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Abstract

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JEL Classification: N/A

Keywords: N/A

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Do banks price environmental risk? Only when local beliefs are binding!

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November 20, 2023

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JEL classification: G12, G18, G21

Key words: Climate change, bank credit, personal beliefs.

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1 Introduction

The last decade has seen an increasing awareness of global warming and the role of firms for environmental sustainability. The issue has also taken centre stage among both economists and regulators, and 194 countries have to date signed the Paris Agreement, committing to reach the net zero targets. Climate change however remains subject to a heated debate, and climate change supporters and deniers support different steps of action. In the March 2023 Gallup Survey, only 39% of Americans believe that global warming poses a threat to their way of life, and only 62% of Americans believe that global warming is due to the pollution from human activities[1]. In June 2017, Trump called global warming a "hoax" and announced the withdrawal of the United States from the Paris Agreement. In 2020, Biden based his presidential campaign on environmental sustainability and reversed the withdrawal from the Paris Agreement on his first day of presidency. Given the widespread disagreement, how do banks reflect climate risk in their lending decisions, and reconcile these diverse perspectives?

In this paper, we investigate how banks price the environmental footprint of the borrowers in a sample of U.S. syndicated loans during 2004-2019. We first document stylized facts on the sensitivity of the syndicated loan prices to the direct and indirect environmental impact of the borrowers. We document that banks charge higher rates to the borrowers with a higher impact on the environment, such as water, air, and land pollution, use of natural resources, and waste. The same lender in the same year charges a 0.9 percentage point (pp) higher rate relative to the mean to borrowers with a one-standard-deviation higher level of total impact on the environment, controlling for borrower characteristics. We also exploit the heterogeneity of these effects across the lenders, and document the sensitivity to be greater among the banks with weaker capitalization, suggesting that low-capital banks perceive the environmental damage of their borrowers as an additional source of risk. This effect is robust to controlling for both borrower characteristics and other loan term features, including but not limited to the loan size, loan maturity, and the type of the loan (*i.e.*, the presence of covenants and collateral, and non-bank participation).

To investigate what drives the pricing of environmental footprint, we study the role of biodiversity and personal beliefs. We first explore the cross-sectional dispersion in the extent to which a firm is subject to the biodiversity risk. Using the geographic dispersion across the U.S. states, we provide novel evidence that biodiversity risk has an impact on the loan rates. If firms are in the states where the local biodiversity is at a high risk of extinction, lenders demand higher compensation for environmental risk even more. We also use the firm-level news-based measures developed by Giglio et al. (2023) that capture biodiversity risk from the firms' 10-K regulatory filings. Using these firm-level

[1] https://news.gallup.com/poll/474542/steady-six-say-global-warming-effects-begun.aspx

measures of biodiversity risk, we find that while banks demand additional compensation for bearing biodiversity risk, the latter has no explanatory power in explaining the relationship between the loan prices and the environmental impact of the borrowers. The results suggest that biodiversity risk and environmental impact are likely perceived as separate sources of risk by the lenders at the loan origination.

We then study the role of personal beliefs and preferences in the local environment of the borrower. Using the Yale Survey of Climate Change beliefs, we classify states as climate change believers and deniers and document that lenders penalize firms for their environmental impact only in the states that are aware of global warming and that are not heavily subject to climate change denial. This suggests that the environmental risk perception depends on the local beliefs and preferences as lenders may perceive environmental risk to be material if a higher proportion of the public is concerned that global warming will harm them personally. To further understand the role of beliefs, we also study a set of extreme weather events that may affect local beliefs by making the environmental risks more salient. We find that lenders become more risk averse and charge higher rates on average to all the borrowers after an extreme weather event has taken place. The effect is short-lived, and it disappears within the first two years of the event. The sensitivity to the environmental impact is not however larger. These results suggest that our effects are unlikely to be a result of temporary biases driven by salience.

One challenge in our study is that lenders may penalize borrowers for their environmental impact not only because they are seen as riskier, but also because lenders themselves are environmentally conscious and adopt a sustainable and ESG-driven business model. We tackle this challenge in two ways. We first analyse the sensitivity of the loan prices to the environmental impact of the borrowers with a lender $\times$ year FE, looking at the cross-section of loan rates across the borrowers with different levels of environmental impact for the same lender and in the same year, insulating our effects from the business model and attitudes of the bank. We also require a shock to the environmental risk of the borrowers, leaving the firm fundamentals and lender preferences unchanged. To this end, we propose to study the Trump withdrawal from the Paris agreement as the move represents a decommitment from the net-zero targets. Our set-up gives us a distinction between the firms that are affected and unaffected by the deregulation, as a series of states and cities did immediately sue the Trump administration in Court. We also expect the borrowers in the states with a Republican majority that have a political mindset similar to the Trump government to be more affected as they were unlikely to challenge the government *ex post*.

We show that the environmental deregulation led banks to reduce the sensitivity of their loan pricing to the environmental footprint of the borrowers in the areas that did not sue the Trump government and in the Republican states. To gain deeper insights into the underlying mechanism, we also study the role of beliefs and find that the reduction in the price sensitivity to the environmental impact is stronger in the states that are not heavily prone to the climate change denial, suggesting that local beliefs are reflected in the loan prices. Our results suggest that lenders are more likely to demand compensation for environmental risk if they anticipate higher social pressure and regulatory enforcement. We also control for the lender $\times$ year fixed effects in all our specifications to absorb the time-varying changes in the green attitudes and preferences. Moreover, we find that the pricing effects appear only in the types of environmental impact covered by the deregulatory initiatives of the Trump government, such as the land and water impact, air pollution, and GHG emissions. Overall, our results suggest that the environmental deregulation has resulted in a reduction in the lenders' environmental price sensitivity, but only if the local beliefs and attitudes are likely to be supportive.

Our paper first contributes to the literature on the implications of the environmental impact of firms on the cost of financing. Several papers show that investors require a premium for holding the stock of firms with high levels of carbon emissions (Bolton and Kacperczyk (2021a)[2] and Bolton and Kacperczyk (2021b)[3]). A nascent and growing literature also investigates the impact of climate change on bank lending and has found evidence of pricing effects Degryse et al. (2023). However, there has been very little effort to understand what drives banks to price environmental risks. Our contribution to this literature is two-fold: First, rather than focusing on carbon emissions, we consider the overall and different types of environmental impact and damage on the loan rates. Second, we investigate what drives the loan pricing behaviour of banks.

