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Corporate ESG Profiles and Banking Relationships

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We show that banking relationships promote corporate environmental, social, and governance (ESG) policies. Specifically, banks are more likely to grant loans to borrowers with ESG profiles similar to their own and positively influence the borrower's subsequent ESG performance. Their influence is more pronounced when (1) banks have significantly better ESG ratings than borrowers and (2) borrowers are bank dependent. We exploit M&A among lenders as a source of quasi-exogenous variation in the lender's ESG standard to alleviate endogeneity concerns. Overall, our study presents the first evidence on the interplay between responsible bank lending and borrowers' ESG behavior. (*JEL* G21, G28, G38)

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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, firms face growing internal and external pressures to improve their performance along various nonfinancial dimensions, including environmental impacts, social welfare, and fair labor practices. While these pressures 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.[1] Relatedly, in April 2019, a group of

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[1] We find that banks are more actively discussing how ESG fits into their business models. The total frequency of mentions of the keyword "ESG" in Bank of America, JPMorgan Chase, and Wells Fargo's proxy statements increased from 2 in 2015 to 81 in 2019.

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stakeholders promoting gun control released a well-publicized report card ranking banks on their ties to firearm manufacturers and firearm organizations, such as the National Rifle Association (NRA). Growing evidence indicates that pressure from stakeholders is being indirectly passed along to borrowers through the concrete steps taken by their lenders. As an interesting example, a recent *Wall Street Journal* article describes how a group of lenders structured a deal with BlackRock where the stability of lending relationship was explicitly tied to BlackRock's ability to meet certain goals related to diversity hiring and increasing assets in ESG-related funds.[2] Despite the observed actions taken by banks and the heightened public interest in the social economic impact of bank lending practices, there is no apparent consensus in the literature on whether banks can and should effectively shape borrowers' ESG activities.[3]

In this paper, we propose a novel economic mechanism to explain the propagation of ESG policies through lending relationships. Despite the considerable evidence that bankers may affect their borrowers' policies and investments (Shleifer and Vishny 1997; Chava and Roberts 2008; Nini, Smith, and Sufi 2012), whether lenders use this leverage to specifically influence borrowers' ESG policies remains an open question. One view is that lenders primarily focus on borrowers' financial performance, and consequently resist costly investments that chiefly benefit other nonbank stakeholders. This view is consistent with the classic argument made by Friedman (1970) that the firm's only responsibility is to increase its profit. Brammer and Millington (2008) present evidence in support of this argument showing that high social responsibility firms score the lowest in short-term financial performance.[4]

However, beyond this narrow view, we hypothesize two further avenues by which banks are concerned about the ESG performance of their potential borrowers. The first avenue is that poor ESG performance may ultimately translate into greater credit risk. Arguably, firms with poorer ESG performance are more likely to face costly backlash from various stakeholders. Stakeholder backlash may draw negative publicity, as well as induce consumer boycotts, employer backlash, and increased regulation and litigation. Ultimately, we

[2] For details on these two examples, see Hsu (2019) and Lim (2021).

[3] The literature on the causes and effects of firm ESG policies is long-standing. Earlier studies largely focused on the determinants motivating the cross-sectional differences in the observed levels of ESG ratings, as well as the wealth effects of these policies, with a particular emphasis on the positive impact of institutional investors (Starks, Venkat, and Zhu 2020; Cao et al. 2020; He, Kahraman, and Lowry 2020; Dimson, Karakaş, and Li 2015, among others). Given this focus, most studies have concentrated on public firms. Nevertheless, the data from RepRisk, a Zurich-based data science company that scans negative ESG news incidents, reveal 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 a 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 underexplored.

[4] Extensive discussions have ensued on how ESG engagements help improve *long-term* firm performance by, for example, (1) avoiding myopic managerial decisions (Bénabou and Tirole 2010), (2) attracting customers who will pay more for environmentally and socially responsible products (Baron 2009), and (3) reducing litigation risks (Eccles, Ioannou, and Serafeim 2014), among others.

would expect these risks to affect the likelihood of debt repayment and that bankers would incorporate these factors into the structure and pricing of loan agreements. Consistent with this financial motivation, 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 (Sharfman and Fernando 2008; Goss and Roberts 2011; Chava 2014; Hasan et al. 2017; Hauptmann 2017).

The second possible avenue is that bankers are concerned about their own reputation and social capital, and fear that the value of this capital may be diminished by doing business with poor ESG-rated borrowers. Banks that suffer a hit to their reputation because of their dealings with poor-ESG borrowers may particularly find it difficult to engage future business in other areas (Homanen 2018). Banks may also face considerable negative media coverage and increased regulatory scrutiny. Given that they are heavily regulated and are often the focus of public condemnation, 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 left 17 injured, Bank of America announced 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. This event is hardly an isolated occurrence. In another example, Morgan Stanley and Wells Fargo stopped lending to firms that extract coal using methods that, while legal and lucrative, are often very harmful to the environment (Nussbaum 2015). This anecdotal evidence collectively demonstrates that banks' ESG-related concerns extend beyond a simple consideration of credit and liability risk.[5]

Altogether, these arguments suggest that banks have *financial* and *reputational* motivations for focusing on a borrower's ESG performance. We further hypothesize that banks are differentially concerned about the ESG performance of their potential borrowers, and that a bank's degree of concern is partially captured by its own ESG rating. In one respect, the bank's own ESG rating may provide a strong signal of its views on ESG-related issues. If so, we would expect banks with strong ESG performance to tilt toward borrowers with strong ESG ratings. Alternatively, banks with poor ESG performance may be more interested in repairing their social capital and therefore may subsequently tilt toward borrowers with strong ESG ratings in an attempt to enhance their image. Consequently, the connection between a lender's ESG performance and that of its potential borrowers remains an empirical question.

[5] We show that the level of bank reputational risk exposure is positively related to risk-adjusted capital ratios. See Appendix A.2 for details.

To explore these issues, we conduct a series of tests using the RepRisk database to obtain the negative news coverage and ESG ratings of both borrowers and lenders. The database is uniquely suited for our study because its coverage includes a wide range of *private* borrowers and because of 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 that often receive a minimal level of scrutiny from the equity market.[6] RepRisk also focuses on ESG-related events that are actually reported. By contrast, many other databases primarily assign ESG ratings based on whether the firm "claims" to enact certain policies that are more discretionary and subject to greenwashing bias.[7]

To the extent that banks are concerned about their borrowers' ESG performance, they can express these concerns in multiple ways, each of which can be linked to the literature that highlight how principals may use a combination of *voice* or *exit* to influence an agent's behavior. The first way that a bank may influence borrower ESG-related behavior is through the initial decision whether or not to lend. To the extent that a bank tilts away or completely avoids lending to certain types of borrowers, this becomes a form of exit that imposes costs on borrowers with poor ESG ratings. Thus, in our first set of "matching" tests, we show that lenders tend to match with borrowers who have similar ESG profiles. Specifically, we first remove the firm-level time-series mean from both the lender and borrower's ESG ratings. Then for each given year, we equal-weight and value-weight (by loan amount) the ESG ratings of the borrowers who initiated loans from the same lender. We scatter plot the equal-weighted and value-weighted ESG ratings of the borrowers in the loan portfolio against the ESG rating of the lender for each observed lender-year. The fitted linear relationship and the corresponding 95% confidence interval point to a significant and positive cross-sectional correlation between the loan portfolio's average ESG rating and the lender's own ESG rating. Note that we only consider lenders and borrowers without prior lending relationships, to rule out the possibility that the observed ESG ratings are the reverse outcome of a prior lending relationship, rather than the determinant of the establishment of new relationship.

While these results strongly demonstrate that ESG factors are an important determinant of whether a particular lender matches with a particular borrower,

6 To the best of our knowledge, other ESG databases such as KLD and Asset4 focus on large, public firms. The limited coverage inevitably introduces selection and reverse causality problems that confound our understanding of the interactions between lenders and borrowers in the corporate loan market.

7 An increasing number of studies in ESG focus on the real outcomes, instead of discretionary disclosures, which are often subject to greenwashing bias, for example, legal and litigation risks (Schiller 2018 and toxic and/or carbon emissions (Bartram, Hou, and Kim 2021; Shive and Forster 2020; Xu and Kim 2021, 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. Notably, the rating system incorporates not only 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. See WRDS RepRisk data manual for details.

we fully recognize that these factors are not the only factor influencing lending decisions. Consequently, it remains likely that individual borrowers may align with lenders with different levels of ESG performance. Given this last point, our second set of tests ask whether these differences persist, and if lenders systematically influence borrower ESG performance over time. More directly, do borrowers' ESG levels evolve in ways that are consistent with the lender's views about ESG issues? If so, this suggests a second way in which bankers may influence a borrower's ESG policy through a "dynamic" channel.

In these tests, we provide evidence that lenders significantly influence the evolution of their borrowers' ESG profile. Here, we find that a one-standard-deviation increase in the difference between the borrower and lender's ESG ratings is associated with a 0.66 increase in the borrower's RepRisk rating over a 2-year window centered on the package initiation date, which is equivalent to 6% of the standard deviation of the changes in borrowers' ESG ratings during the same 2-year window. These results confirm that banks, as a unique and novel source of influence, can affect 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 borrowers' 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*).[8] To alleviate these concerns, we exploit M&A in the banking industry as a source of quasi-exogenous variations of the lender's ESG standard (Asker and Ljungqvist 2010; Hong and Kacperczyk 2010; Chen, Harford, and Lin 2015).[9] In a difference-in-differences setting, we examine whether the variation in lenders' ESG standard transmits through the *established* lending relationship to affect the evolution of borrowers' ESG ratings following the M&A. We apply a wide range of fixed effects on the (1) borrower, (2) industry, and (3) year levels to absorb the remaining unobservable time-invariant heterogeneities across borrowers and industries, and to preclude the effects of common time trends. This test helps us identify the dynamic component of bank impact on borrower ESG performance, in a setting that is not confounded by borrower-lender matchings or other selection issues.

We further explore banks' incentives to shape borrowers' ESG activities. If both *financial* and *reputational* channels are driving banks' actions, we suspect

[8] The flip side of the selection problem is that the more effective a bank is at improving a borrower's ESG performance ex post, the more willing it might be to accept ESG risk ex ante.

[9] 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).

that banks are particularly concerned with (1) borrowers' ESG practices that could potentially expose lenders to liability risk and (2) controversial social and/or environmental issues that would cast lenders in the spotlight of media coverage. In support of this financial channel, we show that the bank's influence is stronger among secured loans where the liability risk exposures dramatically increase if there is an adverse shock. To better understand the areas that banks care most about when assessing borrower exposure, we examine the 28 news topics tracked by RepRisk. Consistent with the reputational channel, we find that banks are most likely to discipline borrowers in cases of (1) human rights abuse, (2) social discrimination, and (3) climate change. In contrast, their impact on other issues such as executive compensation is negligible. We interpret the results as evidence showing that banks have incentives to minimize negative exposures in catastrophic social and environmental scandals in order to preserve future business opportunities.

While we find evidence supporting both the financial and reputational motivations, we acknowledge the difficulty in completely isolating them, as these two incentives are by no means mutually exclusive.

Moreover, while these results show that banks have strong incentives to discipline and shape borrower ESG activities, the exact mechanisms in which lenders influence borrower ESG performance over time are not immediately clear. We can think of at least three reasons we observe these findings. First, "when in Rome, do as the Romans do"; this argument suggests that agents may tend to adopt the behavior of those they contract with over time. While certainly plausible, directly testing this possible mechanism seems quite challenging.

Another possibility is that high-quality lenders directly force or nudge borrowers to improve their ESG performance. One important limitation is that lender liability concerns may strongly constrain the lender's ability to directly impose specific constraints on borrowers' decision-making. For these same reasons, it may be difficult to observe actual cases in which banks are explicitly directing borrowers to take certain actions.

Nevertheless, bankers may be able to impose indirect pressure on their borrowers to improve their ESG performance. Ultimately, the third and key element that may facilitate these improvements is the subsequent decision whether to renew the loan. In the process of lending to a firm, a bank acquires proprietary firm-specific information that is unavailable to nonlenders (Schenone 2009). Switching lenders is costly for borrowers and is often accompanied by reduction in the availability of credit (Petersen and Rajan 1994). In the context of the exit/voice dichotomy, banks may be able to imperfectly use their "voice" to influence borrower behavior, but the ultimate hammer may be the fear of subsequent exit. This possible mechanism provides a third way in which banks may influence borrower ESG behavior.

