken steps to induce their key suppliers to become more socially responsible. Given the importance of a sound evaluation of efficacy and real effects of responsible lending, it is surprising how little empirical work has been done on this front. Our work aims to fill this gap.

At the same time, our paper also contributes to the vast literature on banking relationships, by highlighting another important factor that influences the choice of lender and the role that lenders play in influencing firm performance and investment decisions (Shleifer and Vishny (1997), Chava and Roberts (2008), Nini et al. (2012), Schwert (2018), among others). In this vein, our work is related to the long standing theories of relationship lending (Sharpe (1990), Berger and Udell (1995), among others) and bank monitoring (Holmstrom and Tirole (1997), Diamond (1991), among others).

The rest of the paper is organized as follows. Section 2 summarizes the data employed in the various tests. Section 3 presents our main results. Section 4 describes sources of endogeneity and our identification strategy. Section 5 offers several robustness tests. Section 6 concludes.

2. Data

2.1. ESG Data

This study employs an event-based outcome measure of firm-level environmental, social, and governance (ESG) profile for both public and private firms using data from RepRisk. The RepRisk data provides a monthly unbroken time-series ESG rating, and coverage on negative ESG news incidents from January 2007 to June 2017.[9] A dedicated team of analysts leverage a combination

[9]Positive ESG events are *not* covered by RepRisk and reported less often in traditional or social media. Part of the reasons can be attributed to the fact that positive news are more likely to be self-reported for branding and marketing purposes, and are subject to greenwashing biases. To the best of our knowledge, we are not aware of the existence of any positive ESG news database. See Li and Wu (2017) for extended discussions on the collection of positive news.

of artificial intelligence and curated human analysis to track a universe of over 95,000 firms globally, among which 82,000 are private firms with no self-reported ESG compliance information. On a daily basis, over 80,000 public sources and stakeholders in 20 languages are screened. Once an incident is identified, analysts conduct additional analysis to (1) confirm that the incident is indeed ESG-related, (2) remove possible duplicate media coverage on the same incident to make sure each risk event only enters once into the RepRisk Platform, and (3) identify the specific nature of the incident, by mapping it to 28 ESG Issues and 45 ESG topics. Each incident is assigned three proprietary scores based on severity (harshness), reach (influence), and novelty (newness). Finally, the RepRisk Index (RRI hereafter) is updated, reflecting the impact of the news incident.

Compared with the widely used annual KLD database (now MSCI ESGSTATS), the RepRisk data is uniquely suited for our study for three reasons. First, the event-based data evaluates the outcome of ESG activities, which can be directly linked to the societal impact of ESG compliance. The KLD data instead relies on the firm's self-reported information which varies largely with the firm's discretionary disclosures related to ESG compliance. RepRisk arguably provides a more objective assessment of the societal impact of each firm over time, because it is more difficult for firms to endogenously manipulate media attention/negative news detection, than to manipulate self-disclosed policy adoptions. Second, the KLD data does not cover private firms, which are predominant in the corporate loan market. Third, RepRisk has unparalleled granularity. It employs a monthly, continuous ESG rating ranging from 0 to 100, while most of the KLD ratings are structured as an annual, indicator variable that equals 0 or 1.

2.2. Banking Data

We obtain loan pricing and contract information from Loan Pricing Corporation's (LPC) Dealscan database, for the sample period from 2007 to 2017. We focus on the loans granted to U.S.-incorporated firms. Dealscan provides characteristics information for each loan such as size, maturity, type, and purpose, as well as information about the outstanding financial covenants and other terms. We hand-match the Dealscan loan data to RepRisk ESG ratings using company names. We use S&P Capital IQ as well as Google search to track the historical names of each company to verify the accuracy of matches.

We study the evolution of borrower ESG ratings over time at the loan level. Specifically, we consider each loan as a relationship between a borrower and a lead lender that finances the loan. We follow the approach that Bharath et al. (2009) used to classify lead lenders for each loan. We classify a lender as lead lender if the "LeadArrangerCredit" field indicates "Yes" or if the "LenderRole" field indicates one of the following: administrative agent, agent, arranger, lead arranger, lead bank. For some loans in our sample we have multiple lead lenders in the syndicate. In these cases, we calculate the equally-weighted average of ESG ratings of lenders in the syndicate.[10]

2.3. M&A Data

From the SDC M&A database, we extract the set of completed merger and acquisitions in the financial industry from 2007 through 2017. The following filters are applied: 1) both the acquirer and the target have SIC codes between 6000 and 6999, 2) the acquirer owned less than 50% of the target bank's shares six months before the transaction and more than 50% of the shares after the transaction, and 3) we exclude deals with missing transaction values.

We then subsequently match the acquirer and the target's names to the lender's names in the Dealscan database. We view the merger as an exogenous shock to the ESG-related standards of the involved lender(s). This setup enables us to determine whether borrower ESG performance evolve differently if their lender(s) undergo an exogenous shift in their ESG standard. The magnitude of the shock depends on the relative size of the acquirer and target (see detailed discussion in section 2). Our final sample consists of 423 treated loans initiated from 2007 to 2017 where the borrower, lender, and acquirer (or target, if the lender is the acquirer) have non-missing RepRisk ESG ratings.

2.4. Financials

After constructing the sample of loans with corresponding deal characteristics as well as borrower and lender ESG ratings, we also incorporate a broad range of firm-level control variables from Compustat. Specifically, we collect the reference firms' financial information from Compustat, for the most recent fiscal year ending within one-year window prior to the loan start date (i.e., lagged). We use the Chava and Roberts (2008) linking file to link loans from Dealscan to firms in Compustat. We then supplement the firm controls with S&P credit ratings.

[10]Alternatively, as a robustness test, we select a unique lead lender for each loan following Ivashina and Kovner (2011). This procedure selects the lead lender that the firm has the strongest relationship by considering the past borrowing history. We present our findings under this alternative approach in the robustness section 5.2.

An important dimension of our study is that it includes both public and private firms. We classify a firm as a public if we we can find a stock price available from the Center for Research in Security Prices (CRSP) for the same fiscal year, and as a private firm otherwise. The list and detailed definitions of required firm- and loan-level variables are provided in Appendix A.

2.5. Summary Statistics

Table 1 presents the summary statistics for our sample of loans and the corresponding borrowers. In our sample, we have 12,495 loans, taken out by 2,407 borrowers and granted by 116 lenders from 2007 to 2017. The median borrower has an ESG rating of zero, which suggests that median firm has no publicly known issues (the lower the ESG rating, the better). The median lender on the other hand has an ESG rating of 17, which indicates that it has some known issues. These differences could be explained by two possible factors: (i) the median bank in our sample is larger than the median borrower, and larger firms are more likely to receive publicity; (ii) financial industry firms often receive more attention and greater scrutiny, especially during our sample period which corresponds to the financial crisis and post crisis periods. Overall, our interest is the relative standing of each borrower and lender within its own industry, as well as the difference in their ESG ratings.

[Insert Table 1 here]

To account for the size as well as credit risk of the borrower we include firm level controls. About 61% of the loans are granted to rated borrowers, and 29% of all loans are granted to investment grade firms. Similarly, we find that 62% of the loans are granted to public firms. These statistics suggest that a significant portion of our sample has limited access to public debt and equity markets.

An important dimension of our analysis is to test the conditions when the lender has stronger influence over the borrowers. Therefore, although we do not have the corresponding accounting information for about 40% of the loans in our sample, we still include these loans in our baseline tests to determine the importance of creditor control in shaping the ESG policies of bank-dependent borrowers. In addition to the existence of credit ratings and outside borrowing options, we use other proxies for the strength of lender control. In particular, we use the number of covenants as a proxy for the strength of lender control (Nini et al. (2012)).

[Insert Figure 1 here]

One of the empirical challenges in ESG studies is the comparability of scores and ratings across industries and years. In Figure 1, we calculate the mean level of RRI of all borrowers in our sample. Figure 1A documents a rising level of RRI over time, partly driven by an increasing number of ESG related news coverage in recent years. Figure 1B shows that the level of ESG exposures vary by industry. Borrowers in Utilities, Energy, and Chemicals on average have a higher level of RRI. We address this issue by subtracting the industry-country-month average RRI from the borrower's raw RRI to obtain the monthly adjusted RRI, which we use as the independent variable. We also include the time, and year fixed effects to mitigate similar concerns on the dependent side.[11]

3. Main Results

3.1. Matching

This section explores whether lenders are more likely to grant loans to borrowers with similar ESG profiles. Following Houston, Lee and Suntheim (2018) and Cai et al. (2012), we run a linear probability model with the adjusted and unadjusted pairwise similarity measure, $Close_{i,j,t-1}$ as the main right-hand-side (RHS) variable.