Our paper is related to the new literature on biodiversity. Biodiversity risk has received surprisingly little attention in the finance literature. With a conceptual framework on financing biodiversity, Flammer et al. (2023) argue that biodiversity can be financed with pure private capital and blended financing structures in which private capital is blended with public and philantropic capital to de-risk the private capital investments. Using deal-level data from a leading biodiversity finance institution, they show that projects with higher expected returns tend to be financed by pure private capital while larger-scale projects tend to attract blended financing. A group of recent working papers empirically study whether biodiversity is a priced risk factor. Giglio et al. (2023) construct news-based measures of the U.S. firms' biodiversity risk using the disclosure of biodiversity issues in the 10-K filings. They document that exposures to biodiversity risk significantly differ across industries and affect equity prices as portfolios sorted on

[2]Bolton and Kacperczyk (2021a) document a carbon premium in the cross-section of U.S. stock returns, and show that stocks of firms with higher emissions earn higher returns, controlling for size, book-to-market, and other return predictors. The carbon premium is not explained by known risk factors, suggesting that investors demand compensation for exposure to carbon emission risk.

[3]Bolton and Kacperczyk (2021b) also find that the carbon premium is global and captures the carbon transition risk. They show that the short-term transition risk is greater in the countries with greater reliance on fossil energy and lower economic development whereas the long-term transition risk is higher in the countries with stricter domestic climate policies.

biodiversity risk exposure covaries positively with innovations in aggregate biodiversity risk. Garel et al. (2023) conduct this study for a global sample, and they document that in the aftermath of the Kunming Declaration, investors started to require compensation for firms with a high biodiversity footprint. Our paper is the first study that looks at the impact of biodiversity risk on the loan prices. We find evidence that banks consider biodiversity risk in their lending decisions.

Our work is also related to the literature concerned with the effects of heterogeneous beliefs on the pricing behaviour. The empirical literature in this area has focused on the role of beliefs on the housing prices. Baldauf et al. (2020) use transactional data on housing prices and future inundation forecasts, and document that houses projected to be underwater sell at a discount compared to houses in the denier neighbourhoods. They also use the Yale Climate Opinion survey for data on climate beliefs. The role of beliefs has however attracted surprisingly little attention in the banking literature. We provide novel evidence that the heterogeneity of beliefs is reflected in the price of environmental risk in bank lending. We further show that belief differences about climate change affect the implications of environmental deregulation, suggesting that banks consider local beliefs and preferences as the underlying source of environmental risk. Dursun-de Neef and Ongena (2023) provide complementary evidence on the deposit-side and show with branch-level deposit data from the United States that depositors move their money away from fossil-fuel-financing banks when experiencing warmer-than-usual temperatures.

We finally add to the growing literature that studies the role of bank regulation on climate finance. Kacperczyk and Peydró (2022) show that banks that committed to carbon neutrality reduced their credit to firms with higher carbon emissions. Delis et al. (2019) find that after the Paris Agreement, banks started to charge higher rates to brown firms with larger fossil fuel reserves. Degryse et al. (2023) document that after the Paris Agreement, banks rewarded firms that voluntarily disclose their carbon emissions to the Carbon Disclosure Project (CDP) in the form of cheaper loans. A related line of work investigates the impact of the cap-and-trade policies. Antoniou et al. (2020) find that the 2013 EU Emissions Trading System led banks to reduce their loan spreads, driven by the expected reduction in carbon emissions. Using the discontinuities in the California cap-and-trade programme, Ivanov et al. (2023) show that high emission firms face higher interest rates and that the effects are concentrated among private firms [4]. The novelty of our paper is our focus on environmental deregulation. We provide novel evidence that the surprise withdrawal of Trump from the Paris agreement in the U.S. has reduced the sensitivity of the loan prices to the environmental damage of the borrowers. The effects only operate on the non-challenger and non-denier states, consistent with our

[4] Bartram et al. (2022) provide evidence of geographic arbitrage using U.S. plant-level data. They find that in response to the California- cap-and-trade programme, financially constrained firms shifted emissions and output to states with under-utilized plants while not reducing the overall level of their total emissions.

interpretation that local enforcement and beliefs affect the climate risk perception.

2 Data

We extract our data from the Reuters Dealscan Database where each observation corresponds to a facility loan agreement in the syndicated loans provided to the U.S. firms. Syndicated lending is characterized by the presence of multiple lenders: lead arranger (s) that screen and monitor the borrowers, and participants that rely on the information provided by the lead arranger (s) (Ivashina (2009) and Sufi (2007)). Since the loan pricing decisions are taken by the lead arrangers, we focus our sample on the lead arrangers as in previous literature (Degryse et al. (2023)).

Our data sample covers the period 2004-2019. Dealscan provides us with information on the loan characteristics, such as the interest rate, loan size, and loan maturity. We also have data on the non-pricing characteristics of the loans, such as the covenant and the collateral status, and the syndicate structure such as the presence of a non-bank investor. We report the summary statistics in Table 1. Our key left-hand-side variable of interest is the all-in-spread-drawn measure, which we winsorize at the 1% level to remove outliers, has an average value of 224 basis points (bps). The all-in-spread-drawn captures the interest rate paid by the borrower over LIBOR at the loan origination, including any annual and upfront fees.

We obtain our climate change data from the S&P Trucost Database. Trucost provides granular information on the environmental impact of firms. We provide information on the data variables and the summary statistics in Table 1. The key variable of interest in our analysis is the total environmental impact, that is defined by Trucost as the environmental costs that a company has on the environment through its own activities as a percentage of revenue. The total environmental impact measures the sum of the direct and indirect environmental impact ratios. The direct environmental impact is defined as the direct environmental costs that a company has on the environment through its own activities as a percentage of revenue. The indirect environmental impact is on the other hand the environmental impact that a firm has on the environmental through the goods and services that it purchases.