In our final set of tests, we present evidence supporting this novel disciplinary mechanism. We find that borrowers are significantly more likely to observe a shift in lead lender(s) following negative shocks to their ESG-related reputation.

More specifically, conditional on obtaining new loan financing within a 2-year period centered on the end date of the original loan, we find that borrowers are 3% less likely to renew loans with the same lead lender(s) if there was a negative ESG-related reputational shock. 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 (1) the level and (2) 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 further 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.

This "fear of subsequent exit" should also vary across borrowers. It is intensified among bank-dependent borrowers and borrowers with relatively poor ex ante ESG ratings. We find that lenders have a more profound influence if the borrower is bank dependent. We also document important asymmetry: banks that have better ESG-related ratings relative to the borrower are more likely to induce borrowers to improve their ESG performance over time. On the other hand, the lender's impact on the borrower's ESG evolution is indistinguishable from zero if the lender's ESG rating is worse relative to that of the borrower.

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 2020; Lins, Servaes, and Tamayo 2017; Starks, Venkat, and Zhu 2020; Chava 2014; Dimson, Karakaş, and Li 2015; Bartram, Hou, and Kim 2021; Gillan, Koch, and Starks 2021; Avenancio-León and Shen 2021). Most notably, recent papers by Schiller (2018) and Dai, Liang, and Ng (2020) 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 bank lending, it is surprising how little empirical work has been done on this front. Our work presents the first evidence on the interplay between responsible bank lending and borrower ESG behavior to fill this gap.[10]

At the same time, our paper 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, Smith, and Sufi 2012; Schwert 2018, among others). In this vein, our

[10] Instead of examining the impact of bank lending on borrower ESG activities, Flammer (2021) and Tang and Zhang (2020) examine through the lens of announcement returns, operating performance, and/or green innovations whether the issuance of "green" bonds is beneficial to the firm and shareholders. Also, a recent study by Kim et al. (2021) examines the factors determining the emergence of ESG lending and green bonds in the global market.

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).

1. Data

1.1 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 provide a monthly unbroken time-series ESG rating and coverage on negative ESG news incidents from January 2007 to June 2017.[11] A dedicated team of analysts leverage a combination 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 ensuing impact of the news incident.[12] A higher level of RRI indicates a greater history of negative events (i.e., worse ESG performance).

Compared with the widely used annual KLD database (now MSCI ESGSTATS), the RepRisk data are uniquely suited for our study for three reasons. First, the event-based data evaluate the outcome of ESG activities, which can be directly linked to the societal impact of ESG compliance. The KLD data instead rely 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 do not cover private firms, which are predominant in the corporate loan market. Third, RepRisk has

[11] RepRisk does *not* cover positive ESG events. Part of the reason can be attributed to the fact that positive news is more likely to be self-reported for branding and marketing purposes and is 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 (2020) for an extended discussion of the collection of positive news.

[12] The RRI is constructed as a function of negative news coverage that may be correlated with firm financials, such as firm size and growth opportunities. Larger firms and firms with higher growth opportunities may be cast in the spotlight and attract greater media attention. In our regressions, we control for a variety of variables, such as *log assets*, *Book leverage*, *Return on assets*, and *Tobin's q*, to mitigate the confounding impacts of firm financials.

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.[13]

Figure 1 presents the cross-sectional distribution of the RepRisk ratings. We first calculate the average RepRisk index of all firms covered by the database (9,500 + firms as of 2018) and plot the distribution in Figure 1, panel A. We also calculate the average RepRisk index of the borrowers in our sample, and plot the distribution in Figure 1, panel B. The cross-sectional distributions in both figures are positively skewed, with medians at 2.02 (all RepRisk firms) and 3.87 (borrowers in our sample), and standard deviations at 3.32 (all RepRisk firms) and 6.90 (borrowers in our sample). Notably, the number of firms that are involved with severe ESG incidents is much smaller than the number of firms that do not receive any negative ESG-related news coverage. We suspect that the skewness arises from the underlying skewed nature of news reporting (a few high-profile events attract large attention) and the large sample of firms tracked by the database.

The evolution of a firm's RRI is notably path dependent. That is, the change in a firm's RRI from year t to t+1 is correlated with the level of firm's RRI in year t. We highlight two reasons underlying the observed time-series pattern. First, borrowers who are exposed in negative ESG-related news are more likely to proactively manage the crisis. The chance of showing up in the headlines of negative news for consecutive months is low. Second, according to the data manual of RepRisk, the ESG rating of any firm decays over time, and the speed of decay depends only on the current level of RRI.[14] The decay assumes that the perceived ESG risk decreases over time. In other words, a borrower who has not been involved in any ESG-related scandals for 2 years is considered to have a lower risk than the same borrower who is scandal-free for only one year. In our empirical analysis, we regress the evolution of the borrower's ESG ratings as a function of the difference between the lender and borrower's ESG ratings observed one year before the loan initiation. Given the documented time-series patterns above, we conclude that it is necessary to control for the ex ante level of the borrower's RRI when we study the lender's impact on the evolution of the borrower's ESG performance.

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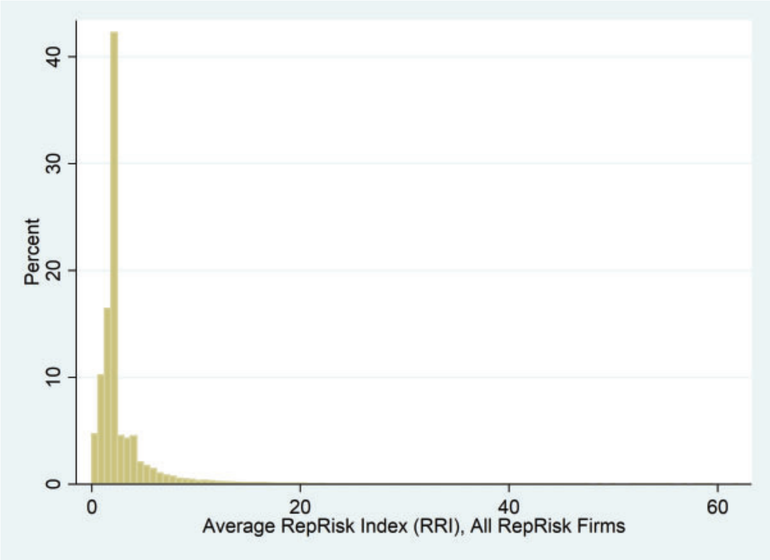
13 The RepRisk database is not perfect. We cannot fully separate the attention effects of news media from the deterioration of the borrower's ESG activities. RepRisk does not provide news content, and, thus, we are not able to evaluate whether changes in ESG ratings are triggered by news reporters' shifting attention. In fact, any judgment of reporters' motivation would be subjective, even if the content of the news coverage can be properly obtained.

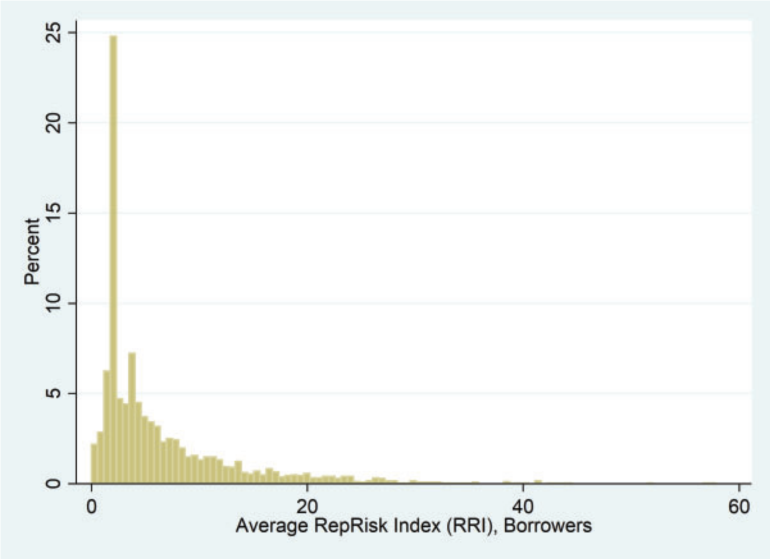
14 According to the RepRisk data manual (December 2020) obtained from Wharton Research Data Services (WRDS), for any given month, two events drive the change in RRI: (1) New risk incidents for a company or project, in which case the RRI is recalculated. The magnitude of the increase depends on the severity, reach, and novelty of the incident. Or (2) there is no new risk exposure, in which case the RRI decays. The RRI decays over time as follows: for the first 14 days after a significant risk incident, the RRI remains at the same value. If no new exposure is captured, the RRI then decays to zero over a maximum period of two years. The decaying speed occurs at a rate of 25 every 2 months until it reaches 25, then a rate of 25 every 18 months until it reaches zero.

A



Distribution of the average RepRisk index, all RepRisk firms

B



Distribution of the average RepRisk index, borrowers

Figure 1
Cross-sectional distribution of the RepRisk index
Panel A reports the cross-sectional distribution of the average RepRisk index (RRI) of all firms covered by RepRisk. We also calculate the average RepRisk index of the borrowers in our sample and plot the distribution in panel B. The average RepRisk index of each firm is calculated as the time-series mean of the firm's monthly RRIs observed during our sample period.

1.2 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.

One concern is that the borrower ESG profile, which we use to construct the main independent variable of interest, is the same across facilities within the same package, which inevitably inflates the statistical significance of the coefficient estimates. Consequently, we study the evolution of borrower ESG ratings over time at the package level, instead of the facility level. Specifically, we consider each package as a relationship between a borrower and a lead lender that finances the package. Following Bharath et al. (2009), 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 packages in our sample, we have multiple lead lenders in the syndicate. In these cases, we calculate the equally weighted average of ESG ratings of lead-lenders in the syndicate.[15] Finally, we drop a small part of our sample, specifically 3.6% of the total number of packages, where different facilities within the same package have different lead lenders.

1.3 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 6 months before the transaction and more than 50% of the shares after the transaction, and (3) we exclude deals with missing transaction values. The output sample is merged with both the RepRisk and Compustat Bank databases to obtain the acquirer and target's RRI and total assets. This step leaves us with 28 M&As with nonmissing RepRisk profiles and bank financial data.

We subsequently match the acquirer and the target's names to the lender's names in the DealScan database. We exploit the merger as a quasi-exogenous shock to the ESG-related performance of the borrowers who have an established lending relationship with the lender involved in the M&A. This setup enables

15 Alternatively, as a robustness test, we select a unique lead lender for each loan following Ivashina and Kovner (2011). This procedure considers the past borrowing history between lenders and firms and selects the lead lender that the firm has the strongest relationship with. We present our findings under this alternative approach in Section 4.2.

us to determine whether borrower ESG performance evolve differently if their lender(s) undergo a 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 3). Our final merged sample consists of 423 treated loans initiated from 2007 to 2017. These 423 treated loans are linked to 266 unique packages, associated with 17 out of the 28 M&As. Among the treated loans, the ESG shock variable (i.e., *ESG_shock*) has a mean of -3.28 and a standard deviation of 6.52. Eighty-five percent of the treated loans have a negative *ESG_Shock*, suggesting that their old lender was acquired by another firm with a better ESG profile.

1.4 Financials

After constructing the sample of packages with corresponding deal characteristics as well as borrower and lender ESG ratings, we also incorporate a broad range of firm-level control variables in the subsample analysis that consists of only public borrowers. Specifically, we collect firms' financial information from Compustat for the most recent fiscal year ending within a 1-year window prior to the package 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. An important dimension of our study is its inclusion of both public and private borrowers. We classify a borrower as a public borrower if 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 borrower otherwise. Appendix A.1 lists and defines required firm- and package-level variables in detail.

1.5 Summary statistics

Table 1 presents the summary statistics for our sample of packages and the corresponding borrowers. In our sample, we have 8,128 packages, 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 18, which indicates that it has some known issues. Two factors could explain these differences: (1) the median bank in our sample is larger than the median borrower, and larger firms are more likely to receive publicity; (2) financial industry firms often receive more attention and greater scrutiny, especially during our sample period, which corresponds to the financial crisis and postcrisis 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.