In constructing the possible lender-borrower pairs, we consider all the unique banks that act at least once as lead lender in year t, and all the unique borrowers that borrow at least once in year t. The match dummy for each possible lending relationship is constructed on the lender-borrower-year level. Borrowers and lenders that never participate in the corporate loan market in year t are not considered potential candidates for the pairing test. This reduces the heterogeneity in the demand and supply side of the loan market by focusing only on the borrowers (lenders) actively seeking (providing) loan financing in year t. The empirical analysis is based on the following Probit specification:

$$Pr(Match_{i,j,t} = 1) = \phi(\alpha + \beta Close_{i,j,t-1} + \gamma X_{i,t-1} + S_j + I_{ffindustry} + \delta_t + \xi_{i,j,t}) \tag{1}$$

In the Probit Model, $\phi(.)$ denotes the cumulative distribution function (CDF) of the standard normal distribution. $Match_{i,j,t}$ is a dummy variable that equals one if the lender j extends a loan

[11]In the robustness test section, we show that our baseline results are *not* quantitatively changed if we use the unadjusted RRI as independent variables.

to the borrower i in year t. $Close_{i,j,t-1}$ is the main explanatory variable that measures the lagged distance between the lender's, i, and the borrower's, j, yearly average RepRisk ratings in year t-1. $X_{i,t-1}$ is the vector of borrower's characteristics that we use as control variables. These variables include the prior lending relationship dummy (prior), size (log assets), book leverage, Tobin's Q, and the investment grade dummy. Note that some banks may lend more than other banks in the syndicated loan market. Likewise, borrowers from certain industries may be more favored by lenders. To address these issues, S_j, $I_{FFindustry}$ and δ_t respectively denote the dummies for lender, the Fama-French 12 industry categories, and year fixed effects. Finally, standard errors are clustered at the lender-borrower pair level.

[Insert Table 2 here]

The results are presented in Table 2 Panel A. In columns 1, 2 and 3, we use the unadjusted ESG difference measure as the independent variable; while in columns 4, 5 and 6, we adjust both the lender and the borrower's RRI with their country-industry-month means to account for heterogeneity across industries and time. Columns 1 and 4 use the whole sample, while columns 2 and 5 focus only on the sub sample of public borrowers whose financials are available. In Columns 3 and 6, we further exclude all borrowers whose RRI are clustered at zero. Some of the borrowers are never exposed to negative ESG-related news, and therefore maintain a consistently zero RRI. Arguably these firms may have other unobservable firm and industry level characteristics that explain their consistently zero ratings.

The key coefficients of interest in all columns are both statistically and economically significant. Take columns 2 and 4 for example, where the coefficient estimates of the ESG difference measure are significant at the 0.1% level. Using marginal effects estimated at the sample means, we show that a standard deviation decrease in the ESG difference is associated with a 0.34% (0.000188×18.05) increase in the likelihood of matching. A standard deviation decrease in the adjusted ESG difference is associated with a 0.23% (0.000144×16.21) increase in the likelihood of matching. The economic magnitudes are sizable given the unconditional likelihood of matching between a potential borrower and lender is only 3%.

In Panel B, we repeat the analysis in Panel A using the sample of single-lead loans only. This reduces the stacking of multiple matching pairs between the same borrower but different co-lead lenders, which inevitably reduces the standard errors of the coefficient estimates and inflate the Z statistics. We show our results are robust after removing multiple-lead loans.

3.2. Evolution of Borrower's ESG Performance

This section explores how corporate ESG policies propagate through lending relationships. We examine the direct impact of banks on the evolution of the borrowers' ESG performance using facility-level data. The empirical analysis is based on the following OLS specification:

$$\begin{aligned} ESG\_Chg_i = &\alpha + \beta ESG\_Diff_{i,j,t-1} + \lambda Lender\_Chg_j + \theta ESG\_Borrower_{i,t-1} \\ &+ \gamma X_{i,t-1} + I_{ffindustry} + \delta_t + \xi_{i,j,t} \end{aligned} \tag{2}$$

For each facility, the change in the borrower's ESG profile (ESG_Chg) is defined as the difference between the borrower's RRI over a two-year window, from one year before (t-1) to one year after the loan initiation date (t+1). The ex-ante difference between the lender and borrower's ESG ratings (ESG_Diff) is defined as the difference between the lender and borrower's RepRisk ESG rating measured one year before the loan initiation date. To alleviate potential concerns about the comparability of ESG scores across industries and years, both the lender and the borrower's RRI have been adjusted by the country-industry-month mean. Lender_Chg controls for the evolution in the lender's ESG rating over the same two-year window.

We realize that the evolution of the borrower's ESG rating is path-dependent. Borrowers with ex-ante *poor* ESG rating are more likely to improve over time, than borrowers with ex-ante *pristine* ESG rating. The control variable, ESG_Borrower, alleviates the concerns for the potential path-dependency problem and is defined as the borrower's RepRisk ESG rating one year before the loan initiation date. Other control variables include the log loan amount, country of syndication USA, the borrower's public status, and the number of covenants in the loan to control for the heterogeneity in size, regulatory environment, managerial myopia, and the credit risk, respectively. $I_{FFindustry}$ and δ_t denote the dummies for the Fama-French 12 industry and year fixed effects. We cluster the standard errors at the borrower level.

[Insert Table 3 here]

These results are presented in Table 3. In columns 1, 2 and 3, we run the regressions with only basic control variables related to the borrower and lender's ESG ratings; in column 4, we include the control variables that are available for both public and private borrowers including loan amount, country of syndication, public dummy, and number of covenants in the loan; in column 5, we further restrict our analysis to a sub-sample consisting of public firms with additional publicly available control variables including size (log assets), book leverage, return on assets (ROA), and Tobin's Q.

The key coefficient of interest, the difference between lender and borrower ESG ratings (i.e. ESG_Diff), is statistically significant at the 1% level in all five columns. The economic magnitude is also sizable. Take column 4 for example. A standard deviation increase in ESG_Diff is associated with a 0.70 (18.39 × 0.038) increase in the borrower's RRI over time, which is equivalent to 37% (0.70/1.89) of the standard deviation of ESG_chg in our sample.

3.3. Cross Sectional Variation in Bank Dependency

In Table 4, we focus on those cases where we expect the lender to have a particularly strong influence on its borrowers. We first consider whether bankers are more able to influence unrated borrowers. Unrated borrowers typically have less access to public financing, which arguably makes them more bank-dependent and more sensitive to holdup problems:

$$
\begin{aligned}
ESG\_Chg_i =& \alpha + \beta ESG\_Diff_{i,j,t-1} \times I_{dependency} + \varsigma ESG\_Diff_{i,j,t-1} + \tau I_{dependency} + \lambda Lender\_Chg_j \\
&+ \theta ESG\_Borrower_{i,t-1} + \gamma X_{i,t-1} + I_{ffindustry} + \delta_t + \xi_{i,j,t}
\end{aligned}
\tag{3}
$$

where $ESG\_Diff_{i,j,t-1} \times I_{dependency}$ is an interaction term between the lender and borrower ESG difference and our proxies for bank dependency. These proxies include indicators for credit rating, investment grade status, number of covenants, and secured loan status.

In column 1 of Table 4, we find that lenders have greater influence on borrowers' ESG policies if the borrower is unrated. We repeat this test with investment grade versus non-investment grade firms in column 2 of Table 4. We similarly find that lenders have greater influence over the non-investment grade borrowers' ESG policies.

[Insert Table 4 here]

We next explore other proxies of bank dependency. Nini et al. (2012) find that there is a significant change in the management of covenant-violating firms, which suggests that lenders exert their influence on firm decision-making and governance. In addition, Strahan (1999) shows that loans to riskier borrowers – smaller borrowers, borrowers with less cash, and borrowers that are harder to value by outside investors – are more likely to be secured by collateral. We therefore use the number of financial covenants on the loans, and the indicator for secured loans as proxies for the strength of creditors' control over the borrower.

Columns 3 and 4 of Table 4 present our results. We find that firms with financial covenants and firms with secured loans are more likely to be influenced by the lender in their ESG policies. Overall, our results suggest that the influence of lender on the borrower is greater if the borrower is bank dependent.

3.4. Asymmetric Bank Influence

While our baseline results demonstrate that the gap between the lender and borrower's ESG ratings is significantly related to the evolution of a borrower's rating over time. A natural question arises whether the results are symmetric depending on whether the borrower has a higher or lower rating than its lender. One scenario explaining the observed results is that banks with ESG rating that are relatively stronger than that of the borrowing firm take implicit and explicit steps to force the borrower to improve their ratings. Another explanation is that when a bank has a relatively weaker ESG rating than its lender, its failure to nudge the borrowing firm creates an environment where the borrower may feel freer to take actions that ultimately weaken its ESG rating. If the effects are symmetric, both explanations may be equally relevant. Alternatively, the effects may be asymmetric, in which case the results are driven primarily by one of these two scenarios.

To empirically address this issue, we start by sorting the loans into groups where the lender has a better industry-year adjusted ESG rating than the borrower ("Better bank = 1"), and into groups where the lender has a worse ESG rating than the borrower ("Better bank = 0"). Table 5 Panel A presents the results. In columns 1 and 2, we regress the borrower ESG changes for the subsample of loans where the lenders have a better ESG rating. We find that the economic effect of the ESG difference is even greater when the lender has a better ESG rating. This suggests that lenders have a disciplining influence over the borrowers when they have relatively better ESG ratings.

[Insert Table 5 here]

In columns 3 and 4 of Panel A, we run the test for the subsample of loans where the lenders have worse ESG ratings than their borrowers. In these circumstances, we find no evidence of lenders influencing the evolution of their borrowers' ESG ratings. Overall, our findings suggest that while "good" lenders from an ESG perspective may encourage their borrowers to become more socially responsible, "bad" lenders do not induce their borrowers to become less responsible.