Graph 1 presents the histogram of the total environmental impact of the U.S. firms in our sample. The distribution shows that most firms have a total environmental impact ratio as a proportion of their total revenue that ranges between 0 and 10 %. The average value of the total environmental impact of the U.S. firms has remained persistent over time and is around 4-8 % (Graph 2) even though it has declined slightly after 2015. As also shown in the Summary Statistics (Table 1), we observe a substantial dispersion in the environmental impact of the firms: while on average the total environmental impact as a percentage of revenue 4% percent, the distribution is heavily right-skewed, with a standard deviation of 8 %.

Trucost decomposes the total environmental impact of firms into six different categories: the natural resources, air pollutants, ghg emissions, water, land and water, and waste impact ratio. They also classify firms into six different sectoral groups. Based on the Trucost sectoral categorisation, we document the average total and direct environmental impact of firms in different sectors (Graph 3). We observe that the total environmental impact of the U.S. firms is more concentrated among certain sectors, such as Consumer Staples, Energy, Materials, and Utility. We also observe that whereas the *direct* environmental impact is the main source of the *overall* environmental impact, some sectors such as Consumer Staples and Materials have higher *indirect* environmental impact ratios. This suggests that some firms have a greater impact on the environment through their own activities relative to their impact through the goods and services that they purchase through the third parties. We winsorize all the impact ratios at the 1% level to mitigate the impact of the potential outliers.

We obtain data on the environmental beliefs and attitudes of the U.S. society from the Yale Climate Opinion surveys. From these surveys, we obtain, at the state level, the percentage of the respondents who somewhat/strongly agree that they have personally experienced the effects of global warming and the estimated percentage who think global warming will harm them a moderate amount/great deal. The Yale Climate Opinion surveys are conducted every year and span our entire sample.

We draw our biodiversity risk measures from two separate sources. First, we use the state biodiversity risk rankings from the 2002 April NatureServe Report. The rankings are based on the status and distribution of 21395 plant and animal species drawn from the NatureServe Central Databases and attempt to provide a complete picture of the extinction risk across America. NatureServe constructs the biodiversity risk rankings in terms of percentage of the state's plants and animals that are at risk of extinction due to rarity or other conservation challenges and consist of species classified as extinct, endangered, and vulnerable. Both the data and rankings are publicly available. Second, we use the biodiversity risk measures proposed by Giglio et al. (2023). The authors construct both firm and industry-level measures of biodiversity risk and have made the data publicly available. They propose three measures of biodiversity: (i) *count* that is an indicator that equals one if the company mentions biodiversity in at least two sentences in the 10-K statements, (ii) *negative* that is the number of negative biodiversity sentences minus the number of positive biodiversity sentences, and (iii) *regulation* which is an indicator variable that is one if the company mentions biodiversity in at least two sentences and at least one of them is about regulation in the 10-K statements. Finally, we use the Dealscan-Compustat Linking Database (Chava and Roberts (2008)) and obtain the financial statement data for the borrowers from Compustat. As consistent with the prior literature, we use the accounting data of the borrowers to control for their credit risk and add a variety of measures such as firm size, cash holdings, profitability, and leverage ratios.

3 Empirical Design

We use a simple loan pricing model to study whether banks penalize firms for their environmental impact. The baseline regression specification we run is the following:

$$Loan\ Rate_{ijt} = \beta \times Impact_{ijt} + \alpha \times X_{it-1} + \gamma \times Z_{ijt} + \eta_{j\times t} + \epsilon_{ijt} \tag{1}$$

where i indexes firms, j indexes lender, and t year of the loan origination. The loan rate refers to the annual interest rate spread over $LIBOR$ paid by the borrower i to the lender j in basis points for each dollar drawn down, including the fees. $Impact_{ijt}$ is the impact that the borrowing firm has on the environment as a percentage of total revenue at the time of the loan origination. We use a variety of dependent variables to capture the environmental impact, such as the direct impact ratio, indirect impact ratio, and total impact ratio (the sum of the direct and indirect impact ratio). We also study the different types of environmental impact separately and replace the impact variable with the natural resources, air pollutants, ghg emissions, water, land and water, and waste impact ratio.

As our aim is to capture the impact of the environmental footprint on the loan prices, we control for other factors that may affect the cost of debt. X_{it-1} are the borrower controls such as log(assets), log(total debt), and ebitda/assets in the year prior to the loan origination controlling for the borrower characteristics that have been shown to affect loan prices. Smaller, more indebted, and less profitable firms pay higher rates on their borrowing (Ivashina (2009), Lim et al. (2014), and Berg et al. (2016)). In our baseline specification, we include $FE_{j\times t}$ to control for any time-varying and unobservable heterogeneity across the lenders. The interpretation is that we compare, for the same lender and in the same year, the penalty imposed on a borrower with a higher environmental footprint. However, in other specifications, we add FE_j as the lender fixed effects and separately control for the lagged lender-specific characteristics such as capitalization, log(total assets), and return on assets. Larger, more capitalized, and more profitable lenders may lend at more favourable rates at the loan origination. The lender controls are consumed when $FE_{j\times t}$ is included. As the loans issued by the same lender may have correlated spreads, we cluster the standard errors by lender.

All our specifications include state and sector fixed effects to absorb the average impact of the borrower state and industry on the loan rates. We control for the sector by adding the sectoral classification dummies. Z_{ijt} is the set of controls for the non-price loan terms such as the loan size and maturity as larger and longer-maturity loans have been shown to have lower spreads (see for example Carey and Nini (2007)). This may be due to the greater transparency of the larger borrowers who take larger loans, and the fixed costs of issuing a loan. We also add dummy variables for the loan purpose[5], the presence of covenants, and non-bank participation. Ivashina (2009) and Lim et al., (2014) have shown that loan facilities with non-bank institutional investors are associated with higher spreads than similar bank-only facilities. We also control for the relationship lending by adding a variable that captures the number of past interactions with the lender. Thus, our coefficient of interest β captures the rate penalty imposed on a borrower with a higher environmental impact ratio across the loans originated by the same lender, controlling for borrower characteristics and non-price loan terms.