To account for the size and credit risk of the borrower, we include firm-level controls. About 62% of the packages are granted to rated borrowers, and 34% of all packages are granted to investment-grade firms. Similarly, we find that 64% of the packages are granted to public firms. These statistics suggest that a

Table 1
Descriptive statistics

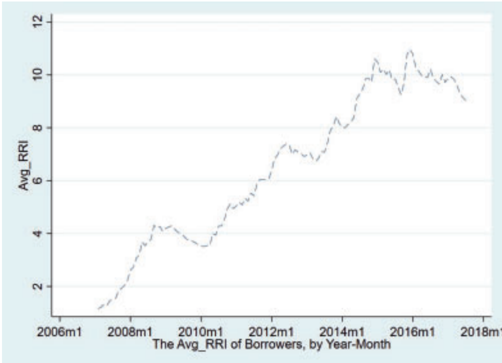
Variable	N	Mean	SD	P10	P50	P90
ESG_chg	8,128	1.83	11.38	−12.00	0.00	18.00
ESG_borrower	8,128	7.86	11.73	0.00	0.00	24.00
ESG_lender	8,128	19.12	21.15	0.00	18.00	61.00
Unadjusted ESG_diff	8,128	11.26	22.97	−16.00	1.50	45.00
ESG_diff	8,128	16.37	18.42	−3.50	15.00	41.00
log package amt	8,128	20.04	1.23	18.42	20.03	21.54
Num of facilities	8,128	1.41	0.84	1.00	1.00	2.00
Rated	8,128	0.62	0.49	0.00	1.00	1.00
Investment grade	8,128	0.34	0.48	0.00	0.00	1.00
Public	8,128	0.64	0.48	0.00	1.00	1.00
Avail for public borrowers						
log assets	5,855	8.55	1.62	6.53	8.50	10.62
Book leverage	5,855	0.32	0.23	0.06	0.29	0.59
Return on assets	5,753	0.04	0.11	−0.03	0.04	0.12
Tobin's q	5,121	1.73	0.98	0.99	1.46	2.68
Avail for switching tests						
Same	2,662	0.56	0.50	0.00	1.00	1.00
Same res	2,662	0.51	0.50	0.00	1.00	1.00
Num rep event	2,662	2.43	3.01	0.00	1.00	7.00
Original package length	2,662	3.15	1.75	1.00	3.00	5.00

This table summarizes sample statistics. All variables are constructed on the loan package level. *Rated*, *Investment grade*, *Public*, *Same*, and *Same res* 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. *Same*, *Same res*, *Num rep event*, and *Original package length* are the main variables of interest in the switching (loan renewal) tests. Appendix A.1 defines the variables in detail.

significant portion of our sample has limited access to public debt and equity markets. An important dimension of our analysis considers cases where the lender has stronger influence over its borrower. Arguably, these cases arise more frequently in the roughly 40% of packages where the borrower does not have access to public markets. Consequently, even though we do not have accounting information for these private firms, we still include these packages in our baseline tests to determine the importance of creditor control in shaping the ESG policies of bank-dependent borrowers. In subsample regressions in which we consider only the public borrowers, we include controls, such as log assets, book leverage, return on assets, and Tobin's q. Our results are robust to these additional considerations.

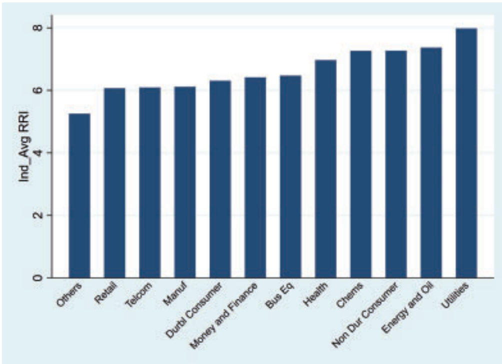
One of the empirical challenges in ESG studies is the limited comparability of scores and ratings across industries and years. In Figure 2, we calculate the mean level of RRI of all borrowers and lenders in our sample. Figure 2, panel A, documents a rising level of RRI over time, partly driven by an increasing number of ESG related news coverage in recent years. Figure 2, panel B, shows that the level of ESG exposures vary by industry. Borrowers in Utilities, Energy, and Chemicals on average have a higher level of RRI. Figure 2, panel C, presents a similar rising level of RRI of lenders over time. We address the comparability across industries and time by subtracting the sector-month average RRI from

A



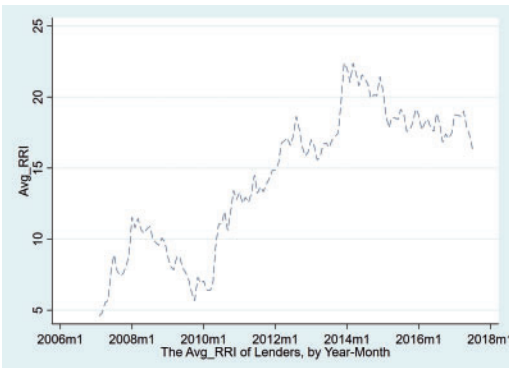
Avg RRI of borrowers

B



Avg RRI of borrowers by industry

C



Avg RRI of lenders

Figure 2
RepRisk index by year and industry
The panels show the mean level of an unadjusted borrower's RepRisk index (RRI) by year-month (Figure 2, panel A), the mean level of an unadjusted borrower's RRI by industry (Figure 2, panel B), and the mean level of an unadjusted lender's RRI by year-month (Figure 2, panel C). The sample includes 126 monthly RRI for each borrower in our sample (from January 2007 to June 2017). Industry classifications are based on the Fama-French 12 industry classifications.

the borrower and lender's raw RRIs to obtain the sector-month-adjusted RRIs, which we use to construct the independent variables.[16]

2. Main Results

2.1 ESG ratings and the matching of borrowers and lenders

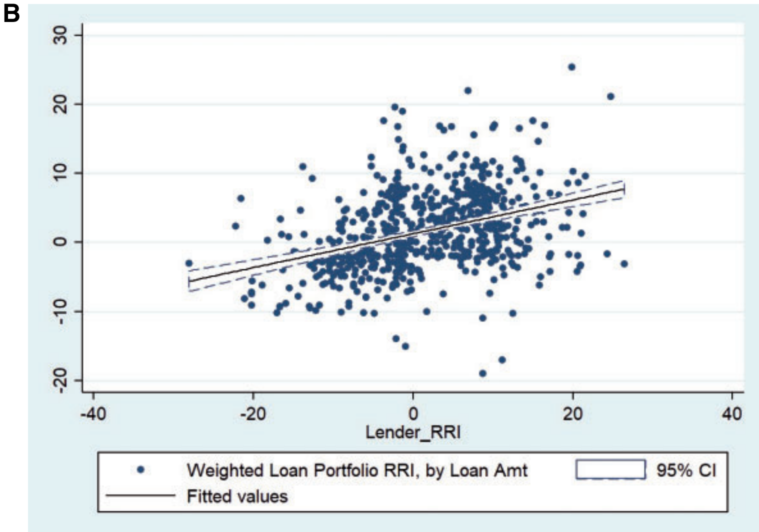
We first consider whether lenders are more likely to grant loans to borrowers with similar ESG profiles. One might expect that a lender's attitude regarding the desirability of a borrower's ESG performance to be related to its own views regarding ESG-related policies, which are reflected in the bank's own ESG rating. Alternatively, lenders may view the borrower's ESG rating as largely immaterial when making lending decisions. Finally, there may be cases where banks with poor ESG ratings tilt toward lending to high ESG-rated borrowers, perhaps as a means of indirectly improving the bank's image. To explore these alternative hypotheses, we present the cross-sectional correlation between the borrower's and the lender's ESG ratings using scatter plots.

Specifically, we first remove the firm-level time-series mean from the lender and borrower's RepRisk index (RRI). In Figure 3, panels A and B, we only consider the matching of borrowers and lenders with no prior lending relationships. In Figure 3, panel A, we equally weight the RRIs of the borrowers who obtained loan financing from the same lead lender in the same year and generate an aggregate lender-year-level RRI of the loan portfolio. We plot the lender's RRI (x-axis) and that of the loan portfolio (y-axis) for each year during our sample period. The fitted linear relationship and the corresponding 95% confidence interval point to a significant and positive cross-sectional correlation between the loan portfolio's average ESG ratings and the lender's own ESG ratings.

In Figure 3, panel B, we further confirm the robustness of the cross-sectional correlation. For the loans initiated in the same year by the same lead lender, we weight every borrower's RRI by the total loan amount between the lender and borrower in a given year, and generate an aggregate lender-year-level RRI of the loan portfolio. We choose to weight the borrower's ESG rating by the total loan amount, instead of equally weighting, based on the assumption that the lender's exposure to a borrower's ESG misconduct increases with the loan amount. Using this new weighting method, we plot the lender's RRI (x-axis) and that of the loan portfolio (y-axis) for each year during our sample period. The fitted linear relationship once again confirms the significant and positive correlation between the loan portfolio's average ESG ratings and the lender's own ESG ratings.

[16] We obtain the sector-month average from RepRisk. The variable name is "Country_sector_average." Since we focus on packages granted to U.S.-incorporated firms, there is no variation at the country level. In the robustness test section (Table 10), we show that our baseline results are robust if we use the unadjusted RRI as independent variables.

Equally weight borrowers' RRI



Weight borrowers' RRIs by loan amount

Figure 3
Distribution of the Lender and its Loan Portfolio's RepRisk index (RRI)
The figures present the scatterplots of the lender and its loan portfolio's RRIs. Lenders and borrowers' RRIs are adjusted by the time-series means, by subtracting the firm-level average RRI observed during our sample period. The sample only includes lenders and borrowers without prior lending relationship and matched for the first time. In each year, we weight the RRIs of the borrowers who obtained loan financing from the lender, and obtain an aggregate lender-year-level RRI for the lender's loan portfolio. In Figure 3, panel A, borrowers' RRIs are equally weighted. In Figure 3, panel B, borrowers' RRIs are weighted by loan amount. In both panels, we report the RRI of the loan portfolio on the *y*-axis, and the lender's RRI on the *x*-axis. The fitted linear relationship is represented by a solid line, and the corresponding 95% confidence interval is represented by a dashed line.

Overall, we show consistent evidence that banks tend to match with borrowers with similar ESG levels. These results may be driven by two possible channels. One is that banks with higher RRI (i.e., worse ESG performance) have demonstrated that they are less concerned with ESG policies. Consequently, these banks are less likely to reward low RRI borrowers with lower lending rates and/or to penalize high RRI borrowers with higher lender rates. In this case, the likely equilibrium outcome is that borrowers and lenders with similar ESG levels are more likely to gravitate together. A second possible channel is that ESG policy is part of a two-sided matching problem similar to the market for underwriters described by Fernando, Gatchev, and Spindt (2005). In this scenario, loans with similar risk are priced similarly by all lenders, but the allocation of lenders and borrowers are driven by *nonprice* factors such as the perceived reputation related to ESG issues.

These two channels are by no means mutually exclusive, and it is difficult to completely isolate the motivation for the observed matching. We partially disentangle these effects by looking at the connection between loan pricing and the ESG ratings of the borrower and lender. We show related results in Appendix A.3. Interestingly, we find some (but fairly weak) evidence suggesting that, all else equal, banks with worse ESG ratings offer slightly lower loan spreads. Moreover, after controlling for the lender's RRI, we find no significant link between the borrower's ESG rating and loan pricing. Put more directly, banks price loans largely based on the traditional borrower and loan characteristics, but are more likely to ultimately match with borrowers on nonprice factors, such as perceived reputation on ESG issues. On balance, these results seem to suggest an equilibrium similar to the matching of underwriters described by Fernando, Gatchev, and Spindt (2005).

2.2 Evolution of borrowers' 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 package-level data. The empirical analysis is based on the following ordinary least squares (OLS) specification:

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

where i indexes borrower, j indexes lender, t indexes the package initiation year. For each package, the change in the borrower's ESG profile ($ESG\_Chg_{i,t-1,t+1}$) is defined as the change in the borrower's RRI over a 2-year window, from one year before (t-1) to one year after the package initiation date (t+1). The ex ante difference between the lender and borrower's ESG ratings ($ESG\_Diff_{i,j,t-1}$) is defined as the difference between the lender and borrower's RepRisk ESG rating measured one year before the package initiation date. To alleviate potential concerns about the comparability of ESG scores across industries and years, we adjust both the lender and the borrower's RRI by the sector-month mean. $Lender\_Chg_{j,t-1,t+1}$ controls for the evolution in the lender's ESG rating over the same 2-year window.