Another question is whether the magnitude of the ESG difference is relevant. We next investigate whether the distance between lenders' and borrowers' ESG ratings influences the evolution of borrowers' ESG ratings. To address this question, we partition the sample into quintiles with respect to the ESG difference variable (ESG_Diff). We then investigate the changes in borrowers' ESG for these subsamples. We present the first and fifth quintiles for brevity - smallest and greatest distances, respectively. Panel B of Table 5 shows our results. In columns 1 and 2, where we have the greatest distance between the lender's and borrower's ESG ratings, we observe the greatest economic effect. When the ESG difference is large, we find a significant improvement in borrowers' ESG ratings. With similar intuition, we consider the subsamples in columns 3 and 4, where the distance between the lender's and the borrower's ESG is the smallest. Consistent with the worse lender results, we find no evidence of lender's influence over the borrowers for these subsamples.

Overall, our findings suggest that the lenders' influence over borrowers' ESG ratings is asymmetric. In particular, the magnitude as well as the sign of the distance (ESG_Diff) are strong determinants of the evolution of borrowers' ESG.

3.5. Propagation of Bank Influence along E, S, and G

We believe that creditors may be particularly concerned with some sub-components of the borrower's ESG policies (Dimson et al. (2015)). For example, the governance (G) issues, which by definition include executive pay, internal audits, and other shareholder rights, primarily affect the interests of shareholders. On the other hand, lenders may focus on environmental (E) issues under the lender liability laws. According to Comprehensive Environmental Response, Compensation, and Liability Act (CERCLA), lenders could be held liable for borrower's environmental disasters. In addition to the litigation costs, the cleaning up costs of the pollution become senior to lender's claims. Indeed, Chava (2014) finds that firms with environmental concerns pay higher interest on their loans and have fewer banks participating in their loan syndicates.

With these concerns in mind, we take a closer look at the components of ESG ratings. In addition to the overall ESG rating, RepRisk reports a proportion that represents each of the three factor's contribution to the overall score. From these proportions, we construct specific ratings for environmental risk, social risk, as well as governance risk, by multiplying the overall ESG rating with the proportion of each factor. We then study the changes in each of these three factors for each loan, which are calculated as follows:

$$Chg\_E = RRI_{t+1} \times Environment\ Weight_{t+1} - RRI_{t-1} \times Environment\ Weight_{t-1} \tag{4}$$

$$Chg\_S = RRI_{t+1} \times Social\ Weight_{t+1} - RRI_{t-1} \times Social\ Weight_{t-1} \tag{5}$$

$$Chg\_G = RRI_{t+1} \times Governance\ Weight_{t+1} - RRI_{t-1} \times Governance\ Weight_{t-1} \tag{6}$$

Table 6 presents our results where we separately consider the three components. In columns 1, 2, and 3, we look at the changes in the environmental, social, and governance components of ESG ratings, respectively. We find that banks have the most significant impact on the environmental component of ESG rating, which is consistent with banks having stronger incentives to discourage firms from polluting activities. The second significantly affected factor is the social component of ESG ratings. Finally, we do not find any significant evidence of banks influencing their borrower's governance practices.

[Insert Table 6 here]

In columns 4, 5, and 6 of Table 6, we repeat this test for the sub sample of public firms, once again controlling for other firm characteristics. We similarly confirm that environmental and social factors play a significant role while governance factor does not change. Overall, our results in this section suggest that ESG ratings change more significantly when the lenders have strong incentives to influence the borrowers' ESG policies.

3.6. Negative Reputational News Events and Changes in Banking Relationship

So far, we have documented a positive impact from banks on the borrowers' ESG performance. However, if the borrowers continue to engage in negative ESG practice, does it lead to disruptions in the lending relationship? In this section, we answer this important second-stage question by examining the relationship between the borrower's negative reputational news coverage, and the likelihood of initiating new loan(s) with the same lead lender within 12 months of the original loan's end date.

$$Pr(Same_{i,j,te} = 1) = \phi(\alpha + \beta Num\ Rep\ Event_{i,ts,te} + \gamma X_{i,te-1} + S_{i,j} + I_{ffindustry} + \delta_t + \xi_{i,j,t}) \quad (7)$$

In the Probit Model, $\phi(.)$ denotes the cumulative distribution function (CDF) of the standard normal distribution. $same_{i,j,te}$ is a dummy variable that equals one if at least one of the lead lenders (j) in the original loan extends a new loan to the borrower i within 12 months of the original loan's end date, te. $Num\ Rep\ Event_{i,ts,te}$ is the main explanatory variable that measures the number of months with negative news coverage on the borrower i from the start (ts) to the end (te) dates of the original loan. $X_{i,te-1}$ is the vector of borrower's characteristics that we use as control variables. These variables include the ex-ante level, and change in book leverage, size (log assets), return on assets, and Tobin's Q. $S_{i,j}$ denote additional control variables that include the original loan length (in years), and the investment grade dummy. $I_{FFindustry}$ and δ_t respectively denote dummies for Fama-French 12 industry, and year fixed effects. Finally, standard errors are clustered at the borrower level.

[Insert Table 7 here]

Note that we restrict the regression sample to borrowers who received at least one loan financing within 12 months of the end date of the original loan. This mitigates concerns related to demand side heterogeneities, because we are only looking at borrowers actively seeking new loan financing.

Column 1 and 2 in Table 7 report the results. The coefficient estimates of *Num Rep Event* are statistically significant, and negatively related to the likelihood of retaining the same lead lender. It indicates that borrowers with greater negative news coverage are more likely to switch lead lender(s) after the end date of the original loan, controlling for the length of the original loan. In

Column 3 and 4, we define the dependent variable more restrictively. *Same res* (restrictive) is the dummy variable that turns on if the borrower initiates new loan(s) with exactly the same group of lead lenders within 12 months of the original loan end date. Our main results remain statistically and economically robust to the variation. Finally, in Column 5 and 6, we define *same sgl* (single lead lender) most restrictively, as the dummy variable that turns on if the original loan has a single lead lender, and the borrower initiates new loan(s) with the same lender within 12 months of the original loan end date. The coefficient estimate is not statistically significant, partly driven by the dramatic drop in sample sizes and the power of the empirical tests. However, the economic magnitude is comparable to that estimated from earlier regressions.

4. Source of Endogeneity and Identification

4.1. Source of Endogeneity

We document a direct and positive impact of bank on the evolution of borrower's ESG profile. However, interpreting the result as causal evidence can be confounded by a few endogeneity concerns.

The first source of endogeneity is the reverse causality introduced by selection problems. There are two types of selection problems embedded in our current framework. One is that borrowers with certain level of ex ante ESG rating ($ESG\_borrower_{i,t-1}$) may self-select to borrow from high ESG standard banks. We alleviate this concern by controlling for the borrower's ex ante ESG rating. By holding the borrower's ESG standard constant, we explore how the difference in the bank's ESG standard affect the borrower's ex post improvement in ESG performance. The second type of the selection problem is that borrowers who expect to improve their ESG performance ($ESG\_Chg_{i,t-1,t+1}$) may self-select to borrow from high ESG standard banks. If this is the case, the borrower's ex post ESG evolution reversely leads to the lending relationship with high ESG standard bank.

The second source of endogeneity is omitted variable bias. One such potentially omitted variable is the CEO's awareness/concern related to ESG issues. Specifically, borrowers with CEOs who are sensitive to ESG issues are more likely to improve their ESG performance over time; at the same time, they are also more likely to borrow from high quality and high ESG standard banks. This behavior simultaneously causes variations in both the dependent and independent sides of the regression, which contaminates the causal interpretation of the main results.

4.2. Difference-in-Difference Analysis using Bank Mergers

Following Asker and Ljungqvist (2010), Hong and Kacperczyk (2010), Ergungor et al. (2015) and Chen and Vashishtha (2017), our identification strategy leverages exogenous shocks to the bank's ESG standard arising from bank mergers. Specifically, we examine how borrowers react to exogenous variations in the lead lender's ESG standard. This Diff-in-Diff strategy is best suited to our study for two reasons. First, it helps disentangle the selection and treatment effects, by looking at shocks to lenders in the already established lending relationships. In other words, the shocks take place after the borrower-lender matching is completed. Second, the timing and the decision of bank M&A activities are arguably exogenous to the borrowers' firm-level unobservable characteristics. As noted by prior studies, the bank merger waves were largely driven by regulatory, technological, and competitive changes (Pilloff (2004)).