We then propose to use the sudden Trump withdrawal from the Paris Agreement as a shock to the environmental riskiness of the borrowers. Our key identification feature lies in the fact that the environmental deregulation was suddenly challenged by a group of green and left-wing states, and it is thus unlikely to equally affect all borrowers. Borrowers in the non-green states are unlikely to face green social and political pressure and thus more likely to relax their environmental attitudes in response to the deregulatory moves of the Trump administration. Most importantly, the environmental deregulation is likely orthogonal to the lender characteristics such as bank capitalization, or borrower demand. We augment our baseline specification in a triple differences-and-differences specification as follows. Our deregulation indicator takes one after Trump has announced the withdrawal from the Paris Agreement and zero otherwise. We classify a borrower as treated if it is in a state that has challenged the environmental deregulation in the court or in a state unlikely to challenge the government as it is predominantly Republican. We run the following specification.

$$\begin{aligned} Loan\ Rate_{ijt} = {} & \beta \times Impact_{ijt} + \mu \times no\text{-}lawsuit\text{-}state + \delta \times no\text{-}lawsuit\text{-}state \times deregulation \\ & + \kappa \times Impact_{ijt} \times deregulation + \lambda \times deregulation \times Impact_{ijt} \times no\text{-}lawsuit\text{-}state \\ & + \alpha \times X_{it-1} + \gamma \times Z_{ijt} + \eta_{j \times t} + \epsilon_{ijt} \end{aligned} \tag{2}$$

where μ captures the time-invariant characteristics of the firms in the states that have not challenged the deregulation relative to the other states and δ reflects the relative change in the loan rates in the non-challenger states after the deregulation. κ is the average change in the price of the environmental impact after the deregulation. Finally, λ is our triple difference-in-differences-in-differences coefficient of interest that captures the change in the sensitivity of the loan rates to the environmental impact after the deregulation in the affected states relative to the unaffected states. Our full specifications

[5] Loans for acquisitions and LBOs tend to lead to higher spreads due to risk

also control for the borrower characteristics that affect demand and the non-price features such as loan size and maturity that may also be affected by the deregulation. We also control for lender × year FE, to account for the time-varying changes in the lender green attitudes and preferences.

4 Empirical Results

We first study whether banks consider the environmental damage of their borrowers in their lending decisions. We find that they charge higher rates to the borrowers with a higher impact on the environment, such as water, air, and land pollution, use of natural resources, and waste. The effects are robust to the inclusion of borrower fundamentals, and non-price deal characteristics. In all our specifications, we control for the lender × year FE to account for the time-varying changes in the green attitudes and preferences of the lender. We then go on to study the borrower- and lender-level heterogeneity to understand the underlying mechanism behind the price response.

4.1 Pricing of Environmental Damage

In this section, we report the baseline results on the impact of environmental footprint on the cost of bank credit. We run our main specification 4.2.4 and analyse the relationship between the loan prices and environmental damage (the ratio of environmental costs as fraction of total revenue). All our columns have lender × year FE, as we compare for the same lender in the same year the differential rates charged to the borrowers with a greater environmental footprint. This is important as in our pricing regressions, we aim to insulate our pricing effects from time-varying unobserved shocks and lender characteristics that determine the credit supply. We also want to control for the green attitudes and preferences of the lenders and focus on the risk management motive, *i.e.*, demand compensation for bearing more environmental risk.

The premise of our empirical design lies on the hypothesis that lenders account for the environmental impact of the borrowers in their credit origination. We report the baseline results in Table 2. In column 1, our coefficient of interest is both statistically and economically significant. For a one-standard deviation increase in the total environmental impact, lender charge a 2 percentage points (pp) higher interest rate on the loan relative to the mean (8.32 × 0.555 / 224). In Column 2, we control for the borrower characteristics that have been shown to affect the cost of credit. We control for the size, leverage, and profitability of the borrower as these characteristics affect the informational asymmetry and riskiness of the borrower. We also control for the sector and state of the borrower to control for the time-invariant sectoral and geographical factors affecting borrower demand and absorb the cross-sectional differences across different states and industries. We find a small reduction in our coefficient of interest to 0.9 percentage point (pp) (8.32 $\times$ 0.555 / 224), consistent with our interpretation that banks perceive environmental damage as a material risk factor.

As we aim to capture the impact on the price of credit, we also include the non-price loan characteristics such as loan size and loan maturity, in addition to the dummies that classify the loan type and loan purpose to control for any mechanical cross-sectional differences that may arise due to the riskiness of the loan. We control for the size and maturity of the loan, non-bank participation, presence of covenants, and deal purpose. Our results remain qualitatively unchanged. This suggests that banks demand compensation for their exposure to the environmental risk in the form of higher interest rates.

One question that arises is whether lenders price all sources of environmental impact or rather focus on the short-term and salient risks. We therefore analyse the direct and indirect environmental impact separately. The direct impact is the direct costs on the environment whereas the indirect impact captures the environmental impact that arises through the goods and purchases purchased by the firm from the third parties. Column 4-6 replaces the total impact with the direct impact measure in our baseline specification 4.2.4. We find that the impact-price relationship is mainly due to the direct impact as our coefficient of interest is only slightly reduced. In economic terms, for a one-standard deviation increase in the direct environmental damage, lender charge a 3 percentage points (pp) higher rate on the loan. The effects again remain robust to the addition of borrower and loan-level controls. When we replace our impact variable with the indirect impact measure, our results become statistically insignificant in our most complete specifications. These results suggest that lenders scrutinize borrowers mainly based on their direct exposure to the environment. This may be because the indirect effects are less salient and thus seen as less material.

Trucost categorizes the environmental footprint of firms into six main categories: natural resources, air pollutants, ghg emissions, water, land and water, and waste. These groups reflect the environmental reliance and damage of borrowers in a variety of categories: Natural resources impact (the use of natural resources such as minerals, metals, natural gas, oil, coal, forestry, and agriculture), air pollutants (the costs of air pollutants), ghg emissions (the value of GHG emissions), water use (the dollar value of the use of water), land and water pollutants (the value of land and water pollutants), and waste generation (the dollar value impact of the waste generation). All variables are scaled by revenue and thus reflect to what extent the production and revenues of the firm depend on and affect the environment. To understand the pricing sensitivity to these different types of environmental impact, we replace our impact measure with these six different categories and replicate our baseline analysis with 4.2.4. We report the results in 3. We find that even though the total environmental impact of firms is reflected in the cost of credit, only certain types of impact is priced. In Panel A, we find that the reliance and use of natural resources is seen as a material risk factor, but the economic magnitude is small. For a one-standard deviation increase in the direct environmental impact on natural resources, lenders charge a 0.5 percentage points (pp) higher interest rate on the loan.