We realize that the evolution of the borrower's ESG rating may be both path dependent and mean-reverting. That is, borrowers with ex ante poor ESG rating are more likely to improve over time (i.e., converge to the mean level), compared to borrowers with an ex ante pristine ESG rating. By including the control variable $ESG\_Borrower_{i,t-1}$, we effectively compare the ESG evolution among borrowers with similar ex ante ESG ratings to alleviate concerns of path-dependency. Other control variables include the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status. $I_{FFindustry}$ 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.

Table 2 presents these results. 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 the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status; and in column 5, we further restrict our analysis to a subsample consisting of public firms with additional publicly available control variables including size (*log assets*), *Book leverage*, *Return on assets*, 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 the first four columns, and at the 5% level in column 5. The economic magnitude is also sizable. Take column 4, for example, which uses the full sample whose summary of statistics are reported in Table 1, a standard deviation increase in *ESG_Diff* is associated with a 0.66 (18.42 × 0.036) increase in the borrower's RRI over time, which is equivalent to 6% (0.66/11.38) of the standard deviation of *ESG_Chg*.

Given the cross-sectional and time-series characteristics of the RRI documented in Section 1.1, a reasonable concern is that our empirical specification only picks up mechanic/spurious correlation hardwired in the data, instead of identifying the economic relationship.

We rule out this possibility with two additional tests. In the first test, we generate 10,000 randomized borrower-lender pairs. For 10,000 times, we randomly draw from the pool of unique borrowers who initiated loans during our sample period, and pair it with a random lender from the pool of unique lenders.[17] We then generate a random year-month as the

[17] The size of the randomly generated sample is larger than the size of the sample in Table 2. The fact that the coefficient estimate is insignificant in the placebo test is unlikely explained by the difference in the power of the tests.

Table 2
Evolution in corporate ESG profile and bank lending

	(1) ESG_chg All	(2) ESG_chg All	(3) ESG_chg All	(4) ESG_chg All	(5) ESG_chg Public
ESG_diff	0.0718***	0.0718***	0.0616***	0.0357***	0.0295**
	(10.03)	(8.69)	(6.64)	(4.05)	(2.57)
Lender_chg	0.0617***	0.0617***	0.0465***	0.0208*	0.0299**
	(5.85)	(5.03)	(3.68)	(1.70)	(1.99)
ESG_borrower	−0.396***	−0.396***	−0.409***	−0.517***	−0.603***
	(−37.23)	(−17.51)	(−15.99)	(−22.09)	(−22.73)
Num of facilities				−0.784***	0.0139
				(−4.23)	(0.07)
log package amt				1.905***	0.503**
				(13.18)	(2.37)
USA				−2.844**	−0.118
				(−1.99)	(−0.07)
Public				1.246***	
				(4.10)	
log assets					2.371***
					(12.87)
Book leverage					−2.342***
					(−2.90)
Return on assets					−1.655
					(−1.30)
Tobin's q					0.765***
					(3.72)
Ind FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Cluster	No	Yes	Yes	Yes	Yes
N	8,128	8,128	8,104	8,104	5,120
Adj. R^2	.220	.220	.227	.264	.320

This 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 2-year window, from one year before to one year after the package 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 package initiation date. *Lender_chg* controls for the evolution in the lender's ESG indexes over the same 2-year window. *ESG_borrower* controls for the potential path dependency problem and is defined as the borrower's RepRisk index one year before the package initiation date. In column 1, we report the basic regression without fixed effects and clustering of standard errors. Column 2 clusters the standard errors at the borrower level. Column 3 adds industry and year fixed effects. In column 4, we also include the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status as control variables. In column 5, we show that our results are robust in the subsample of public firms only, and we further control for borrowers' financials, including *log assets*, *Book leverage*, *Return on assets*, and *Tobin's q*. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

"package initiation date," assuming the likelihood of initiating the loan is equal at any time during our sample period. Note that the random pairing and assignment of package initiation date do not alter the cross-sectional and time-series characteristics in ESG ratings. If our model is picking up the spurious correlation hardwired in the data, we should observe a significant coefficient estimate in this placebo test. Column 1 of Appendix A.4 reports the results. The relationship between the change in borrowers' RRI and the difference between the lender and borrower's ESG ratings is not significant, thereby alleviating concerns.

In the second test, we construct the group of "potential borrowers" under a more restrictive assumption: for each "realized" borrower-lender pair in our current sample, a "pseudo"-potential borrower is defined as a company (1) with the same public/private status, (2) in the same SICH industry, and (3) operating within a 50 miles radius of the borrower who successfully secured the package. We implicitly assume that companies (1) with similar access to public market, (2) in the same industry, and (3) clustered in the same neighborhood are likely to act together (in time) to search for corporate loan financing, and the group of lenders they approach are likely to be the same. If there are multiple matched "pseudo"-potential borrowers, we keep the one with closest ex ante RRI to the "realized" borrower as measured at one year before the package initiation date. In this way, we replace the "realized" borrower with the "pseudo"-borrower one-to-one, and construct a sample consisting of the "pseudo"-potential borrower-lender pairs.[18] We rerun the evolution regression to examine whether the bank's impact on the group of potential borrowers is persistent.

Columns 2 and 3 in Appendix A.4 report the results. We use the same specification employed in Table 2 but exclude the package-level control variables: the *Num of facilities* in the package, *log package amt*, and the country of syndication - *USA*. This is because the matching between potential borrower and lender is based on a "virtual loan package" that never existed. Borrower-level control variables are included in column 3.

The coefficient estimates of *ESG_Diff*, which is defined as the difference between the lender's and the potential borrower's RRIs, are neither statistically nor economically significant. However, if we look at the coefficients of the control variables in columns 2 and 3, we see that the directions of association and the levels of statistical significance are consistent with those in Table 2, as they should be. Overall, the results from the two placebo tests confirm that our results are unlikely driven by spurious correlations that may be hardwired in the data and model specification.

2.3 Asymmetric bank influence

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 an ESG rating that is 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 borrower, 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,

[18] Our original sample contains 8,128 packages. We are only able to find matched potential borrowers for 6,946 (or 85.5%) of them after applying the matching criteria discussed above.

Table 3
Asymmetric bank impact

A	(1)	(2)	(3)	(4)
	Better bank = 1		Better bank = 0	
	ESG_Chg	ESG_Chg	ESG_Chg	ESG_chg
ESG_diff	0.066**	0.072**	0.013	0.013
	(2.39)	(2.46)	(1.11)	(0.83)
Lender_chg	0.045	0.040	−0.017	−0.002
	(1.32)	(1.02)	(−0.94)	(−0.08)
ESG_borrower	−0.488***	−0.624***	−0.584***	−0.629***
	(−10.38)	(−12.53)	(−20.48)	(−17.86)
Num of facilities	−0.677*	0.312	−0.889***	−0.136
	(−1.83)	(0.81)	(−3.48)	(−0.52)
log package amt	4.152***	1.508***	1.562***	0.456*
	(12.69)	(2.94)	(8.35)	(1.65)
USA	−10.367***	−3.714	−0.255	1.378
	(−3.60)	(−1.27)	(−0.16)	(0.76)
Public	1.809**		1.103***	
	(2.05)		(2.80)	
log assets		3.485***		2.101***
		(8.33)		(8.74)
Book leverage		−2.037		−2.431**
		(−1.00)		(−2.43)
Return on assets		3.373		−3.345*
		(0.76)		(−1.93)
Tobin's q		1.089**		0.706***
		(2.39)		(2.67)
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	1,539	1,154	4,132	2,447
Adj. R^2	.328	.415	.240	.273

(*Continued*)

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 packages into groups where the lender has a better (i.e., smaller (<)) ESG rating than the borrower ("Better bank = 1"), and into groups where the lender has a worse (i.e., greater (>)) ESG rating than the borrower ("Better bank = 0"). Table 3, panel A, presents the results. In columns 1 and 2, we regress the borrower ESG changes for the subsample of packages 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.

In columns 3 and 4 of panel A, we run the test for the subsample of packages 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

Table 3
(Continued)

B	(1)	(2)	(3)	(4)
	Better bank (adj) = 1		Better bank (adj) = 0	
	ESG_chg	ESG_chg	ESG_chg	ESG_chg
ESG_diff	0.212***	0.256***	0.025**	0.020
	(3.76)	(4.52)	(2.49)	(1.51)
Lender_chg	0.058**	0.061*	0.021	0.030*
	(2.16)	(1.72)	(1.44)	(1.69)
ESG_borrower	−0.447***	−0.553***	−0.526***	−0.593***
	(−10.31)	(−10.86)	(−20.88)	(−20.96)
Num of facilities	−0.544	−0.067	−0.793***	0.054
	(−0.97)	(−0.08)	(−4.13)	(0.29)
log package amt	2.552***	1.107**	1.676***	0.318
	(8.72)	(2.52)	(10.64)	(1.38)
USA	−7.324	−1.234	−2.041	0.044
	(−1.59)	(−0.33)	(−1.49)	(0.03)
Public	1.615**		1.046***	
	(2.33)		(3.24)	
log assets		2.527***		2.290***
		(7.00)		(11.55)
Book leverage		−1.132		−2.535***
		(−0.57)		(−2.83)
Return on assets		0.181		−2.548*
		(0.06)		(−1.80)
Tobin's q		1.046**		0.831***
		(2.29)		(3.74)
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	1,384	899	6,482	4,079
Adj. R^2	.368	.439	.211	.262

This 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 package 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 package initiation date. *ESG_borrower* controls for the potential path dependency problem and is defined as the borrower's RepRisk index one year before the package initiation date. Panel A presents the results for the subsamples where lender has a better or worse unadjusted ESG rating than the borrower. Samples in columns 1 and 2 include only loans where the bank's unadjusted RRI is smaller (<) than the borrower's unadjusted RRI. Samples in columns 3 and 4 include those where the bank's unadjusted RRI is larger (>) than the borrower's. Panel B presents the results for the subsamples where lender has a better or worse sector-month-adjusted ESG rating than the borrower. We also include the *Num of Facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status as control variables. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

more socially responsible, "bad" lenders do not induce their borrowers to become less responsible.

Panel B of Table 3 repeats the analysis using alternative definitions of "better bank." In columns 1 and 2, we consider the subsample of packages where the lender's sector-month-adjusted RRI is smaller (<) than the borrower's sector-month-adjusted RRI (better bank (adj) =1). In those cases, we find a significant improvement in borrowers' ESG ratings. With similar intuition, we consider the subsamples in columns 3 and 4, where the lender's sector-month-adjusted RRI is greater (>) than the borrower's sector-month-adjusted RRI (better bank (adj) =0). While the coefficient estimate of *ESG_Diff* in column 3 of panel B is statistically significant, the economic magnitude is about one-ninth of that in column 1 of panel B. Overall, we find little evidence of the lenders' influence over the borrowers for these subsamples.[19] Lastly, we compute the Wald chi-square statistics using the post-estimation command *suest*, and confirm that we can reject the equality of the coefficients (*ESG_Diff*) across pairwise regression samples (panel A, column 1 vs. 3; panel A, column 2 vs. 4) at the 10% level, and across the pairwise regression samples (panel B, column 1 vs. 3; panel B, column 2 vs. 4) at the 1% level.

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 performance.

2.4 Cross-sectional variation in bank dependency and liability risk

In Table 4, we focus on those cases in which we expect the lender to have a particularly strong influence on its borrowers. We posit that bank dependent borrowers have stronger incentives to preserve the existing lending relationship, and are thus more likely to discipline themselves when lenders hold a high ESG lending standard. We test our hypothesis using the following specification:

$$\begin{aligned} ESG\_Chg_{i,t-1,t+1} = &\alpha + \beta ESG\_Diff_{i,j,t-1} \times I_{dependency,t-1} \\ &+ \varsigma ESG\_Diff_{i,j,t-1} + \tau I_{dependency,t-1} \\ &+ \lambda Lender\_Chg_{j,t-1,t+1} + \theta ESG\_Borrower_{i,t-1} \\ &+ \gamma X_{i,t-1} + I_{ffindustry} + \delta_t + \xi_{i,j,t}, \end{aligned} \quad (2)$$

where i indexes borrower, j indexes lender, t indexes the package initiation year. $ESG\_Diff_{i,j,t-1} \times I_{dependency}$ is an interaction term between the lender and borrower ESG difference and our proxies for bank dependency. These proxies include indicators for credit rating (*Rated*) and investment-grade status (*Investment grade*). We include the same set of control variables (X) as specified in Equation (1), including the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status.