To further absorb the impact from borrower level and lender level omitted variables, we include the borrower, lender, year, and industry FEs in the following Diff-in-Diff specification:

$$\begin{aligned} RRI_{i,t} =& \alpha + \beta ESG\_Shock_j \times Post_t + \varsigma ESG\_Shock_j + \tau Post_t \\ &+ \gamma X_{i,j} + I_{ffindustry} + \nu_i + \chi_j + \delta_t + \xi_{i,j,t} \end{aligned} \tag{8}$$

This specification represents a Panel OLS regression of the borrower's monthly RepRisk Indexes (RRI) over a 48-month window around the M&A event. The treatment group consists of all loans where the lender is involved in an M&A event within a five-year window after the loan initiation date.[12] We obtain the monthly RRI (if available) from 24 months before to 24 months after the M&A date. ESG_Shock is the exogenous variation to the lender's ESG standard in the merger and acquisition. Post dummy equals one if the date of the monthly RepRisk Index is after the M&A event date. We also include the log loan amount, country of syndication USA, the borrower's public status, and the number of covenants in the loan to control for the heterogeneity in size, regulatory environment, managerial myopia, and the credit risk, respectively. ν_i, χ_j, $I_{ffindustry}$

[12]The median length of loans in our sample is five years. We require that the M&A event happens less than five years ($\leq$ 4 years) since the loan initiation date, to allow at least one year for the exogenous variation to transmit through lending relationship.

and δ_t denote the dummies for borrower, lender, Fama-French 12 Industry and year fixed effects. Finally, standard errors are clustered at the borrower level.

We quantify the magnitude of the shock to the lender's ESG standard by incorporating the size effect. If the lender is the acquiror in the M&A, and the target is extremely small relative to the acquiror, we assume that the shock to the acquiror's ESG standard post-M&A is virtually zero. Empirically, we calculate ESG_Shock_j for the treatment group using the following specification, and assign zero to all control units:

$$ESG\_Shock_j = (RRI_a - RRI_t) \times Size_a/(Size_a + Size_t)\ , if\ the\ lender\ j\ is\ the\ target \tag{9}$$

$$ESG\_Shock_j = -(RRI_a - RRI_t) \times Size_t/(Size_a + Size_t)\ , if\ the\ lender\ j\ is\ the\ acquiror \tag{10}$$

We pair each treated loan one-to-one with a control group. We first require the control unit to be initiated in the same year-month as the treated loan. This guarantees that the DiD inferences are not being driven by time-series dynamics in the syndicated loan market. The second binding requirement is that the borrower and the lender in the control unit must be different from the borrower and the lender in the treated loan. Third, we choose the borrower with the closest ex ante RRI (measured at the time of loan initiation) to that of the borrower in the treated group. This setup ensures that the assignment of treatment vs. control is orthogonal to the main endogenous variable of interest – borrower's historical RRI. Finally, if there are multiple potential control units with the same ex-ante borrower's RRI, we compare and pick the one with the closest ex-ante lender's RRI.

[Insert Table 8 here]

Table 8 reports the balancing test between the ex-ante characteristics of borrowers in the treatment and control groups. Facility date is the loan initiation date. RepRisk Index is measured ex-ante at the facility start date, rather than at the merger and acquisition date. Public refers to the public status of the borrowers. Log (assets) (if publicly available) compares the size of the borrowers between the treatment and control group. The T-statistics of two-side difference tests are reported in parentheses. None of the reported characteristics are statistically different across groups. Finally, we apply both borrower and lender fixed effects in the DiD to absorb any remaining unobservable heterogeneities between the control and treatment units.

[Insert Table 9 here]

Table 9 reports the main results from the DiD analysis. The key coefficient estimate of the interaction term, $ESG\_Shock_j \times Post_t$, is positive and statistically significant at the 1% level. It indicates that shocks to the lender's ESG standard propagates through the lending relationship post-M&A, causing a change in the borrower's ESG performance in the same direction, and in proportion to the magnitude of the exogenous shock to the lender's ESG rating. Significant coefficient of Post captures an upward trend in the RRI over time. In columns 1 and 2, we regress with only control variables. In column 3, we add the lender fixed effects. In column 4, we apply both the borrower and the lender fixed effects, and observe a significant reduction in the explanatory power of the control variables. The coefficient of interaction term remains positive and statistically significant, and our DiD inference is robust to variations in specifications.

5. Robustness Tests

In this section, we conduct several robustness tests to confirm our baseline results related to borrower ESG rating evolution. Section 5.1 calculates the main explanatory variable using the raw, instead of adjusted RRIs. Section 5.2 considers alternative method to define lead lender(s). Section 5.3 examines alternative sampling criteria. Section 5.4 performs analysis on alternative specifications.

5.1. Measuring ESG Rating Difference Between Borrowers and Lenders

In our main specifications, we adjust both the borrower and lender ESG ratings by the industry-year averages. This alleviates the potential concerns about the comparability of ESG ratings across industries and years.

We now investigate whether our results are sensitive to using raw ESG ratings of lenders and borrowers when comparing their relative standing. Table 10, columns (1) presents the results. We find that our results do not change if we do not adjust the borrower and lender ESG ratings by industry-year averages.

[Insert Table 10 here]

5.2. Lender Profile, Single Lead Loans, and Strongest Relationship Lead Lenders

In our main specifications, when there are multiple lead lenders in the loan syndicate, we calculate the lead lenders' ESG rating by taking the average lender ESG rating for each loan. It is not clear which lender dictates the relationship and influences the borrower, therefore we follow this conservative approach. However, would the results change if we were to instead choose one of the lead lenders randomly, or if we have followed an alternative approach? We empirically address this robustness concern in this section.

We first start with a conservative, simplistic approach. We run the baseline estimation for the subsample of loans where there is a single unique lead lender in the loan syndicate. Columns (2) of Table 10 presents the results. We find that our results are unchanged for the subsample of loans where we have a single lender.

Other alternative approaches for choosing lead lenders include choosing the lead lender with the strongest historical relationship with the borrower, or randomly choosing one of the lead lenders as the lead for the loan. We test the former approach as it is more intuitive (Ivashina and Kovner (2011)). We classify a lead lender as the strongest relationship lead lender if the lead lender financed the greatest fraction of loan amount in the past five years before the current loan. Columns (3) shows our results under this alternative approach. We again find that if the lender has a better ESG rating, the borrower's ESG rating is more likely to improve.

5.3. Sample Selection Criteria

A final, sample related robustness check is related to sample selection criteria. In our main regressions we try to keep our sample as large as possible for representativeness as well as statistical power. In this section, we test our findings to the usage of alternative sample selection criteria. We impose the most common filters on banking and syndicated loans literature. Specifically, we require the loans to be USD denominated, and issued by non-financial, non-utility, US-incorporated borrowers. Columns (4) of Table 10 presents our findings under these criteria. We find that our results are in fact stronger under this approach. Overall, the robustness tests confirm our finding that high ESG rating lenders influence their borrowers in their ESG policies.

5.4. Alternative Specification

In our main analysis, we regress the improvement in the borrower's ESG over time, on the ex-ante difference between the lender's and borrower's ESG ratings, while controlling for the borrower's ex-ante ESG standard. This empirical specification views each loan initiation as an "event" and makes sure each facility enters only once into the analysis. The empirical design alleviates concerns on the stacking of sticky ESG scores/ratings in the panel regression.

In this section, we repeat our baseline analysis in Table 3 using levels, rather than changes as main variables of interests using the following specification:

$$\begin{aligned} RRI\ borrower_{t+1} = &\alpha + \beta RRI\ lender_{t-1} + \varsigma RRI\ borrower_{t-1} + \tau Lender\ Chg_j \\ &+ \gamma X_{i,t-1} + I_{ffindustry} + \delta_t + \xi_{i,j,t} \end{aligned} \tag{11}$$

$RRI\ borrower_{t+1}$ is defined as the level of borrower's RepRisk Indexes (rather than the change) one year after the loan initiation date. $RRI\ lender_{t-1}$ is defined as the level of lender's RepRisk Indexes one year before the loan initiation date. $RRI\ borrower_{t-1}$ is defined as the level of borrower's RepRisk Indexes one year before the loan initiation date. We also include the loan amount (in millions), country of syndication USA, the borrower's public status, and the number of covenants in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. In column 4, we perform a sub sample analysis in the public space only, and control for borrower's financials including log assets, book leverage, ROA, and Tobin's Q. Note that the level of observation in this analysis is facility. Each loan only enters once into the regression. And the year t is defined as the year of loan initiation.

Results are reported in Appendix B. In column 1, 2 and 3, the coefficients are statistically significant and economically sizable. Column 4 presents the subsample analysis focusing on public borrowers only. The T statistic of 1.53 is not significant at the 10% level, but the economic magnitude remains comparable to estimates in earlier columns.

6. Conclusion

We demonstrate that banks have an important influence on firm ESG policies. Specifically, we find that banks are significantly more likely to partner with borrowers that have similar ESG ratings. This result suggests that ESG policies influence the construction of bank lending relationships and that different banks have different attitudes towards borrower ESG policies that are at least partly influenced by the bank's own ESG-related policies and experiences.

We also find that banks have an important influence on the evolution of their borrowers ESG levels. Firms that from banks with relatively better ESG reputations are more likely to improve their own ESG levels over time. By contrast, banks with relatively worse reputations are less likely/less able to nudge their borrowers to take steps to enhance their ESG-related investments. We also find that banks are more likely to influence bank-dependent borrowers, and that their influence is predominantly concentrated among the environmental component of the ESG spectrum. In our third set of tests, we find that borrowers are more likely to experience a shift in their lending relationship following an adverse shock to their ESG-related reputation.

All in all, our results clearly demonstrate that the banking system has an important systematic effect on corporate ESG policies. In this regard, we further demonstrate a specific channel in which a key stakeholder can profoundly promote socially responsible decision making.