We then extend our analysis to the water pollution, and the impact on the land and water in Column 4 and 9. We find that our coefficient of interest is significant in our most complete specifications in Column 6 and 9. In terms of the economic magnitudes, a one-standard deviation increase in the total environmental impact on the water (the land and water), lenders charge a 1.6 (5.6) percentage points (pp) higher interest rate on the loan relative to the mean. Surprisingly, the impact on the land and water pollution is seen as the most material risk factor. One potential interpretation is that in the U.S., the water and land remain among the most controversial environmental regulations. For example, the Waters of the United States (WOTUS) rule frequently updates the scope of the federally protected waters under the Clean Water Act and changes the protections for the protected land and the threatened species.

In Panel B, we also investigate the pricing implications of air pollution and GHG emissions. Remarkably, we find that lenders fail to account for air pollution in the loan prices. One potential explanation is that banks account for air pollution at the extensive margin rather than in the form of higher interest rates. For example, after the Paris Agreement, many firms committed to net-zero targets and reduced their carbon emissions. The U.S. has also introduced a variety of regulations that limit air pollution. Ivanov et al. (2023) study the impact of the cap-and-trade policies on the GHG emitting firms and show that the California and Waxman-Markey cap-and-trade bills led to a reduction in the loan maturities, a lower access to term loans, and higher interest rates[6]. In a related paper, Kacperczyk and Peydró (2022) show that in response to the commitment to the net-zero targets of the Paris Agreement, banks have reduced their total lending to firms with high scope-1 emission levels and reallocated credit towards the green firms.

We finally consider the impact of waste generation. Our coefficient of interest is negative and statistically significant in Columns 7-9, suggesting that waste is perceived as a natural outcome of production that is not a material risk factor. Broadly taken, our results indicate that lenders demand compensation for the environmental risk in the form of higher interest rates, but the effects mask substantial heterogeneity as lenders only scrutinize salient and certain types of environmental risk.

[6]The cap-and-trade programs cap the GHG emissions at a threshold, and requires firms to use the allocated emission permits or purchase the permits at auctions, leading to a market price for carbon.

4.2 Heterogeneity

4.2.1 Lender-Based Heterogeneity

We now raise the question why banks price the environmental impact and damage of their borrowers. Banks may require higher prices for lending to environmentally reliant firms more heavily exposed to the physical or regulatory transition risk. If this is the case, we would expect the pricing effects to apply more forcefully to the weakly capitalized banks. Equity issuance is costly due to asymmetric information as bank investors may interpret a bank's decision to issue equity as a signal that the stock is overvalued. In the presence of asymmetric information, banks that are weakly capitalized may be more risk averse as they are less likely to issue new equity and able to absorb losses in the face of unexpected environmental losses.

A large body of literature has studied the impact of low capital on bank pricing behaviour. In an early study, Boot et al. (1993) study the trade-off between reputational and financial capital and theoretically show that low capital makes banks more willing to exploit borrowers to raise their short-term earnings. In Froot and Stein (1998), banks with low capital become more risk averse and charge a higher risk premium to their riskier and bank-dependent borrowers. In Diamond and Rajan (2000), the risk of bank runs leads weakly capitalized banks to extract higher rents from their borrowers as it makes liquidation threat more credible and increases their bargaining position. Motivated by these theories, a large body of empirical work has documented that bank capital impacts loan rates. In a sample of U.S. bank loans to public firms, Hubbard et al. (2002) show that low-capital banks charge higher rates to borrowers with high-switching costs. Mattes et al. (2013) provide evidence from the U.K. that low capital firms charge higher rates to privately firms than publicly held firms. In a more recent study, Santos and Winton (2019) study the publicly traded U.S. firms and show that banks charge higher prices to their borrowers with low cash flow.

We therefore conjecture that compared to the high capital banks, low capital banks would be more likely to penalize borrowers for their environmental impact and divide our sample between loans extended by banks with low and high capitalization. We categorize banks as weakly capitalized based on whether they have lower equity to asset ratios than the sample median in any given year. We then re-run our baseline regression specification 4.2.4 on these two sub-samples separately in Table 4. All our specifications are fully saturated and include both lender $\times$ year FE and borrower and loan controls. The coefficient of interest is positive and statistically significant, and its economic magnitude significantly increases relative to our baseline regressions. Most importantly, the effect is small and statistically insignificant in the subsample of weakly capitalized banks. Turning to direct environmental impact, we find similar results. These results suggest that banks consider the environmental impact of their borrowers in their loan pricing, but only if they are weakly capitalized, consistent with theoretical predictions that low bank capital makes banks more risk averse and lead them to charge higher rates to their riskier borrowers (Froot and Stein (1998)).

4.2.2 Borrower-Based Heterogeneity

To gain better insights on the bank behaviour, we use a cross-sectional analysis and study what drives banks' environmental risk perception. In a notable contribution, Krueger et al. (2020) use survey evidence and show that institutional investors acknowledge the financial implications of climate risk and believe that regulatory risks already started to materialize. Banks may see environmental risks as material and adjust their pricing behaviour if they expect future financial losses that they are unable to hedge and diversify. In the context of syndicated bank loans, we consider three different channels: biodiversity, local beliefs and preferences, and bank deregulation.

4.2.3 Bio-diversity

One potential channel that may lead banks to account for environmental risks is biodiversity risk. Biodiversity refers to the variety of life on Earth, including animals, plants, bacteria, and fungi. The 2022 United Nations Biodiversity Conference in Montreal (COP15), the United Nations Assessments documented that 80% of the world species are threatened by economic activity, and that 40% of global land surfaces are degraded. Based on the 2023 NatureServe report, 34% of plant species and 41% of animal species are at a risk of extinction in the United States.