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. 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

[19] Note that in both panels A and B, we drop the packages where the lender's RRI it equal to the borrower's RRI (adjusted RRI in panel B). The sample size in panel A is smaller than that in panel B because of the clustering of unadjusted RRIs at zero, in which case packages are dropped from the (combined) better and worse lender subsamples.

Table 4
Bank dependency, secured loans, and bank lending

	(1) ESG_chg	(2) ESG_chg	(3) ESG_chg
ESG_diff	0.060***	0.055***	0.023**
	(5.12)	(5.62)	(2.22)
Rated	1.820***		
	(4.11)		
ESG_diff × Rated	−0.046***		
	(−3.17)		
Investment grade		3.924***	
		(8.18)	
ESG_diff × Investment grade		−0.077***	
		(−4.74)	
Secure			−2.313***
			(−6.27)
ESG_diff × Secure			0.033**
			(2.40)
Lender_chg	0.019	0.018	0.020
	(1.59)	(1.52)	(1.64)
ESG_borrower	−0.528***	−0.549***	−0.529***
	(−22.13)	(−23.87)	(−23.08)
Num of facilities	−0.732***	−0.559***	−0.661***
	(−3.99)	(−3.32)	(−3.77)
log package amt	1.762***	1.604***	1.852***
	(11.39)	(11.09)	(13.06)
USA	−2.823**	−2.624**	−2.710*
	(−2.03)	(−1.98)	(−1.91)
Public	0.943***	0.836***	1.294***
	(2.92)	(2.70)	(4.30)
Ind FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
N	8,104	8,104	8,104
Adj. R^2	.267	.276	.270

This 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 package 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 package initiation date. Interaction terms of *ESG_diff* and proxies of bank dependency are included. Proxies of bank dependency include the *Rated* dummy and *Investment-grade* dummy. *Secure* is the dummy variable that turns on if the loan is a secured loan. *ESG_borrower* controls for the potential path dependency problem and is defined as the borrower's RepRisk index one year before the package initiation date. We also include the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status as control variables. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. *t*-statistics for the regressions are reported in parentheses. **p* <.1; ***p* <.05; ****p* <.01.

similarly find that lenders have greater influence over the non-investment-grade borrowers' ESG policies.

Lastly, we posit that the bank's impact is stronger among secured packages, where a negative shock to the borrower could significantly increase the lender's liability risk. Strahan (1999) shows that loans to smaller borrowers, borrowers with less cash, and borrowers who are difficult to value by outside investors are more likely to be secured by collateral. Column 3 of Table 4 presents results consistent with our hypothesis.

2.5 Propagation of bank influence along E, S, and G

Arguably, creditors may react differently to certain borrower ESG-related behaviors (Dimson, Karakaş, and Li 2015). We suspect that banks are particularly concerned with controversial social and/or environmental issues that would focus the spotlight on their lenders, thereby harming their reputation, reducing their social capital, and ultimately diminishing the opportunities to engage future business.

To further explore these issues, we analyze the lender's impact across a variety of ESG issues. RepRisk database tracks company negative news related to 28 different issues spanning across E, S, and G dimensions. However, it does not provide a "by issue" RRI. We construct a proxy of the borrower's evolution along the specific issues using the following method:

$$\begin{aligned} &Chg\_RRI_{j,t-1,t+1} = (RRI_{t+1} - RRI_{t-1}) \times \\ &(\#\ of\ News\ Associated\ with\ Issue\ j\ from\ t-1\ to\ t+1) / \\ &(Total\ \#\ of\ News\ Associated\ with\ All\ Issues\ from\ t-1\ to\ t+1), \end{aligned} \tag{3}$$

where $Chg\_RRI_{j,t-1,t+1}$ is the change in borrowers' RRIs attributable to issue j from years $t-1$ to $t+1$. RRI_{t+1} and RRI_{t-1} are borrowers' RRIs measured at years $t+1$ and $t-1$, respectively.

Table 5 reports the regression results. We find that banks are more likely to discipline borrowers along (1) climate change, (2) human rights abuse, and (3) social discrimination. In contrast, their impact on other issues, including executive compensation, is negligible. Note that the borrowers in our sample are not in the news related to 3 of the 28 issues, where we mark the regression results as n/a. Overall, other than the regression related to the issue of animal mistreatment (*am*), our results confirm that banks have stronger incentives to minimize negative exposures in borrowers' catastrophic social and environmental scandals in order to engage in future business.

2.6 Negative reputational news events and changes in banking relationship

So far, we have demonstrated circumstances in which banks with high ESG ratings have a positive influence on the evolution of their borrowers' ESG ratings over time. A natural question arises concerning what drives the mechanism of this evolution? We can think of three possible mechanism in which banks may influence their borrowers to improve their ESG performance over time. One possibility is an "association" effect, in which borrowers tend to gradually incorporate the viewpoints and policies of the parties they contract with (including their bankers). A second scenario is that the bankers may take active steps to encourage their borrowers to improve their ESG ratings over time. While it is difficult for banks to explicitly and overtly mandate such actions (in part because of lender liability concerns), they may take subtle steps to use their "voice" to "nudge" borrowers to improve their ESG rating.

Table 5
ESG Issues and Bank Impact

Environmental issues	(1) chg_rri_cc	(2) chg_rri_lp	(3) chg_rri_iol	(4) chg_rri_oaw	(5) chg_rri_wi	(6) chg_rri_am
ESG_diff	0.0007**	0.0001	0.0005	0.0000	−0.0004	−0.0007*
	(1.975)	(0.055)	(0.550)	(0.137)	(−0.730)	(−1.866)

Community issues	(1) chg_rri_hra	(2) chg_rri_ioc	(3) chg_rri_lpi	(4) chg_rri_sd
ESG_diff	0.0029**	0.0016	0.0004**	0.0009*
	(1.977)	(1.178)	(2.138)	(1.822)

Employee issues	(1) chg_rri_fl	(2) chg_rri_cl	(3) chg_rri_foa	(4) chg_rri_die	(5) chg_rri_oh	(6) chg_rri_pec
ESG_diff	0.0000	0.0002	0.0010	−0.0001	0.0022	−0.0014
	(0.117)	(1.431)	(1.135)	(−0.165)	(1.393)	(−1.499)

Governance issues	(1) chg_rri_cbe	(2) chg_rri_ec	(3) chg_rri_mc	(4) chg_rri_fd	(5) chg_rri_te	(6) chg_rri_to	(7) chg_rri_ap
ESG_diff	−0.0001	0.0005	−0.0000	−0.0012	0.0000	0.0006	0.0007
	(−0.075)	(0.782)	(−0.040)	(−0.594)	(0.038)	(0.977)	(0.854)

Cross-cutting Issues	(1) chg_rri_cp	(2) chg_rri_phe	(3) chg_rri_voi	(4) chg_rri_von	(5) chg_rri_sci
ESG_diff	0.0009	n/a	n/a	n/a	−0.0002
	(1.509)	n/a	n/a	n/a	(−0.288)

This table reports the OLS regression of the change in the borrower's RRI related to 28 issues. The abbreviation of the specific issues are *cc*: Climate change, *lp*: Local pollution, *iol*: Impacts on landscapes, *oaw*: Overuse and wasting, *wi*: Waste issues, *am*: Animal mistreatment, *hra*: Human rights abuses, *ioc*: Impacts on communities, *lpi*: Local participation, *sd*: Social discrimination, *fl:* Forced labor, *cl*: Child labor, *foa*: Freedom of association, *die*: Discrimination in employment, *oh*: Occupational health and safety, *pec*: Poor employment conditions, *cbe*: Corruption, *ec*: Executive compensation, *mc*: Misleading communication, *fd*: Fraud, *te*: Tax evasion, *to*: Tax optimization, *ap*: Anticompetitive, *cp*: Controversial products, *phe*: Health and environmental, *voi*: Violation of international standards, *von*: National legislation, and *sci*: Supply chain. 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 package initiation date. We compressed the coefficients of *Lender_chg*, *ESG_borrower*, the *Num of Facilities*, *log package amt*, *USA*, and the borrower's *Public* status. Year and industry FEs are included. Industry classifications are based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

A third possibility is that borrowers take steps to improve their ESG because they want to ensure that the bank renews their loan and/or provides them with additional financing over time. These "exit" concerns may be particularly relevant for bank dependent borrowers who fear the disruption of their lending relationship.

While they may be relevant, it is difficult to envision a series of empirical tests that will convincingly support the first two possible mechanism. However, it is possible to shed light onto the relevance of the third mechanism. In this section, we answer this important second-stage question by examining the relationship between the damages to the borrower's reputation, and the likelihood of initiating new loan(s) with the same lead lender within a 2-year period centered on the original package's end date. In this test, we define "a hit to the borrower's reputation" as one borrower-month where the borrower is covered in negative ESG-related news.[20] We use "month" as the unit or window of observation, rather than focusing on individual daily news stories because many news stories originate from the same public-image fiasco, where a single accident could lead to an ongoing saga that dribbles out over weeks. In this study, we collectively refer to all news reports (if any) covered within the *same* month as *one* negative reputational shock.

$$Pr(Same_{i,j,te}=1)=\phi(\alpha+\beta Num\ Rep\ Event_{i,ts,te}+\gamma X_{i,te-1}+S_{i,j} + I_{ffindustry}+\delta_t+\xi_{i,j,t}) \tag{4}$$

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 package extends a new package to the borrower *i* within a 2-year period centered on the original package'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 package. $X_{i,te-1}$ is the vector of borrowers' characteristics that we use as control variables. These variables include the (1) ex ante level and (2) change in *Book Leverage*, size (*log assets*), return on assets (*Return on Assets*), and *Tobin's q*. $S_{i,j}$ denote additional control variables that include the *Original Package 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.

Note that we restrict the regression sample to borrowers who received at least one package financing within the 2-year period centered on the original package's end date. This mitigates concerns related to demand side heterogeneities, because we are only looking at borrowers actively seeking new loan financing. Table 1 reports the summary of statistics of key variables in the test. Conditional on initiating new packages around the expiration of the original package, 51% obtain it from exactly the same group of lead lenders, 56% are able to retain at least one of the lead lenders. The median length of the original package is 3 years, and the median borrower experiences at least one negative ESG-related reputational shock during this period.

Columns 1 and 2 of Table 6 report the results. The coefficient estimate of *Num rep event* in column 1 is 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 package, controlling for the length of the original package. The coefficient in column 2 is significant at the 10% level,

[20] RepRisk tracks firm-level negative news in its *News* database. Each piece of news coverage is recorded with a specific news date and is mapped to a related ESG issue and/or topic. For details, please refer to the WRDS RepRisk Data Manual.