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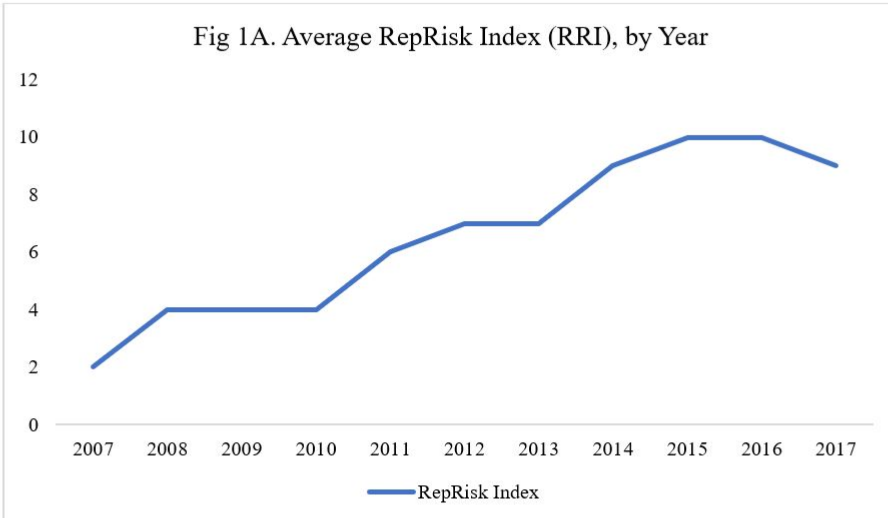
Fig. 1. RepRisk Index (RRI) by Year and Industry

The following figures show the mean level of unadjusted RRI by year, and by industry. The sample includes 126 monthly RRI for each borrower in our sample (from Jan 2007 to June 2017). Industry classifications are based on the Fama-French 12 industry classifications.



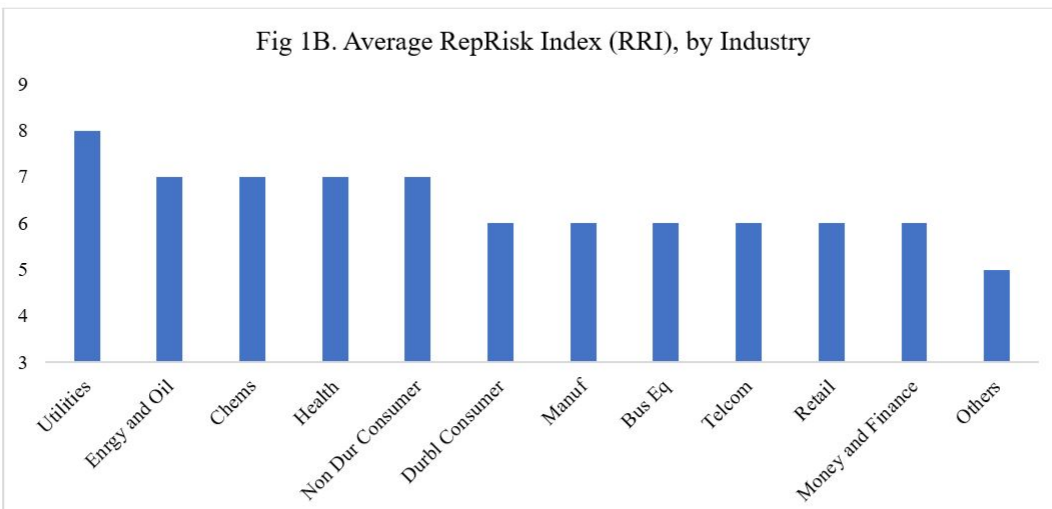


Table 1
Descriptive Statistics

This table summarizes sample statistics. All variables are reported on the loan level (borrower-lender-facility). *Public*, *Secure*, *Rated* and *Investment Grade* are dummy variables. *Log Assets*, *Book Leverage*, *Return on Assets* and *Tobin's Q* are only available for public firms and select private firms through Capital IQ. Detailed variable definitions are available in Appendix A.

Variable	N	Mean	St. dev.	P10	P50	P90
ESG_Chg	12495	1.88	11.46	-12.00	0.00	19.00
ESG_Borrower	12495	7.65	11.74	0.00	0.00	24.00
ESG_Lender	12495	18.60	21.06	0.00	17.00	60.00
Unadjusted ESG_Diff	12495	10.94	23.00	-16.00	1.00	44.00
ESG_Diff	12495	11.39	20.72	-12.00	7.00	40.00
Rated	12495	0.61	0.49	0.00	1.00	1.00
# of Covenants	12495	0.74	1.00	0.00	0.00	2.00
Secure	12495	0.43	0.50	0.00	0.00	1.00
Investment Grade	12495	0.29	0.45	0.00	0.00	1.00
Public	12495	0.62	0.48	0.00	1.00	1.00
Total Assets	8721	22214	87050	699	4858	40293
Book Leverage	8721	0.34	0.23	0.07	0.31	0.62
Return on Assets	8597	0.03	0.10	-0.03	0.04	0.11
Tobin's Q	7660	1.71	0.94	1.00	1.47	2.61

Table 2

Borrower and Lender's Endogenous Matching

The following table reports the Probit regression of the distance between the lender and borrower's ESG indexes, on the likelihood of initiating a loan. *Close* is defined as the absolute value of the lagged difference between the borrower's and lender's (yearly average) RepRisk Indexes. *Close_adj* further adjusts for the country-industry-year average. Match equals one if the lender lends at least once to the borrower in a year. Prior equals one if a loan was previously initiated between the lender-borrower pair in the past 4 years (from year $t = -4$ to $t = -1$). In Panel A column 1, we report the basic regression with lender, industry and year fixed effects, and clustering of standard errors on the lender-borrower pair level. Panel A Column 2 shows that our results are robust in the public space, where we control for borrower's financials including *log assets*, *book leverage*, *tobin's Q* and *investment grade* dummy. Column 4 and 5 repeat the tests in column 1 and 2 using *close_adj*. In column 3 and column 6, we show that our results are robust by excluding borrowers with (adjusted) RepRisk Indexes (*ESG_Borrower*) equal zero. Panel B repeats the regression analysis using the sample of single-lead loans only. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the lender-borrower pair level. Z statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A	(1) match All	(2) match Public	(3) match ESG_Borrower>0	(4) match All	(5) match Public	(6) match ESG_Borrower>0
Close	-0.00791***	-0.00605***	-0.00711***			
	(-14.10)	(-8.28)	(-7.33)			
Close_adj				-0.00639***	-0.00461***	-0.00413**
				(-11.78)	(-6.30)	(-2.15)
Prior		0.934***	0.851***		0.930***	0.645***
		(19.91)	(15.59)		(19.78)	(6.43)
Log Assets		0.0926***	0.101***		0.0946***	0.118***
		(11.33)	(10.28)		(11.61)	(6.62)
Book Leverage		0.161***	0.210***		0.156***	0.420***
		(3.40)	(3.67)		(3.31)	(3.40)
Tobin's Q		0.0176	0.0109		0.0183	0.0197
		(1.41)	(0.73)		(1.46)	(0.81)
Investment Grade		-0.0698***	-0.0628**		-0.0705***	-0.0746
		(-3.07)	(-2.38)		(-3.10)	(-1.49)
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	460408	197328	126764	460408	197328	28589
Pseudo R2	0.291	0.334	0.342	0.290	0.333	0.348

Panel B	(1) match All	(2) match Public	(3) match ESG_Borrower>0	(4) match All	(5) match Public	(6) match ESG_Borrower>0
Close	-0.00660***	-0.00845***	-0.0102***			
	(-7.25)	(-5.84)	(-5.01)			
Close_adj				-0.00403***	-0.00549***	-0.00889**
				(-4.40)	(-3.75)	(-1.98)
Prior		1.016***	0.809***		1.017***	0.783***
		(13.16)	(8.07)		(13.21)	(3.86)
Log Assets		-0.00962	-0.00152		-0.00773	-0.0000221
		(-0.71)	(-0.08)		(-0.57)	(-0.00)
Book Leverage		-0.00901	-0.0189		-0.0162	-0.0543
		(-0.10)	(-0.17)		(-0.19)	(-0.18)
Tobin's Q		-0.0230	-0.0242		-0.0207	-0.0248
		(-0.95)	(-0.79)		(-0.86)	(-0.42)
Investment Grade		-0.0170	-0.0238		-0.0175	-0.0388
		(-0.41)	(-0.43)		(-0.43)	(-0.30)
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	147715	48724	24284	147715	48724	3512
Pseudo R2	0.207	0.250	0.250	0.206	0.248	0.243