Firms that are environmentally reliant may face adverse consequences from global warming that increasingly threatens ecological biodiversity. For example, drought spells may lead food companies to stop or re-allocate production. The extinction of certain species may increase social and moral pressure on fossil fuel firms, leading to stricter limits on carbon emissions. Extreme weather events from global warming can harm agriculture and displace workers, resulting in labour shortages. Firms may also anticipate stricter regulations that preserve biodiversity, in the light of recent global initiatives such as the 2021 Kunming Declaration and the 2022 Montreal Agreement. If banks consider biodiversity risk, we expect their lending to be more sensitive to environmental risk in areas subject to greater biodiversity risk.

Giglio et al. (2023) construct news-based measures of biodiversity for the U.S. firms and show that it varies substantially across sectors and affects equity returns. Garel et al. (2023) introduce a measure of biodiversity and show that in an international sample of stocks, the biodiversity footprint is not priced in the cross-section of stock returns. They however find that in the aftermath of the Kunming Declaration, stocks with large biodiversity footprints lost value, consistent with investors starting to demand a risk premium for biodiversity risk. We test whether banks price biodiversity risk in the loan rates.

To contemplate this possibility, we exploit a variety of measures of biodiversity risk. First, we use the state-level biodiversity index developed by NatureServe. The index ranks the 51 U.S. states based on the extinction risk of local biodiversity, using data from more than 21000 plant and animal species. To facilitate the interpretation, we rearrange the index so that higher ranks relate to greater biodiversity risk. We augment our baseline specification 4.2.4 by interacting our total and direct impact measures with the biodiversity risk rank of the state in which the borrower is located. We report the results in Table 5. We find that being in a state subject to higher biodiversity risk is associated with higher loan rates. Most importantly, the interaction term is positive and statistically significant, suggesting that the sensitivity to environmental impact rises the larger the state-level biodiversity risk.

To explore the cross-sectional variation in bio-diversity risk, we also use the biodiversity measures proposed by Giglio et al. (2023). The advantage of these measures is that they are firm-level and constructed based on corporate news and disclosures. *Count* is an indicator that takes one if the company mentions biodiversity at least twice in the 10-K disclosures whereas *regulation* is a dummy variable that is one if at least one of these disclosures is about biodiversity regulation. *Negative* is the number of negative biodiversity sentences minus the number of positive biodiversity sentences in the 10-K filings. We interact these biodiversity exposure indicators with our impact measures and report the findings from our augmented specifications in Column 3-5. In all three columns, we find that banks demand higher rates from firms subject to higher biodiversity risk and those with a larger total environmental impact. Very interestingly, controlling for the total environmental impact, biodiversity risk is associated with higher rates, and an increase in the biodiversity risk measure is associated with a 20 to 30 bps increase in the loan rates.

The interaction term however is negative and statistically significant in all three specifications, suggesting that even though banks account for biodiversity risk in their lending decisions, the responsiveness of the bank pricing to a borrower's environmental impact is not driven by biodiversity risk. One potential explanation is that lenders view and price environmental and biodiversity risk as distinct risk factors unless biodiversity risk is local (at the state level). In Columns 5-8, we show that all our results warrant a similar interpretation when we replace total environmental impact with direct environmental impact. Furthermore, the differential sensitivity to the environmental impact increases with all three firm-level measures of biodiversity risk – regardless of whether we consider the number of biodiversity mentions, and account for regulatory or negative news, and the magnitudes also go up to 26 to 36 bps (Column 6-8). Overall, we are unable to explain the response of the bank loan prices to the environmental impact through the biodiversity risk channel.

4.2.4 Personal Beliefs

To gain deeper insights into what drives the price response to environmental risk, we study whether lenders consider the beliefs and preferences in the local area of their borrowers. Regulators in the states prone to climate change denial may be less likely to enforce climate change rules as they face less political pressure.[7] Firms that damage the environment are also less likely to face unexpected disruptions in demand from the climate activists and pro-climate consumers. Our conjecture is that lenders are less likely to price environmental risk if the borrower is in a "climate-denier" state.

We then split our sample into different groups based on the environmental attitudes in the state in which the borrower is located. We aim to capture the dispersion across borrowers in terms of their climate change attitudes. We use two different measures: personal experience (the estimated percentage who somewhat/strongly agree that they have personally experienced the effects of global warming), and personal harm (the estimated percentage who think global warming will harm them personally a moderate amount/a great deal). Personal experiences undoubtedly increase the awareness of global warming and thus the personal experience measure can proxy for climate awareness. Personal harm, on the other hand, can capture the extent to which the local population is concerned about global warming. We classify the states as climate deniers if the proportion of the respondents who agree that they have experienced the effects of global warming or think that global warming will harm them personally is lesser than the country median.

The Yale survey evidence reveals substantial geographic dispersion in the beliefs and attitudes towards global warming. We draw the histogram of these two measures to understand the distribution of the climate change awareness and concerns in Graph 4. The above figure presents the histogram of the average estimated percentage who think global warming will harm them personally in the Yale Climate Opinion Survey during our sample period. As can be seen, there is substantial variation in the social attitudes, and climate change denial is surprisingly common as on average, as only half the local population tends to have pro-climate preferences and the distribution is heavily right-skewed. In the below figure, we show the average estimated percentage who agree that they have personally experienced the effects of global warming in the Yale Climate Opinion Survey. The distribution of the two measures is strikingly similar, and they have a correlation of 81% in our data, suggesting that both measures capture very similar aspects of the local pro-climate attitudes.

To study the role of the climate beliefs and preferences, we split our sample into two

[7] Climate change denial is also subject to a global policy debate. van der Ploeg and Rezai (2019) study the price of carbon with an agnostic approach that assigns a positive probability that climate change deniers are right, and show that the price of carbon is only marginally reduced.

different sub-samples and run our baseline regression 4.2.4 in the states that are (not) climate deniers separately. In Panel A, we do our sample splits based on the percentage of borrowers who reported that global warming will harm them personally. We report our results in Table 6. Column 1 shows that the coefficient on the total environmental impact is insignificant for the borrowers located in the climate denier states. In the pro-climate states, however, our coefficients are all statistically significant and more than doubles in magnitude relative to our baseline specifications (Column 2). We obtain similar effects when we look at the direct environmental impact of the borrowers. To put these differences into perspective, we also augment our baseline specification by interacting our coefficient of interest with a dummy variable that is one if the borrower is in a climate denier state. The coefficient on the interaction term is negative and statistically significant. Compared with the pro-climate states, lenders are likely to penalize 1 bps less for every one percentage increase in the environmental impact of the borrower. Thus, loan rates reflect the geographic dispersion of public concerns about global warning.