Table 6
Negative reputational news incidents and switch in lending relationship

	(1) Same All	(2) Same Public	(3) Same res All	(4) Same res Public	(5) Same sgl All	(6) Same sgl Public
Num rep event	−0.0489***	−0.0242*	−0.0546***	−0.0278**	−0.0704***	−0.0624**
	(−4.99)	(−1.75)	(−5.60)	(−1.99)	(−3.01)	(−1.97)
ESG_borrower_start	0.0147***	0.00401	0.0117***	0.00245	0.0191***	0.00843
	(5.54)	(1.23)	(4.55)	(0.77)	(3.53)	(1.14)
Num of facilities		−0.107		−0.102		−0.303**
		(−1.58)		(−1.45)		(−2.14)
Book leverage		0.0762		−0.0387		0.128
		(0.39)		(−0.19)		(0.36)
Tobin's q		−0.0432		−0.0902		−0.223**
		(−0.75)		(−1.54)		(−2.08)
Return on assets		0.654		0.595		1.951**
		(1.48)		(1.25)		(2.19)
log assets		0.0273		−0.0415		0.0718
		(0.81)		(−1.25)		(1.15)
Chg in book leverage		0.0705		0.114		−0.0249
		(0.26)		(0.42)		(−0.05)
Chg in Tobin's q		0.00496		−0.0378		−0.0484
		(0.08)		(−0.63)		(−0.44)
Chg in return on assets		0.562**		0.603*		1.921***
		(2.03)		(1.88)		(2.83)
Chg in log assets		−0.0531		−0.0907		0.0394
		(−0.68)		(−1.16)		(0.26)
Original package length		−0.143***		−0.125***		−0.0598
		(−5.57)		(−4.78)		(−1.22)
Investment grade		0.0181		0.213**		−0.0314
		(0.20)		(2.41)		(−0.18)
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes	Yes
N	2,880	1,903	2,880	1,903	950	543
Pseudo-R^2	.035	.065	.027	.056	.038	.079

This table reports the probit regression of the number of the borrower's negative reputational news on the likelihood of initiating new loan package(s) with the same lead lender from 12 months before, to 12 months after the original package's maturity date. *Num Rep Event* is the number of borrower-months with negative news coverage from the start to the end dates of the original package. *Same* is the dummy variable that turns on if the borrower initiates new package(s) with at least one of the same lead lenders from 12 months before, to 12 months after the original package's maturity date. *Same res* is defined more restrictively, as the dummy variable that turns on if the borrower initiates new package(s) with exactly same group of lead lenders. *Same sgl* 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 package(s) with the same lender. 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 package. *Original package length* refers to the number of years between the start and end dates of the original package. Controls include the borrower's ex ante level and change (during the original loan window) in *log assets*, *Book Leverage*, *Return on Assets*, and *Tobin's q*. Industry FE is based on the Fama-French 12 industry classification. Year FE is based on the end year of the original package. Standard errors are clustered at the borrower level. z-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

after including all of the control variables and focusing on the public borrowers. 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 package(s) with exactly the same group of lead lenders within the 2-year period centered on the original package's end date. Our main results remain statistically and economically robust to this variation. Finally, in columns 5 and 6, we define *same sgl* (single lead lender) most restrictively, as the dummy variable that turns on if the original package has a single lead lender, and the borrower initiates new package(s) with the same single lead lender within the 2-year period centered on the original package's end date. The economic magnitudes in all regressions are sizable. Taking column 6, for example, which has the most restrictive specification and richest set of controls, a marginal unit increase in *Num rep event* is associated with a 0.03 decrease in the likelihood of retaining the same lead lender(s). Here, the marginal effects of the probit model (0.03) are estimated at the sample means.

Lastly, we examine the ESG profile of the new lead lender(s) as a function of the number of borrowers' reputational incidents during the original package period. We posit that borrowers with deteriorating ESG profile are matched to lenders with worse ESG ratings at the expiration of the original package. Specifically, we look at the same sample of borrowers who received at least one loan financing within the 2-year period centered on the original package's end date. Then we calculate the difference between the lender ESG rating of the new package and the lender ESG rating of the original package, which we use as the dependent variable. We perform an OLS regression using the following specification:

$$\begin{aligned} Lender\_Diff =& \alpha + \beta Num\ Rep\ Event_{i,ts,te} + \sigma Same_{i,j,te} \\ & + \gamma X_{i,te-1} + S_{i,j} + I_{ffindustry} + \delta_t + \xi_{i,j,t}. \end{aligned} \tag{5}$$

Here, *Lender_Diff* is defined as the ESG rating of the lender(s) of the new package minus the ESG rating of the lender(s) of the original package. $Num\ Rep\ Event_{i,ts,te}$ 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 package. $Same_{i,j,te}$ is a dummy variable that equals one if at least one of the lead lenders (*j*) in the original package extends a new package to the borrower *i* within a 2-year period centered on the original package's end date, *te*. $X_{i,te-1}$ is the vector of borrowers' characteristics that we use as control variables. These variables include the (1) ex ante level and (2) change in *Book leverage*, size (*log assets*), *Return on assets* (ROA), and *Tobin's q*. $S_{i,j}$ denote additional control variables that include the *Original package 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.

Table 7 presents the corresponding results. The coefficients of $Num\ rep\ event_{i,ts,te}$ are positive and statistically significant in all of the columns. It confirms that borrowers who are exposed in greater number of reputational events obtain loan financing from lenders with much worse ESG ratings at the expiration date of the original loan package. The coefficients of the $Same_{i,j,te}$ are negative, and statistically significant in columns 1 and 2. We interpret the results as evidence that borrowers who switch lenders

Table 7
Negative reputational news incidents and change in lenders' ESG profile

	(1) Lender_diff All	(2) Lender_diff Public	(3) Lender_diff Public	(4) Lender_diff Public
Num rep event	0.912***	1.258***	1.235***	0.510***
	(6.79)	(7.81)	(7.49)	(2.67)
ESG_borrower_start	−0.233***	−0.195***	−0.199***	−0.0836**
	(−7.62)	(−5.21)	(−5.35)	(−2.22)
Same	−2.335***	−1.670*	−1.339	−0.195
	(−2.85)	(−1.79)	(−1.44)	(−0.21)
Num of facilities		0.877	1.120*	0.519
		(1.49)	(1.83)	(0.82)
Book leverage		1.238	−0.848	−0.415
		(0.57)	(−0.32)	(−0.16)
Tobin's q		−0.729	−0.323	−0.125
		(−1.31)	(−0.48)	(−0.19)
Return on assets		5.224	1.226	−1.090
		(1.02)	(0.18)	(−0.16)
log assets		−1.137***	−0.879**	−0.0847
		(−3.18)	(−2.43)	(−0.22)
Chg in book leverage			−3.933	−4.640
			(−0.96)	(−1.17)
Chg in Tobin's q			0.908	0.586
			(1.12)	(0.72)
Chg in return on assets			−5.223	−5.177
			(−0.98)	(−1.01)
Chg in log assets			2.581**	1.666
			(2.16)	(1.44)
Original package length				3.041***
				(9.86)
Investment grade				0.502
				(0.47)
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	2,698	1,908	1,796	1,796
Adj. R^2	.102	.113	.121	.163

This table reports the OLS regression of the number of borrower-months with negative news coverage on the changes in the lead lenders' ESG ratings (average ESG ratings of the new lead lenders minus the average ESG ratings of the lead lenders of the original package). The new group of lenders are the banks that lend money to the borrower within 12 months of the original package's expiration date. *Num rep event* is the number of borrower-months with negative news coverage from the start to the end dates of the original package. 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 package. *Same* is the dummy variable that turns on if the borrower initiates new package(s) with at least one of the same lead lenders from 12 months before, to 12 months after the original package's maturity date. *Original package length* refers to the number of years between the start and end dates of the original package. Controls include the borrower's ex ante level and change (during the original loan window) in *log assets*, *Book leverage*, *Return on assets*, and *Tobin's q*. Industry FE is based on the Fama-French 12 industry classification. Year FE is based on the end year of the original package. Standard errors are clustered at the borrower level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

generally engage lenders with worse ESG profiles, instead of pairing with lenders with higher ESG standard. Taken together, we show that borrowers with higher number of reputational events are more likely to switch lenders, and also more likely to engage lenders with worse ESG ratings at loan renewal.

3. Source of Endogeneity and Identification

3.1 Source of endogeneity

We document that lenders have a direct and positive impact on the evolution of borrowers' ESG profile. However, interpreting the result as causal evidence can be confounded by endogeneity concerns.

First, two types of selection problems are embedded in our current framework. One concern is that borrowers with a 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 ex ante ESG standard constant, we explore how the difference in the bank's ESG standard affect the borrower's subsequent improvement in ESG performance. The second type of selection bias is that borrowers who expect to improve their ESG performance ($ESG\_chg_{i,t-1,t+1}$) may self-select to borrow from banks with high ESG standards. If this is the case, the borrower's ex post ESG change reversely leads to the establishment of a lending relationship with a bank with high ESG standards.

Furthermore, there may be other omitted variables. A notable one is the CEO's awareness of/concern about ESG issues. Borghesi, Houston, and Naranjo (2007) document various factors that motivate managers to make socially responsible investments. In particular, borrowers with CEOs who are attuned to ESG issues are more likely to improve their ESG performance over time; at the same time, they are 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.

3.2 Difference-in-differences 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 the quasi-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 DiD 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 existing 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).

We quantify the magnitude of the shock to the lender's ESG standard by incorporating the size effect. If the lender is the acquirer in the M&A, and the target is extremely small relative to the acquirer, we assume that the shock to the acquirer's ESG standard post-M&A is virtually zero. Empirically, we calculate

Table 8
Balancing table

	Treatment				Control					
Name	Mean	SD	Min	Max	Mean	SD	Min	Max	Diff-in-mean	t-statistic
Package 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*)	5.67	11.49	0	62	7.40	10.31	0	39	−1.73	(−1.48)
Public (Y/N)	0.61	0.49	0	1	0.69	0.47	0	1	−0.08	(−1.60)
log assets	8.49	1.96	2.37	13.93	8.50	1.68	3.76	13.34	−0.01	(−0.06)

The following table reports the balancing test between the ex ante profiles of borrowers in the treatment and control groups. *Package date* is the package initiation date. We construct the control group by selecting packages initiated in the same year-month as the treated packages. *RepRisk index* is measured *ex ante* at the package 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-sided difference tests are reported in parentheses. *p <.1; **p <.05; ***p <.01.

ESG_Shock_j for the treatment group using the following specification, and assign zero to all control units:

$$\begin{aligned} &ESG\_Shock_j = (RRI_a - RRI_t) \times Size_a / (Size_a + Size_t), \\ &\qquad \textit{if the lender j is the target} \\ &ESG\_Shock_j = -(RRI_a - RRI_t) \times Size_t / (Size_a + Size_t), \\ &\qquad \textit{if the lender j is the acquirer}. \end{aligned} \tag{6}$$

We pair each treated loan one-to-one with a control unit using a method similar to that used in Barko, Cremers, and Renneboog (2021). 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, the borrower in the control group is selected as the one with closest ex ante RRI (measured at the time of package initiation) to that of the borrower in the treated group. This setup ensures that the assignment of the treatment versus the control is orthogonal to the main endogenous variable of interest, that is, borrowers' historical RRI. Finally, if multiple potential control units have the same ex ante borrower's RRI, we compare and pick the (control) borrower whose lender has the closest ex ante RRI to that of the (treatment) borrower's lender.

Table 8 reports on the balancing test between the ex ante characteristics of borrowers in the treatment and control groups. *Package date* is the package initiation date. *RepRisk index* is measured ex ante at the package 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-sided difference tests are reported in parentheses. None of the reported characteristics are statistically different across groups. Finally, we apply borrower fixed effects in columns 3 and 4 of the DiD analysis (Table 9) to absorb any remaining unobservable heterogeneity between the borrowers in the control and treatment groups.

We present the DiD analysis in Table 9. To be consistent with the level of observation in the earlier regressions, we conduct the analysis at the package level, where we collapse facilities within the same package into one single treatment or control observation. In columns 1 and 2, we employ the following specification:

$$\begin{aligned} RRI_{i,t} = \alpha + \beta ESG\_Shock_j \times Post_t + \varsigma ESG\_Shock_j + \tau Post_t \\ + \gamma X_{i,j} + I_{ffindustry} + \xi_{i,j,t}, \end{aligned} \tag{7}$$

where i indexes borrower, j indexes lender, and t indexes the year of observation. This specification represents a panel DiD regression of the borrower's yearly average RepRisk indexes ($RRI_{i,t}$) over a 4-year 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 5-year window after the package initiation date. We obtain the yearly average RRI (if available) from 2 years before to 2 years after the M&A date. ESG_Shock_j is the quasi-exogenous variation to the lender's ESG standard in the merger and acquisition. $Post_t$ dummy equals one if the year of observation is after the M&A event date. We also include the *log package amt*, country of syndication *USA*, the borrower's *Public* status, and the *Num of Facilities* in the package as control variables. $I_{ffindustry}$ denote the dummies for Fama-French 12 industry fixed effects. Finally, standard errors are clustered at the borrower level.

Table 9 reports the main results from the DiD analysis. The key coefficient estimates of the interaction term, $ESG\_Shock_j \times Post_t$, are positive and statistically significant at the 1% level in columns 1 and 2. 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 quasi-exogenous shock to the lender's ESG rating. The significant coefficient related to *Post* captures an upward trend in the RRI over time. In columns 3 and 4, we repeat the analysis in columns 1 and 2 but replace the *Post* dummy with year FEs, and replace the industry FEs with the borrower FEs. As expected, we observe a significant reduction in the explanatory power of the control variables (absorbed by the borrower FEs). The coefficient of the interaction term remains positive and statistically significant at the 5% level, and our DiD inference is robust to variations in specifications.