Table 3

Evolution in Corporate ESG Profile and Bank Lending

The following table reports the OLS regression of the change in the borrower's ESG profile on the ex-ante difference between the bank and borrower's ESG ratings. The change in the borrower's ESG profile (*ESG_Chg*) is defined as the difference between the borrower's RepRisk Indexes over a two-year window, from one year before to one year after the loan initiation date. The ex-ante difference between the bank and borrower's ESG ratings (ESG_Diff) is defined as the difference between the bank and borrower's RepRisk Indexes measured one year before the loan initiation date. *Lender_Chg* controls for the evolution in the lender's ESG indexes over the same two-year window. *ESG_Borrower* controls for the potential self-selection problem and is defined as the borrower's RepRisk Index one year before the loan initiation date. In column 1, we report the basic regression without fixed effects and clustering of standard errors. Column 2 clusters the standard errors on the borrower level. Column 3 adds industry and year fixed effects. In column 4, we also include the *log loan amount*, *country of syndication USA*, the *borrower's public status*, and the *number of covenants* in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. In column 5, we should that our results are robust in the sub sample of public firms only, and we further control for borrower's financials including *log assets*, *book leverage*, *ROA*, and *Tobin's Q*. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) ESG_Chg All Loans	(2) ESG_Chg All Loans	(3) ESG_Chg All Loans	(4) ESG_Chg All Loans	(5) ESG_Chg Public
ESG_Diff	0.0746***	0.0746***	0.0623***	0.0376***	0.0379***
	(12.71)	(8.93)	(6.40)	(4.04)	(2.91)
Lender_Chg	0.0558***	0.0558***	0.0431***	0.0199	0.0320*
	(6.35)	(4.16)	(3.11)	(1.49)	(1.78)
ESG_Borrower	-0.393***	-0.393***	-0.413***	-0.506***	-0.583***
	(-45.22)	(-12.99)	(-12.13)	(-16.02)	(-17.38)
Log Loan Amt				1.411***	0.350*
				(11.32)	(1.94)
USA				-0.407	2.519
				(-0.32)	(1.64)
Public				2.068***	
				(6.19)	
# of Covenants				-0.596***	-0.195
				(-4.14)	(-1.23)
Log Assets					2.295***
					(10.94)
Book Leverage					-2.073**
					(-2.39)
ROA					-0.146
					(-0.09)
Tobin's Q					0.751***
					(3.64)
Cluster	No	Yes	Yes	Yes	Yes
Ind FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
N	12495	12495	12448	12448	7659
adj. R2	0.217	0.217	0.228	0.263	0.310

Table 4

Bank Dependency, Corporate ESG Profile, and Bank Lending

The following table reports the OLS regression of the change in the borrower's ESG profile on the ex-ante difference between the bank and borrower's ESG ratings. The change in the borrower's ESG profile (*ESG_Chg*) is defined as the difference between the borrower's RepRisk Indexes one year after and one year before the loan initiation date. The ex-ante difference between the bank and borrower's ESG ratings (*ESG_Diff*) is defined as the difference between the bank and borrower's RepRisk Indexes measured one year before the loan initiation date. Interaction terms of *ESG_Diff* and proxies of bank dependency are included. Proxies of bank dependency include the *rating* dummy, *number of covenants*, *secure* dummy, and *investment grade* dummy. *ESG_borrower* controls for the potential self-selection problem and is defined as the borrower's RepRisk Index one year before the loan initiation date. We also include the *log loan amount* (in millions), and *country of syndication USA* to control for the heterogeneities in size and regulatory environment. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T statistics for the regressions are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) ESG_Chg	(2) ESG_Chg	(3) ESG_Chg	(4) ESG_Chg
ESG_Diff	0.066***	0.028***	0.029***	0.059***
	(5.28)	(2.79)	(2.67)	(5.53)
Rated	2.678***			
	(6.29)			
ESG_Diff × Rated	-0.051***			
	(-3.38)			
# of Covenants		-0.537***		
		(-2.74)		
ESG_Diff × # of Covenants		0.016**		
		(2.00)		
Secure			-2.306***	
			(-5.34)	
ESG_Diff × Secure			0.027*	
			(1.76)	
Investment Grade				4.653***
				(7.94)
ESG_Diff × Investment grade				-0.085***
				(-4.01)
Lender_Chg	0.017	0.019	0.018	0.019
	(1.29)	(1.38)	(1.39)	(1.40)
ESG_Borrower	-0.512***	-0.493***	-0.503***	-0.534***
	(-16.08)	(-15.92)	(-16.54)	(-18.37)
Log Loan Amt	1.308***	1.537***	1.486***	1.227***
	(10.10)	(12.22)	(12.62)	(10.67)
USA	-0.513	-0.342	-0.401	-0.464
	(-0.43)	(-0.28)	(-0.34)	(-0.41)
Cluster	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	12448	12448	12448	12448
adj. R2	0.262	0.257	0.262	0.272

Table 5

Asymmetric Bank Impact

The following table reports the OLS regression of the change in the borrower's ESG profile on the ex-ante difference between the bank and borrower's ESG ratings. The change in the borrower's ESG profile (*ESG_Chg*) is defined as the difference between the borrower's RepRisk Indexes one year after and one year before the loan initiation date. The ex-ante difference between the bank and borrower's ESG ratings (*ESG_Diff*) is defined as the difference between the bank and borrower's RepRisk Indexes measured one year before the loan initiation date. *ESG_borrower* controls for the potential self-selection problem and is defined as the borrower's RepRisk Index one year before the loan initiation date. Panel A presents the results for the subsamples where lender has a better or worse ESG rating than the borrower. Samples in column (1) and (2) include only loans where the bank's RepRisk Index is smaller or equal to the borrower's RepRisk Index; samples in column (3) and (4) include those where the bank's RepRisk Index is larger than the borrower's. Panel B presents the results for the subsamples partitioned with respect to the difference between lender and borrower ESG ratings. A positive difference indicates that lender has a worse ESG score than the borrower. Column (1) and (2) focus only on loans where the *ESG_Diff* falls in the bottom quintile (*ESG_Diff*<0), while in column (3) and (4) we focus on loans where *ESG_Diff* falls in the top quintile (*ESG_Diff*>32). We also include the *log loan amount* (in millions), *country of syndication USA*, the borrower's *public* status, and the *number of covenants* in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Panel A	(1)	(2)	(3)	(4)
	Better bank = 1		Better bank = 0	
	ESG_Chg	ESG_Chg	ESG_Chg	ESG_Chg
ESG_Diff	0.133***	0.111***	0.017	0.018
	(4.64)	(3.25)	(1.33)	(1.06)
Lender_Chg	0.038	0.062	-0.014	0.012
	(1.01)	(1.40)	(-0.77)	(0.46)
ESG_Borrower	-0.407***	-0.581***	-0.591***	-0.632***
	(-6.34)	(-9.54)	(-20.87)	(-17.31)
Log Loan Amt	2.759***	0.712**	1.082***	0.059
	(9.23)	(2.09)	(6.77)	(0.24)
USA	-6.224**	-0.347	1.426	4.005**
	(-2.40)	(-0.12)	(1.07)	(2.57)
Public	2.719***		2.100***	
	(3.01)		(4.81)	
# of Covenants	-1.493***	-0.733*	-0.501**	-0.120
	(-3.58)	(-1.66)	(-2.43)	(-0.52)
Log Assets		3.698***		2.164***
		(8.96)		(7.90)
Book Leverage		-2.592		-2.363**
		(-1.14)		(-2.21)
Return on Assets		9.131		-2.689
		(1.58)		(-1.52)
Tobin's Q		0.560		0.821***
		(1.08)		(3.19)
Cluster	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2380	1755	6260	3634
adj. R2	0.303	0.396	0.244	0.275

Panel B	(1)	(2)	(3)	(4)
	Last quintile		First quintile	
	ESG_Chg	ESG_Chg	ESG_Chg	ESG_Chg
ESG_Diff	0.268***	0.275***	0.026	-0.001
	(5.41)	(5.14)	(0.79)	(-0.03)
Lender_Chg	0.084***	0.078**	0.046	0.071
	(3.13)	(2.19)	(1.44)	(1.41)
ESG_Borrower	-0.378***	-0.470***	-0.590***	-0.666***
	(-6.92)	(-7.85)	(-13.02)	(-11.55)
Log Loan Amt	1.754***	0.656*	0.827***	0.034
	(8.09)	(1.85)	(3.86)	(0.10)
USA	-1.804	2.049	3.086	7.295***
	(-0.61)	(0.74)	(1.51)	(2.67)
Public	1.948***		2.392***	
	(2.88)		(3.72)	
# of Covenants	-1.038***	-0.782**	-0.637*	-0.673*
	(-3.36)	(-2.21)	(-1.89)	(-1.65)
Log Assets		2.198***		1.523***
		(5.41)		(3.57)
Book Leverage		-1.885		-1.056
		(-0.99)		(-0.62)
Return on Assets		7.727**		0.557
		(2.05)		(0.28)
Tobin's Q		0.376		0.859**
		(0.84)		(2.11)
Cluster	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	2619	1655	2493	1359
adj. R2	0.349	0.400	0.178	0.223