In Panel B, we do the sample splits based on personal experiences, and the proportion of the survey respondents who responded yes to having personally experienced global warming. Our coefficient of interest is again positive and statistically significant for the pro-climate states. The effects and magnitudes on the sub-sample analysis based on the personal experience in Panel B are consistent with Panel A where the splits are done based on personal harm. The effects on the climate denier sub-sample remain insignificant and the interaction term with the climate denier state dummy is negative and statistically significant. Thus, in the cross-section of loan prices, the dispersion of beliefs and attitudes are reflected in the loan prices demanded by the lenders. Overall, our findings suggest that lenders tend to penalize borrowers for their environmental risk only in the pro-climate states, suggesting that the environmental risk perception is related to the local beliefs and preferences.

One question that may arise is whether the price of environmental risk is affected by short-term increases in attention. To that end, we investigate a series of extreme weather events that may have affected the risk aversion and environmental attitudes of the lenders. We obtain the event dates from the State Climate Extremes Committee and present them in Table 10. The weather stations and observers in the United States record the climatological records of the individual states and notify the State Climate Extremes Committee (SCEC) if an existing record may have been tied or exceeded. The SCEC votes to accept or reject whether the value represents a new extreme weather event based on the historical records of the highest and lowest temperatures, total amount of rain or snow in 24 hours, weight and diameter of hailstones, or highest wind gusts. Thus, we view the classification of a new extreme weather event in a state as random and test whether it increases the price of total environmental impact at the loan origination.

We test whether lenders penalize borrowers for their environmental risk when the latter becomes more salient. The idea is that investors may overweight the probability of left-tail events when they are salient and behave in an irrationally risk-averse manner. To this end, we augment our baseline specification by interacting our total environmental impact measure with dummy variables that indicate whether an extreme event has taken place in the state of the borrower in that year. We focus on the year of the extreme weather event, and the subsequent two years following the event. $POST[0,1]$ is a dummy variable that takes one for the borrowers located in the affected states during the year of the extreme weather event. $POST[1,2]$ and $POST[2,3]$ are indicators that are one after the first and second year after the extreme weather event, respectively. We test the below specification and we report the results in Table 7.

$$\begin{aligned} \textit{Loan Rate}_{ijt} = \beta \times \textit{Impact}_{ijt} + \delta_1 \times \textit{POST[0,1]} \times \textit{Impact}_{ijt} + \\ \delta_2 \times \textit{POST[1,2]} \times \textit{Impact}_{ijt} + \delta_3 \times \textit{POST[2,3]} \times \textit{Impact}_{ijt} + \\ \kappa_1 \times \textit{POST[0,1]} + \kappa_2 \times \textit{POST[1,2]} + \kappa_3 \times \textit{POST[2,3]} + \\ \alpha \times X_{it-1} + \gamma \times Z_{ijt} + \eta_{j \times t} + \epsilon_{ijt} \end{aligned} \tag{3}$$

We also replace our total environmental impact measures with different types of environmental impact in Column 2-8. We find that in all our specifications, the $POST[0,1]$ is positive and statistically significant, suggesting that lenders become more risk-averse in the years that an extreme weather event has taken place. The coefficient on $POST[1,2]$ is much smaller but remains significant in Columns 1-5, and the coefficient on $POST[2,3]$ is statistically insignificant in all our specifications. These results indicate that the higher risk-aversion of the lenders is short-lived. Most importantly, our coefficient of interest δ is either negative or statistically insignificant in Columns 1-9. These results suggest that a short-term over-reaction is unable to explain the price response of lenders to environmental risk, but the latter may likely be driven by persistent differences in beliefs.

4.3 Deregulation

In this section, we study the magnitude of the price of environmental risk, which requires a random variation in environmental risk orthogonal to the firm-level fundamentals that affect demand and credit supply. Any shock to the greenness of the borrowers such as regulatory developments or environmental news are likely to affect demand and bias our estimates. We propose to use the sudden Trump withdrawal from the Paris Agreement as a shock to the environmental risk perception of the borrowers, leaving borrower fundamentals and bank characteristics unchanged.

The Paris Agreement is a global and coordinated effort to tackle climate change which was signed in December 2015 at the UN Climate Change Conference (COP21) in Paris and came into force in November 2016. The agreement is a legally binding international treaty. With the objective of combatting climate change, the treaty requires the signatory countries to commit to reducing their global greenhouse emissions and submit, every five years, a national climate action plan known as Nationally Determined Contribution (or NDC). It also provides a framework for disclosing and monitoring emissions to reach the net-zero targets. During 2016-2023, 194 countries, including the European Union, joined the Paris Agreement. The operational details for the practical implementation were released in December 2018, and finalized in November 2021.

The U.S. withdrew from and recommitted to the Paris Agreement during the 2017 and 2021. During his presidential campaign, Donald Trump called climate change a "hoax" and vowed to withdraw from the Paris agreement. He called for eliminating the restrictions on the energy explorations and opening more federal lands to drilling to reduce the dependency on the foreign energy and to create more U.S. jobs. He also stated that he would push for the approval of the controversial Keystone XL oil pipeline from Canada and withdraw any funding for the United Nations programs. During his presidency, however, he advocated a mixed position, and he stated that he had "an open mind" about climate change. Despite delays and ambivalent statements, Trump announced his decision to withdraw from the Paris Agreement on the June 1st, 2017.

The surprise withdrawal of Trump from the Paris Agreement presents an ideal setting to investigate the impact of the environmental deregulation on bank lending and study the price of environmental risk. The set-up gives us a distinction between treated and untreated firms, as several cities and states have unexpectedly sued against the government for withdrawing from the Paris agreement, making it less likely to be enforced. It is also natural to expect the states with a Republican majority to be more likely to support the deregulation *ex post*. We present the challenger and Republican states in Graph 5, and Table 11-12. As can be seen in Graph 5 (a-b), the states that sued the government are predominantly Left-wing and non-Republican. We conjecture that the environmental deregulation led banks to perceive environmental risk to be less material. If this is the case, we would see a reduction in the response of the loan prices to environmental risk.