Admittedly, the limited sample of packages in the DiD analysis is drastically different from the sample that we use in the rest of the study. The number of borrowers whose lenders are involved in a M&A is very small. To make a transparent comparison across different empirical specifications, we run an OLS regression using the same specification in Table 2, but based on the DiD sample. Each package only enters the regression once (instead of four times involving

Table 9
Diff-in-diff analysis using bank mergers

	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG_chg
ESG_shock × Post	0.186***	0.180***	0.143**	0.147**	
	(3.57)	(3.42)	(2.41)	(2.46)	
ESG_shock	0.130**	−0.029	−0.040	−0.043	0.265***
	(2.59)	(−0.57)	(−0.35)	(−0.38)	(3.05)
Post	2.212***	2.122***			
	(4.91)	(4.85)			
ESG_borrower					−0.701***
					(−12.14)
Num of facilities		−0.213***		0.026	−0.368*
		(−7.44)		(0.71)	(−1.83)
log package amt		2.546***		−0.340	1.396***
		(7.72)		(−1.20)	(3.59)
USA		−8.809***		1.066	−8.335*
		(−5.22)		(0.91)	(−1.77)
Public		4.031***		3.872**	1.284
		(5.56)		(2.19)	(1.21)
Ind FE	Yes	Yes	No	No	Yes
Borrower FE	No	No	Yes	Yes	No
Year FE	No	No	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes	Yes
N	1,851	1,851	1,879	1,879	455
Adj. R^2	.059	.235	.703	.703	.398

This table reports the OLS regression of the borrower's yearly average RepRisk indexes (*ESG*) over a 4-year window around the M&A event. The sample consists of all packages where the lender is involved in a M&A event within a 5-year window after the package initiation date, and the matched loan packages in the control group. We obtain the yearly average RepRisk index (if available) from 2 years before to 2 years 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 year of the RepRisk index is after the M&A event date. In columns 3 and 4, we replace the industry FEs and the *Post* dummy employed in columns 1 and 2 with the borrower and year FEs. We also include the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status as control variables. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

two yearly observations before and after the "shock"), and dependent variable (*ESG_Chg*) is the evolution of the borrower's RRI from before to after the M&A. We present the results from the OLS regression in column 5 of Table 9. The economic magnitudes are different but comparable: a unit increase in the merged lender's RRI is associated with a change of 0.14–0.19 in the borrower's RRI (columns 1–4), compared with a change of 0.27 in the borrower's RRI if we use the OLS specification.

4. Robustness Tests

In this section, we conduct several robustness tests to confirm our baseline results related to borrower ESG rating evolution. Section 4.1 calculates the main explanatory variable using the raw, instead of sector-month-adjusted RRIs. Section 4.2 considers an alternative method of defining lead lender(s). Section 4.3 examines alternative sampling criteria. Section 4.4 analyzes alternative specifications.

Table 10
Robustness tests

	(1) ESG_chg	(2) ESG_chg	(3) ESG_chg	(4) ESG_chg
Unadjusted_ESG_diff	0.022***			
	(2.88)			
ESG_diff		0.031**	0.030***	0.037***
		(2.34)	(3.68)	(3.67)
Lender_chg	0.013	0.001	0.028**	0.018
	(1.05)	(0.04)	(2.33)	(1.36)
ESG_borrower	−0.526***	−0.559***	−0.522***	−0.511***
	(−23.46)	(−14.33)	(−21.42)	(−18.97)
Num of facilities	−0.744***	−0.426	−0.766***	−0.727***
	(−4.07)	(−1.27)	(−3.77)	(−3.39)
log package amt	1.939***	1.157***	1.881***	2.126***
	(13.28)	(4.88)	(12.19)	(12.87)
USA	−2.896**	−6.239***	−2.218	−1.165
	(−2.04)	(−2.79)	(−1.42)	(−0.67)
Public	1.203***	1.369***	1.039***	0.792**
	(3.96)	(2.84)	(3.07)	(2.24)
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Cluster	Yes	Yes	Yes	Yes
N	8,104	2,137	6,864	6,090
Adj. R^2	.262	.238	.265	.265

This table reports on four robustness tests for the baseline result of ESG evolution. Column 1 presents the results if *ESG_Diff* variable is calculated without sector-month adjustments. Sample in column 2 include only packages with a unique lead arranger in the syndicate. In column 3, we 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 packages of nonfinancial and nonutility U.S. 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 package 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 package initiation date. *ESG_Borrower* controls for the potential path dependency problem and is defined as the borrower's RepRisk index one year before the package initiation date. We also include the *Num of Facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status as control variables. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. T-statistics are reported in parentheses. **p* <.1; ***p* <.05; ****p* <.01.

4.1 Measuring ESG rating differences between borrowers and lenders

In our main specifications, we adjust both the borrower and lender ESG ratings by the sector-month 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, column 1, presents the results. We find that the direction of impact does not change, and the level of statistical significance remain at the 1% level.

4.2 Lender profiles, single lead loans, and strongest relationship lead lenders

In our main specifications, when there are multiple lead lenders in the package syndicate, we calculate the lead lenders' ESG rating by taking the average lender ESG rating for each package. Which lender dictates the relationship and influences the borrower is unclear; 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, in which we run the baseline estimation for the subsample of packages where a single unique lead lender is in the syndicate. Column 2 of Table 10 presents the results. We find that our results are unchanged for the subsample of packages where we have a single lender.

Other alternative approaches to 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 package. We test the former approach as it is more intuitive (Ivashina and Kovner 2011). We classify the "strongest relationship" lead-lender as the lead lender who financed the greatest fraction of loan amount in the past 5 years before the current package. Column 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.

4.3 Sample selection criteria

A third robustness check is related to sample selection criteria. In our main regressions, we aim to censor as few observations as possible from the DealScan database, if we are not clearly guided, theoretically and empirically, by earlier works to do so. In this section, we test our findings to the usage of a few additional sample selection criteria. Specifically, we require the packages to be USD denominated, and issued by nonfinancial, nonutility borrowers. Column 4 of Table 10 presents our findings under these criteria. We find that our results are robust under this approach. Overall, the robustness tests confirm our finding that high ESG rating lenders influence their borrowers in their ESG policies.

4.4 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 and borrower's ESG ratings, while controlling for the borrower's ex ante ESG standard. This empirical specification views each package initiation as an "event" and makes sure each package 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 2 using levels, rather than changes, as the main variables of interest. Our regressions follow the specification below:

$$
\begin{aligned}
RRI\_Borrower_{t+1} = {} & \alpha + \beta RRI\_Lender_{t-1} + \varsigma RRI\_Borrower_{t-1} \\
& + \tau Lender\_Chg_j + \gamma X_{i,t-1} + I_{ffindustry} \\
& + \delta_t + \xi_{i,j,t}.
\end{aligned}
\tag{8}
$$

RRI_Borrower$_{t+1}$ is defined as the level of borrowers' RepRisk indexes (rather than the change) one year after the package initiation date. *RRI_Lender*$_{t-1}$ is defined as the level of lenders' RepRisk indexes one year before the package initiation date. *RRI_Borrower*$_{t-1}$ is defined as the level of borrowers' RepRisk indexes one year before the package initiation date. We also include the *log package amt*, country of syndication *USA*, the borrower's *Public* status, and the *Num of Facilities* in the package as control variables. In column 5, we perform a subsample analysis in the public space only, and control for borrowers' financials, including *log assets*, *Book leverage*, *Return on assets*, and *Tobin's q*. Note that the level of observation in this case are at the package level. Each package only enters once into the regression, and the year t is defined as the year of package initiation.

Appendix A.5 reports the results. In columns 1, 2, 3, and 4, the coefficients are statistically significant and economically sizable. Column 5 presents the subsample analysis focusing on public borrowers only. The t-statistic is not significant at the 10% level, but the economic magnitude remains comparable to estimates in earlier columns.

5. Conclusion

Our study demonstrates that banks profoundly influence firms' ESG policies. We find that banks are significantly more likely to partner with borrowers who have similar ESG ratings. This result suggests that ESG policies influence the construction of bank lending relationships and that different banks have different attitudes toward borrower ESG policies. Our findings echo the mounting anecdotal evidence where banks have announced that they are cutting off lending in response to a borrower's reputational shock related to ESG issues.

We also find that banks have a dynamic influence on their borrowers' subsequent ESG performance. Notably, firms that borrow from banks with relatively better ESG profiles are more likely to improve their own ESG performance over time. By examining the decisions on loan renewal, we show that borrowers who continue to engage in risky ESG practice are subject to costly disruptions in lending relationships. We also find that banks are more likely to influence bank-dependent borrowers, and that their influence is predominantly concentrated among environmental and social issues that likely focus the spotlight on the lenders, leading to severe reputational and financial consequences. Overall, our work demonstrates a novel channel by which a key stakeholder can profoundly promote socially responsible decision-making.

Table A.1
Variable Definitions

Variable name	Description	Source
ESG_chg	The change in the borrower's RepRisk index from one year before, to one year after the package initiation date	RepRisk
ESG_borrower	The RepRisk index of the borrower measured one year before the package initiation date	RepRisk
Lender_chg	The change in the lead lender's RepRisk index from one year before, to one year after the package initiation date. If there is more than one lead lender, use the average of the changes	RepRisk
ESG_diff	The difference between the lead lender and borrower's sector-month-adjusted RepRisk indexes measured one year before the package initiation date. If there is more than one lead lender, use the average of the differences	RepRisk
Num of facilities	Number of facilities in the package	DealScan
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
Secure	An indicator that equals one if the loan is secured, and zero otherwise	DealScan
log package amt	The natural logarithm of the size of the syndicated package	DealScan
Public	An indicator that equals one if the borrower firm's equity is publicly traded, and zero otherwise	CRSP
log assets	The natural logarithm of the borrower's total assets (in millions) at the latest fiscal period that ended prior to package 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 the book value of total assets	Compustat
Size of target	The M&A transaction value divided by the percentage of target acquired (in millions)	SDC
Size of acquirer	Value of the acquirer's asset LTM (in millions)	SDC
ESG_diff_MA	The difference between the acquirer and target's RepRisk indexes at the time of the M&A	RepRisk, SDC
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, SDC

Table A.2
Reputational risk exposure and risk-adjusted capital ratios

	(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	1,340	1,340	1,340	1,340	1,340	1,340	1,340
Adj. R^2	.607	.616	.616	.609	.606	.606	.609

This table 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 place the focus on within-bank variations and to preclude the impact of common time trends. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table A.3
Loan pricing and RRI

	(1) log spread	(2) log spread	(3) log spread
log borrower RRI	−0.002	−0.005	−0.008
	(−0.42)	(−1.05)	(−1.04)
log lender RRI	−0.007*	−0.007*	−0.008*
	(−1.76)	(−1.72)	(−1.70)
log borrower RRI × log lender RRI			0.001
			(0.52)
log assets	−0.021***	−0.032***	−0.032***
	(−3.85)	(−4.56)	(−4.56)
log amount	−0.049***	−0.032***	−0.032***
	(−9.00)	(−5.45)	(−5.44)
Commercial paper rating		−0.034*	−0.034*
		(−1.69)	(−1.70)
Book leverage		0.013	0.013
		(0.31)	(0.32)
Tobin's q		−0.053***	−0.053***
		(−6.64)	(−6.64)
Current ratio		0.006	0.006
		(1.16)	(1.17)
Return on assets		−0.283***	−0.284***
		(−2.94)	(−2.95)
log interest coverage		−0.066***	−0.065***
		(−7.65)	(−7.63)
Stock volatility		4.025***	4.017***
		(8.29)	(8.27)
Maturity		0.002***	0.002***
		(6.75)	(6.75)
Num leads		0.019***	0.019***
		(6.30)	(6.28)
Secured dummy		0.246***	0.245***
		(16.26)	(16.23)
Covenant dummy		−0.060***	−0.060***
		(−4.47)	(−4.47)
Performance pricing		−0.020	−0.020
		(−1.47)	(−1.46)
Prime base rate		0.223**	0.223**
		(2.21)	(2.21)
FEs	ratings score, revolver dummy, industry, year		
N	6,582	4,914	4,914
Adj. R^2	.550	.615	.615