Table 6

Evolutions along Environmental (E), Social (S) and Governance (G) Dimensions

The following table reports the OLS regression of the change in the borrower's environmental (E), social (S), and governance (G) profiles on the ex-ante difference between the bank and borrower's ESG ratings. The change in the borrower's environmental profile (*Chg_E*) is defined as the difference between the borrower's environmental component of RepRisk Indexes over a two-year window, from one year before to one year after the loan initiation date. The changes in the borrower's social (*Chg_S*) and governance (*Chg_G*) profiles are constructed in the similar fashions. The ex-ante difference between the bank and borrower's ESG ratings (*ESG_Diff*) is defined as the difference between the bank and borrower's RepRisk Indexes measured one year before the loan initiation date. *Lender_Chg* controls for the evolution in the lender's ESG indexes over the same two-year window. *ESG_Borrower* controls for the potential self-selection problem and is defined as the borrower's RepRisk Index one year before the loan initiation date. In column 1 to 3, we include the *log loan amount*, *country of syndication USA*, the borrower's *public* status, and the *number of covenants* in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. In column 4-6, we show that our results are robust in the public space only, and we control for borrower's financials including *log assets*, *book leverage*, *ROA*, and *Tobin's Q*. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Chg_E	(2) Chg_S	(3) Chg_G	(4) Chg_E	(5) Chg_S	(6) Chg_G
ESG_Diff	0.0143***	0.0161**	0.00767	0.0150***	0.0215**	0.00145
	(3.57)	(2.44)	(1.45)	(2.60)	(2.36)	(0.18)
Lender_Chg	0.00190	0.00922	0.00895	0.00827	0.00695	0.0168
	(0.29)	(1.02)	(1.08)	(0.96)	(0.55)	(1.39)
ESG_Borrower	-0.124***	-0.251***	-0.130***	-0.138***	-0.272***	-0.174***
	(-12.00)	(-14.08)	(-8.30)	(-10.38)	(-14.50)	(-8.94)
Log Loan Amt	0.417***	0.583***	0.413***	0.255***	0.102	-0.00748
	(9.20)	(5.75)	(6.76)	(3.47)	(0.60)	(-0.06)
USA	-0.0845	-0.458	0.140	0.251	0.830	1.438**
	(-0.19)	(-0.55)	(0.24)	(0.37)	(0.75)	(2.22)
Public	0.347***	0.712***	0.999***			
	(2.64)	(3.04)	(5.12)			
# of Covenants	-0.124**	-0.190*	-0.281***	-0.119*	0.0756	-0.152
	(-2.02)	(-1.85)	(-3.41)	(-1.80)	(0.63)	(-1.49)
Log Assets				0.389***	0.974***	0.932***
				(4.81)	(6.68)	(6.66)
Book Leverage				-0.758**	-1.129*	-0.186
				(-2.57)	(-1.85)	(-0.31)
ROA				0.358	-0.770	0.267
				(0.29)	(-0.70)	(0.28)
Tobin's Q				0.287***	0.0327	0.431***
				(2.81)	(0.22)	(2.72)
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12448	12448	12448	7659	7659	7659
adj. R2	0.104	0.133	0.064	0.118	0.153	0.091

Table 7

Exposure to Negative Reputational News Incidents and Switch in Lending Relationship

The following table reports the Probit regression of the number of the borrower's negative reputational news on the likelihood of initiating new loan(s) with the same lead lender within 12 months of the original loan's end date. *Num Rep Event* is the number of months with negative news coverage from the start to the end dates of the original loan. *Same* is the dummy variable that turns on if the borrower initiates new loan(s) with at least one of the same lead lenders within 12 months of the original loan end date. *Same Res* is defined more restrictively, as the dummy variable that turns on if the borrower initiates new loan(s) with exactly same group of lead lenders within 12 months of the original loan end date. *Same Sgl (Single)* is defined most restrictively, as the dummy variable that turns on if the original loan has a single lead lender, and the borrower initiates new loan(s) with the same lender within 12 months of the original loan end date. Note that we construct the sample to include only borrowers who need new financing to minimize the demand side heterogeneity. *ESG_borrower_start* is the borrower's adjusted RepRisk Index measured at the start date of the original loan. *Original loan length* refers to the number of years between the start and end dates of the original loan. Controls include the borrower's ex ante level and change (during the original loan window) in *log assets*, *book leverage*, *ROA*, and *Tobin's Q*. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Year FE is based on the end year of the original loan. Standard errors are clustered on the borrower level. Z statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) All same	(2) Public same	(3) All same res	(4) Public same res	(5) All same sgl	(6) Public same sgl
Num Rep Event	-0.0339**	-0.0378**	-0.0307**	-0.0362**	-0.0248	-0.0463
	(-2.56)	(-2.04)	(-2.34)	(-2.05)	(-0.92)	(-1.17)
ESG_Borrower_Start	0.00827***	0.000211	0.00637**	0.00168	0.00651	0.00200
	(2.64)	(0.06)	(2.14)	(0.43)	(0.97)	(0.22)
Book Leverage		0.383		0.223		-0.0956
		(1.44)		(0.85)		(-0.19)
Tobin's Q		-0.149*		-0.201**		-0.261*
		(-1.88)		(-2.47)		(-1.73)
ROA		1.070		0.619		1.847
		(1.51)		(0.96)		(1.30)
Log Assets		0.0787*		0.00415		0.220***
		(1.93)		(0.10)		(2.95)
Chg in Book Leverage		0.414		0.337		-0.439
		(1.09)		(0.93)		(-0.68)
Chg in Tobin's Q		0.0158		-0.0320		-0.173
		(0.19)		(-0.38)		(-1.20)
Chg in ROA		0.561*		0.395		2.555**
		(1.86)		(1.46)		(2.57)
Chg in Log Assets		0.0372		-0.0170		0.00447
		(0.35)		(-0.16)		(0.02)
Original Loan Length		-0.0369		0.00454		0.0559
		(-1.09)		(0.15)		(0.83)
Investment Grade		0.136		0.357***		-0.309
		(1.08)		(2.85)		(-1.37)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
N	2318	1495	2318	1495	702	388
pseudo R2	0.025	0.043	0.019	0.035	0.043	0.096

Table 8

Balancing Table

The following table reports the balancing test between the ex-ante profiles of borrowers in the treatment and control groups. *Facility date* is the loan initiation date. We construct the control group by selecting loans initiated in the same year-month as the treated loans. *RepRisk Index* is measured *ex-ante* at the facility start date, rather than at the merger and acquisition date. *Public* refers to the public status of the borrowers. *Log (assets)* (if publicly available) compares the size of the borrowers between the treatment and control group. Detailed variable definitions are available in the Appendix A. The T statistics of two-side difference tests are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Name	Treatment				Control					
	mean	std	min	max	mean	std	min	max	diff-in-mean	t-statistic
Facility Date (*initiation year-month*)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.00	(0.00)
RepRisk Index (*ex-ante*)	4.81	10.81	0	62	4.06	8.48	0	39	0.74	(1.10)
Public (Y/N)	0.42	0.49	0	1	0.44	0.50	0	1	-0.03	(-0.76)
Log (assets)	8.38	2.14	3.15	13.86	8.31	1.62	5.45	13.37	0.07	(0.42)

Table 9
Diff-in-Diff Analysis using Bank Mergers

The following table reports the OLS regression of the borrower's monthly RepRisk Indexes (ESG) over a 48-month window around the M&A event. The sample consists of all loans where the lender is involved in a M&A event within a five-year window after the loan initiation date. We obtain the monthly RepRisk Indexes (if available) from 24 months before to 24 months after the M&A date. *ESG_Shock* is the exogenous variation to the lender's ESG profile in the merger and acquisition. *Post* dummy equals one if the date of the monthly RepRisk Index is after the M&A event date. We also include the *log loan amount*, *country of syndication USA*, the borrower's *public* status, and the *number of covenants* in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) ESG	(2) ESG	(3) ESG	(4) ESG
ESG_Shock×Post	0.170***	0.168***	0.195***	0.172***
	(3.15)	(3.11)	(3.37)	(2.87)
ESG_Shock	-0.0805	-0.0667	-0.193*	-0.0404
	(-1.19)	(-0.94)	(-1.84)	(-0.37)
Post	1.112**	1.117**	1.209**	0.923**
	(2.39)	(2.38)	(2.50)	(1.97)
Log Loan Amt	2.703***	2.496***	2.243***	0.0210
	(8.46)	(8.32)	(6.95)	(0.51)
USA		-9.536***	-13.31***	-0.0745
		(-5.22)	(-4.61)	(-0.49)
Public		4.580***	4.691***	1.736***
		(5.38)	(6.15)	(4.69)
# of Covenants		-0.839**	-0.831**	-0.510*
		(-2.17)	(-2.23)	(-1.66)
Borrower FE	No	No	No	Yes
Lender FE	No	No	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	35805	35805	35805	35805
adj. R2	0.176	0.224	0.267	0.636