This table examines the relationship between loan spread and both the borrower and lender's RRI at the facility level. Control variables include the log assets, log loan amount, commercial paper rating, book leverage, Tobin's q, return on assets, current ratio, log interest coverage, stock volatility, loan maturity, number of lead lenders, secure (dummy), covenant (dummy), performance pricing, and prime base rate. We include ratings score, revolver dummy, industry, and year FEs. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table A.4
Evolution in corporate ESG profile and bank lending: Placebo tests on empirical model

	(1) Randomized	(2) One-to-one replacement	(3)
	ESG_chg	ESG_chg	ESG_chg
ESG_diff	−0.004	−0.00228	−0.0102
	(−0.59)	(−0.27)	(−1.02)
Lender_chg	0.008	−0.00351	−0.0118
	(0.99)	(−0.26)	(−0.79)
ESG_borrower	−0.599***	−0.491***	−0.652***
	(−39.94)	(−26.24)	(−33.02)
Public		1.629***	
		(4.25)	
log assets			2.176***
			(22.00)
Book leverage			−1.599***
			(−3.26)
Return on assets			−0.786**
			(−1.99)
Tobin's q			0.191**
			(2.08)
Ind FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Cluster	Yes	Yes	Yes
N	10,000	6,946	4,941
Adj. R^2	.270	.238	.340

The following table reports the OLS regression of the evolution 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 2-year window, from one year before to one year after the package 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 package initiation date. *Lender_Chg* controls for the evolution in the lender's ESG indexes over the same 2-year window. *ESG_Borrower* controls for the potential path dependency problem and is defined as the borrower's RepRisk index one year before the package initiation date. In column 1, we use the sample consisting of 10,000 randomly constructed borrower-lender pairs with randomized package initiation dates. In columns 2 and 3, we replace the borrower in Table 2 "one-to-one" using propensity score matching. Appendix A.1 defines the variables in detail. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. *t*-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

Table A.5
Alternative specification

	(1) RRI_borrower$_{t+1}$ All	(2) RRI_borrower$_{t+1}$ All	(3) RRI_borrower$_{t+1}$ All	(4) RRI_borrower$_{t+1}$ All	(5) RRI_borrower$_{t+1}$ Public
RRI_lender$_{t-1}$	0.0217***	0.0217***	0.0140**	0.0130*	0.00906
	(3.81)	(3.36)	(2.03)	(1.95)	(1.06)
RRI_borrower$_{t-1}$	0.554***	0.554***	0.544***	0.453***	0.372***
	(57.49)	(25.62)	(23.45)	(21.70)	(16.28)
Lender_chg	0.0322***	0.0322***	0.0229*	0.00890	0.0196
	(3.11)	(2.82)	(1.91)	(0.76)	(1.36)
Num of facilities				−0.794***	0.00739
				(−4.25)	(0.04)
log package amt				1.992***	0.554***
				(13.59)	(2.59)
USA				−2.906**	−0.196
				(−2.02)	(−0.12)
Public				1.228***	
				(4.04)	
log assets					2.396***
					(12.95)
Book leverage					−2.272***
					(−2.83)
Return on assets					−1.682
					(−1.32)
Tobin's q					0.771***
					(3.75)
Industry FE	No	No	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes
Cluster	No	Yes	Yes	Yes	Yes
N	8,128	8,128	8,104	8,104	5,120
Adj. R^2	.295	.295	.303	.340	.402

This table replicates the analysis in Table 2 using a different specification. *RRI_Borrower*$_{t+1}$ is defined as the level of borrowers' RepRisk indexes one year after the package initiation date. *RRI_Lender*$_{t-1}$ is defined as the level of lenders' RepRisk indexes one year before the package initiation date. *RRI_Borrower*$_{t-1}$ is defined as the level of borrowers' RepRisk indexes one year before the package initiation date. We also include the *Num of facilities* in the package, *log package amt*, country of syndication - *USA*, and the borrower's *Public* status as control variables. In column 5, we perform a subsample analysis in the public space only, and control for borrowers' financials, including *log assets*, *Book leverage*, *Return on assets*, and *Tobin's q*. Appendix A.1 defines the variables in detail. Industry FE is based on the Fama-French 12 industry classification. Standard errors are clustered at the borrower level. t-statistics are reported in parentheses. *p <.1; **p <.05; ***p <.01.

References

Asker, J., and A. Ljungqvist. 2010. Competition and the structure of vertical relationships in capital markets. *Journal of Political Economy* 118:599–647.

Avenancio-León, C. F., and L. S. Shen. 2021. An asset channel of inequality: The intangible gender gap. Working Paper, University of California, San Diego.

Barko, T., M. Cremers, and L. Renneboog. 2021. Shareholder engagement on environmental, social, and governance performance. *Journal of Business Ethics*. Advance Access published July 6, 2021, 10.1007/s10551-021-04850-z.

Baron, D. P. 2009. A positive theory of moral management, social pressure, and corporate social performance. *Journal of Economics & Management Strategy* 18:7–43.

Bartram, S. M., K. Hou, and S. Kim. 2021. Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*. Advance Access published June 23, 2021, 10.1016/j.jfineco.2021.06.015.

Bénabou, R., and J. Tirole. 2010. Individual and corporate social responsibility. *Economica* 77:1–19.

Berger, A. N., and G. F. Udell. 1995. Relationship lending and lines of credit in small firm finance. *Journal of Business* 68:351–81.

Bharath, S. T., S. Dahiya, A. Saunders, and A. Srinivasan. 2009. Lending relationships and loan contract terms. *Review of Financial Studies* 24:1141–203.

Borghesi, R., J. Houston, and A. Naranjo. 2007. Value, survival, and the evolution of firm organizational structure. *Financial Management* 36:5–31.

Brammer, S., and A. Millington. 2008. Does it pay to be different? an analysis of the relationship between corporate social and financial performance. *Strategic Management Journal* 29:1325–43.

Cao, J., S. Titman, X. Zhan, and W. E. Zhang. 2020. ESG preference and market efficiency: Evidence from mispricing and institutional trading. Working Paper, The Chinese University of Hong Kong.

Chava, S. 2014. Environmental externalities and cost of capital. *Management Science* 60:2223–47.

Chava, S., and M. R. Roberts. 2008. How does financing impact investment? the role of debt covenants. *Journal of Finance* 63:2085–121.

Chen, Q., and R. Vashishtha. 2017. The effects of bank mergers on corporate information disclosure. *Journal of Accounting and Economics* 64:56–77.

Chen, T., J. Harford, and C. Lin. 2015. Do analysts matter for governance? Evidence from natural experiments. *Journal of Financial Economics* 115:383–410.

Dai, R., H. Liang, and L. Ng. 2020. Socially responsible corporate customers. *Journal of Financial Economics*. Advance Access published February 3, 2020, 10.1016/j.jfineco.2020.01.003.

Diamond, D. W. 1991. Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy* 99:689–721.

Dimson, E., O. Karakaş, and X. Li. 2015. Active ownership. *Review of Financial Studies* 28:3225–68.

Eccles, R. G., I. Ioannou, and G. Serafeim. 2014. The impact of corporate sustainability on organizational processes and performance. *Management Science* 60:2835–57.

Ergungor, O. E., L. Madureira, N. Nayar, and A. K. Singh. 2015. Lending relationships and analysts' forecasts. *Journal of Financial Intermediation* 24:71–88.

Fernando, C. S., V. A. Gatchev, and P. A. Spindt. 2005. Wanna dance? how firms and underwriters choose each other. *Journal of Finance* 60:2437–69.

Flammer, C. 2021. Corporate green bonds. *Journal of Financial Economics*. Advance Access published January 31, 2021, 10.1016/j.jfineco.2021.01.010.

Friedman, M. 1970. A friedman doctrine: The social responsibility of business is to increase its profits. *New York Times* 13:32–3.

Gillan, S. L., A. Koch, and L. T. Starks. 2021. Firms and social responsibility: A review of ESG and CSR research in corporate finance. *Journal of Corporate Finance* 101889.

Goss, A., and G. S. Roberts. 2011. The impact of corporate social responsibility on the cost of bank loans. *Journal of Banking & Finance* 35:1794–810.

Hart, O., and L. Zingales. 2017. Serving shareholders doesn't mean putting profit above all else. *Harvard Business Review* 12:2–6.

Hasan, I., C. K. Hoi, Q. Wu, and H. Zhang. 2017. Social capital and debt contracting: Evidence from bank loans and public bonds. *Journal of Financial and Quantitative Analysis* 52:1017–47.

Hauptmann, C. 2018. Corporate sustainability performance and bank loan pricing: It pays to be good, but only when banks are too. In *Academy of Management Annual Meeting Proceedings*, ed. S. Taneja. Briarcliff Manor, NY: Academy of Management.

He, Y., B. Kahraman, and M. Lowry. 2020. ES risks and shareholder voice. Working Paper, University of Manchester.

Hoepner, A. G., I. Oikonomou, Z. Sautner, L. T. Starks, and X. Zhou. 2018. ESG shareholder engagement and downside risk. Working Paper, University College Dublin.

Holmstrom, B., and J. Tirole. 1997. Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics* 112:663–91.

Homanen, M. 2018. Depositors disciplining banks: The impact of scandals. Working Paper, City University London.

Hong, H., and M. Kacperczyk. 2010. Competition and bias. *Quarterly Journal of Economics* 125:1683–725.

Hsu, T. 2019. Gun control group's report card on U.S. banks' firearms ties has several Fs. *New York Times*, April 4. https://www.nytimes.com/2019/04/04/business/gun-control-banks.html

Ivashina, V., and A. Kovner. 2011. The private equity advantage: Leveraged buyout firms and relationship banking. *Review of Financial Studies* 24:2462–98.

Kim, S., N. Kumar, J. Lee, and J. Oh. 2021. ESG lending. Working Paper, University of Florida.

Li, J., and D. A. Wu. 2020. Do corporate social responsibility engagements lead to real environmental, social, and governance impact? *Management Science* 66:2564–88.

Lim, D. 2021. BlackRock must hit ESG targets or pay more to borrow money. *Wall Street Journal*, April 8. https://www.wsj.com/articles/blackrock-must-hit-esg-targets-or-pay-more-to-borrow-money-11617769833

Lins, K. V., H. Servaes, and A. Tamayo. 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. *Journal of Finance* 72:1785–824.

Nini, G., D. C. Smith, and A. Sufi. 2012. Creditor control rights, corporate governance, and firm value. *Review of Financial Studies* 25:1713–61.

Nussbaum, A. 2015. Wells Fargo and Morgan Stanley join banks edging away from coal. *BloomBerg*, November 30. https://www.bloomberg.com/news/articles/2015-11-30/wells-fargo-morgan-stanley-join-banks-edging-away-from-coal

Petersen, M. A., and R. G. Rajan. 1994. The benefits of lending relationships: Evidence from small business data. *Journal of Finance* 49:3–37.

Pilloff, S. J. 2004. Bank merger activity in the united states, 1994-2003. *Federal Reserve Bulletin* 328.

Schenone, C. 2009. Lending relationships and information rents: Do banks exploit their information advantages? *Review of Financial Studies* 23:1149–99.

Schiller, C. 2018. Global supply-chain networks and corporate social responsibility. Working Paper, Arizona State University.

Schwert, M. 2018. Bank capital and lending relationships. *Journal of Finance* 73:787–830.

Sharfman, M. P., and C. S. Fernando. 2008. Environmental risk management and the cost of capital. *Strategic Management Journal* 29:569–92.

Sharpe, S. A. 1990. Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *Journal of Finance* 45:1069–87.

Shive, S., and M. Forster. 2020. Corporate governance and pollution externalities of public and private firms. *Review of Financial Studies* 33:1296-330.

Shleifer, A., and R. W. Vishny. 1997. A survey of corporate governance. *Journal of Finance* 52:737–83.

Starks, L. T., P. Venkat, and Q. Zhu. 2020. Corporate ESG profiles and investor horizons. Working Paper, University of Texas at Austin.

Strahan, P. E. 1999. Borrower risk and the price and nonprice terms of bank loans. *FRB of New York Staff Report* 90.

Tang, D. Y., and Y. Zhang. 2020. Do shareholders benefit from green bonds? *Journal of Corporate Finance* 61:101427.

Xu, Q, and T. Kim. 2021. Financial constraints and corporate environmental policies. *Review of Financial Studies*. Advance Access published May 5, 2021, 10.1093/rfs/hhab056.