Table 10
Robustness Tests

This table reports four robustness tests for the baseline result of ESG evolution. Columns (1) presents the results if *ESG_diff* variable is calculated without country-industry-month adjustments. Sample in columns (2) include only loans with a unique lead arranger in the syndicate. Sample in column (3) repeat the baseline estimation based on the ESG rating of the lead lender with the strongest relationship with the borrower, instead of averaging the ESG ratings of the lead arrangers in the syndicate. Finally, column (4) presents the results under alternative sample selection criteria: USD-denominated loans of non-financial and non-utility US firms. The change in the borrower's ESG profile (*ESG_Chg*) is defined as the difference between the borrower's RepRisk Indexes one year after and one year before the loan initiation date. The ex-ante difference between the bank and borrower's ESG ratings (*ESG_diff*) is defined as the difference between the bank and borrower's RepRisk Indexes measured one year before the loan initiation date. *ESG_borrower* controls for the potential self-selection problem and is defined as the borrower's RepRisk Index one year before the loan initiation date. We also include the *log of loan amount* (in millions), *country of syndication USA*, the borrower's *public* status, and the *number of covenants* in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) ESG_Chg	(2) ESG_Chg	(3) ESG_Chg	(4) ESG_Chg
ESG_Diff	0.022***	0.029**	0.026***	0.039***
	(2.82)	(2.11)	(3.10)	(3.75)
Lender_Chg	0.011	0.004	0.021	0.015
	(0.84)	(0.23)	(1.49)	(1.05)
ESG_Borrower	-0.516***	-0.567***	-0.519***	-0.497***
	(-17.15)	(-12.68)	(-15.12)	(-13.46)
Log Loan Amt	1.442***	0.895***	1.372***	1.577***
	(11.37)	(4.87)	(10.19)	(12.31)
USA	-0.364	-1.721	0.064	-0.534
	(-0.29)	(-0.80)	(0.04)	(-0.27)
Public	2.063***	2.237***	1.994***	1.737***
	(6.16)	(3.99)	(5.36)	(4.59)
# of Covenants	-0.627***	-0.643***	-0.676***	-0.486***
	(-4.32)	(-2.78)	(-4.19)	(-3.10)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	12448	2907	10496	9603
adj. R2	0.261	0.246	0.267	0.259

Appendix A. Variable Definition

Variable name	Description	Source
ESG_Chg	The change in the borrower's RepRisk Index from one year before, to one year after the loan initiation date	RepRisk
ESG_Borrower	The RepRisk Index of the borrower measured one year before the loan initiation date.	RepRisk
Lender_Chg	The change in the lender's RepRisk Index from one year before, to one year after the loan initiation date	RepRisk
ESG_Diff	The difference between the lender and borrower's country-industry-month adjusted RepRisk Indexes measured one year before the loan initiation date.	RepRisk
Rated	An indicator that equals one if the borrower is rated, and zero otherwise.	Compustat
Investment Grade	An indicator that equals one if the borrower is investment grade, and zero otherwise.	Compustat
# of Covenants	Number of financial covenants on the loan.	Dealscan
Secure	An indicator that equals one if the loan is secured, and zero otherwise.	Dealscan
Log Loan Amt	The natural logarithm of the size of the syndicated loan (in millions).	Dealscan
Public	An indicator that equals one if the borrower firm's equity is publicly traded, and zero otherwise.	CRSP
Total Assets	Borrower's total assets at the latest fiscal period that ended prior to loan start date.	Compustat
Book Leverage	The ratio of total book debt to total assets.	Compustat
Return on Assets	The ratio of net income to total assets.	Compustat
Tobin's Q	The ratio of market value of total assets to book value of total assets.	Compustat
Size of Target	The M&A transaction value divided by the percentage of target acquired (in millions).	SDC Platinum
Size of Acquirer	Value of the acquirer's asset LTM (in millions).	SDC Platinum
ESG_Diff_MA	The difference between the acquirer and target's RepRisk Indexes at the time of the M&A.	RepRisk and SDC Platinum
ESG_Shock	The shock to the ESG standard of the lender introduced by the M&A transaction, adjusted by the relative sizes of both parties involved in the transaction.	RepRisk and SDC Platinum

Appendix B. Alternative Specification

This Appendix replicates the analysis in Table 3 using a different specification. $RRI\_borrower_{t+1}$ is defined as the level of borrower's RepRisk Indexes one year after the loan initiation date. RRI_lender_{t-1} is defined as the level of lender's RepRisk Indexes one year before the loan initiation date. $RRI\_borrower_{t-1}$ is defined as the level of borrower's RepRisk Indexes one year before the loan initiation date. We also include the *log of loan amount* (in millions), *country of syndication USA*, the borrower's *public* status, and the *number of covenants* in the loan to control for the heterogeneities in size, regulatory environment, managerial myopia, and the credit risk, respectively. In column 4, we perform a subsample analysis in the public space only, and control for borrower's financials including *log assets*, *book leverage*, *ROA*, and *Tobin's Q*. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered on the borrower level. T-statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) RRI_borrower$_{t+1}$	(2) RRI_borrower$_{t+1}$	(3) RRI_borrower$_{t+1}$	(4) RRI_borrower$_{t+1}$
RRI_lender$_{t-1}$	0.0719***	0.0452***	0.0232***	0.0172
	(6.17)	(5.63)	(2.97)	(1.53)
RRI_borrower$_{t-1}$		0.533***	0.461***	0.383***
		(17.08)	(15.92)	(12.99)
Lender_Chg		0.0329**	0.0115	0.0212
		(2.45)	(0.89)	(1.22)
Log Loan Amt			1.441***	0.381**
			(11.38)	(2.08)
USA			-0.363	2.529*
			(-0.29)	(1.65)
Public			2.050***	
			(6.12)	
# of Covenants			-0.625***	-0.227
			(-4.31)	(-1.43)
Log Assets				2.314***
				(10.94)
Book Leverage				-2.045**
				(-2.36)
ROA				-0.144
				(-0.09)
Tobin's Q				0.755***
				(3.66)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	12448	12448	12448	7659
adj. R2	0.065	0.307	0.338	0.393

Appendix C. The ESG Ratings of New Lead Lenders

The following table reports the OLS regression of the number of the borrower's negative reputational news on the changes in the lead lenders' ESG ratings (average ESG ratings of the new lenders minus the average ESG ratings of the lenders of the original loan). The new group of lenders are the banks that lend money to the borrower within 12 months of the original loan's expiration date. *Num Rep Event* is the number of firm-months with negative news coverage from the start to the end dates of the original loan. Note that we construct the sample to include only borrowers who successfully find new financing to minimize the demand side heterogeneity. *ESG_borrower_start* is the borrower's adjusted RepRisk Index measured at the start date of the original loan. Original loan length refers to the number of years between the start and end dates of the original loan. Controls include the borrower's ex ante level and change (during the original loan window) in *log assets*, *book leverage*, *ROA*, and *Tobin's Q*. Detailed variable definitions are available in the Appendix A. Industry FE is based on the Fama-French 12 industry classification. Year FE is based on the end year of the original loan. Standard errors are clustered on the borrower level. T statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) All Lender_Diff	(2) Public Lender_Diff	(3) Public Lender_Diff	(4) Public Lender_Diff
Num Rep Event	0.858***	1.084***	1.086***	0.386*
	(5.74)	(5.92)	(5.78)	(1.72)
ESG_Borrower_Start	-0.260***	-0.219***	-0.200***	-0.0762
	(-6.67)	(-4.14)	(-4.09)	(-1.54)
Book Leverage		-1.473	-2.386	-2.769
		(-0.57)	(-0.73)	(-0.83)
Tobin's Q		-2.174***	-2.488***	-1.875**
		(-2.73)	(-2.76)	(-2.02)
ROA		15.12**	13.29	10.13
		(2.28)	(1.55)	(1.21)
Log Assets		-1.223**	-1.160**	-0.330
		(-2.54)	(-2.38)	(-0.60)
Chg in Book Leverage			-3.233	-4.944
			(-0.62)	(-0.97)
Chg in Tobin's Q			-0.369	-0.446
			(-0.32)	(-0.38)
Chg in ROA			-1.760	-1.823
			(-0.28)	(-0.30)
Chg in Log Assets			1.636	1.070
			(1.15)	(0.79)
Original Loan Length				2.819***
				(6.29)
Investment Grade				0.351
				(0.25)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	2155	1510	1407	1407
adj. R2	0.103	0.114	0.113	0.147

Appendix D. Reputation Risk Exposure and Risk-adjusted Capital Ratios

The following table is from Houston, Shan and Tian (2019). It reports the OLS regression of the bank's ESG and business conduct risk on the level of risk-adjusted Tier 1 capital ratio. The level of observation is on the bank-quarter level. *ESG_Lag* is the RepRisk Index of the bank at t-1 (lagged quarter). *Num_News* is the number of negative news coverage from t-5 to t-1 (in quarters). *Num_News_H* and *Num_News_VH* count the number of high impact and very high impact negative news coverage during the same window. *Num_News_Env*, *Num_News_Soc* and *Num_News_Emp* count the number of negative news coverage related to environmental, social and employee issues during the same window. Bank and Month fixed effects are included to focus on within-bank variations and to preclude the impact of common time trends. Standard errors are clustered on the bank level. T statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	(1) Tier 1	(2) Tier 1	(3) Tier 1	(4) Tier 1	(5) Tier 1	(6) Tier 1	(7) Tier 1
ESG_Lag	0.0194** (2.61)						
Num_News		0.00911*** (2.90)					
Num_News_H			0.0132*** (3.14)				
Num_News_VH				0.0241** (2.46)			
Num_News_Env					0.0429 (1.37)		
Num_News_Soc						0.0267*** (2.84)	
Num_News_Emp							0.0806** (2.41)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Bank	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1340	1340	1340	1340	1340	1340	1340
adj. R2	0.607	0.616	0.616	0.609	0.606	0.606	0.609