To test this hypothesis, we augment our baseline specification 4.2.4 by interacting our coefficient of interest with an indicator variable that takes one after Trump has announced his decision to withdraw his commitment from the Paris Agreement in June 2017. In our triple difference-in-differences-in-differences (DIDID) specification, we define treated as an indicator variable that takes one if the borrower is in a state that has not sued the Trump government for having withdrawn from the Paris Agreement. We run the specification 2 and report the results in Table 2. Our DIDID coefficient of interest is the interaction term on the total environmental impact, the deregulation event dummy, and the non-challenger state indicator. We find that controlling for the borrower- and deal-level characteristics, the coefficient on the interaction term is negative and statistically significant. The results suggest that after the deregulation, banks have reduced the sensitivity of their loan pricing to the environmental impact of their borrowers. For a borrower with an average total impact ratio, the deregulation is associated with a 4.9 bps decline in the sensitivity to a one percentage point increase in the total environmental impact ratio in the non-challenger-states relative to the states that have sued the Trump government. In Column 2, we replace the treated dummy with an indicator that is one if the borrower is in a state that has consistently voted for the Republican party during our sample period. The coefficient on the interaction term remains statistically significant and increases slightly to 5.27.

To further understand the mechanism driving these results, we investigate the heterogeneity by the area in which the borrower is located. In our augmented specification 2, we replace the treated indicator with other dummy variables that take one if the state is heavily prone to climate scepticism. In Graph 5 (c) we present the states with a higher than median climate denial measure in the year prior to the environmental deregulation, and we see that many of these climate-denier-states include the Republican states. Column 3 and 4 re-define the treatment group based on the personal harm and personal experience measures of climate denial. Our results in Table 9 have a similar interpretation, as the effects appear more forcefully to the climate-denier-states. This is unsurprising as lenders likely consider the possibility that the borrowers located in the climate-denier-states are unlikely to face political pressure and regulatory scrutiny. Thus, our results are driven by the non-challenger and non-denier states, suggesting that the price of environmental risk depends on the local beliefs and enforcement.

We then move on to robustness tests. We test for the presence of pre-trends and add indicators for the years before and after the environmental deregulation. We also add interaction terms to our specification 2 where we define a treated firm as one if it is located in a state that has sued the Trump administration, or in a Republican state more likely to support the environmental deregulation, respectively. We plot the coefficient terms of these interaction terms in Graph 6. We find that the interaction terms with the year dummies before the deregulation are all insignificant, whereas the coefficients on the interaction terms with the years after the deregulation are all large and statistically significant. We find no evidence of pre-trends – which mitigates concerns around reverse causality and suggests that the Trump environmental deregulation led banks to reduce the sensitivity of their loan rates to the environmental impact of their borrowers.

We also acknowledge the fact that the withdrawal of the Trump administration has not applied equally to all environmental regulations. The focus has been on the air pollution, and the protection of the nation's biodiversity and wetlands. For example, the Clean Power Plan was replaced, with weaker restrictions on the GHG and mercury emissions. Other decisions limited the protection of sensitive lands. We acknowledge the different types of restrictions and anticipate that the price of environmental risk may have declined more substantially for land and water impact, air pollution, and GHG emissions. To contemplate this possibility, we replace our total impact measure with measures for different types of environmental impact.

We report our findings in Table 9. Our results are consistent with our predictions. We find that environmental deregulation is associated with a reduction in the price of environmental risk for land and water impact, air pollution, and GHG emissions. The interaction term on our triple DIDID specification is negative and statistically significant in Column 3-5. We find that relative to lawsuit states, firms in no-lawsuit-states have reduced their sensitivity of their loan prices by 8 to 25 bps after the environmental deregulation, controlling for the borrower and deal characteristics. The effects are however insignificant for the natural resources, water, and waste (Column 1, 2, and 6). The results suggest that the withdrawal from the Paris Agreement has significantly reduced the price of environmental risk in the cross-section of the loan rates. In unreported tables, the regressions in 9 warrant a similar interpretation when the treated indicator is instead replaced with other dummy variables that take one if the firm is located in a Republican or climate-denier-state.

5 Conclusion

The rising awareness of global warming and international developments increasingly raise the transition costs of firms subject to climate risk, but the impact on banks' behaviour is largely unknown. What leads banks to adjust their lending to environmental risk is also poorly understood. In this paper, we document that environmental risk is reflected in the cross-section of loan rates, but only when banks are weakly capitalized, and borrowers are not located in areas prone to climate denial. We also show that banks only account for the salient and direct environmental impact of their borrowers, controlling for other known sources of risk and loan characteristics. The price impact of environmental risk also increases when the latter becomes more salient. Our results suggest that banks perceive environmental risk as a material risk factor.

We also show that the Trump withdrawal from the Paris agreement has reduced the sensitivity of the cost of credit to the environmental impact of the firms. We again find these effects only in the areas that have not sued the government for deregulation, and in the states not heavily prone to climate change denial. An important implication of our study is that the pricing adjustments of climate transition may potentially depend on the local beliefs and enforcement rather than on the rules. In a regulatory environment where firms are unlikely to face local pressure and climate risk is seen as dubious, our paper shows that banks are also less likely to adjust their cost of credit!

Table 1: **Summary Statistics**

This table reports the summary statistics for Trucost, Dealscan, and Compustat during the study period. The impact and all-in-spread-drawn variables are all winsorized at the 1% level.

Trucost	Definition	mean	median	standard deviation
total impact (%)	The sum of all the direct and indirect external environmental costs of the company as a percentage of revenue	4.02	1.51	8.32
direct impact (%)	The sum of all the direct external environmental costs of the company as a percentage of revenue	1.81	0.12	6.23
indirect impact (%)	The sum of all the indirect external environmental costs of the company as a percentage of revenue	2.01	1.19	2.85
natural resources impact (%)	The sum of the direct and indirect use of natural resources as a percentage of revenue	0.19	0.04	0.89
water impact (%)	The dollar value of the direct and indirect water pollutant quantities as a percentage of revenue	0.93	0.34	2.09
land and water impact (%)	The dollar value of the direct and indirect land and water pollutant quantities as a percentage of revenue	0.18	0.06	0.45
air pollutants impact (%)	The direct and indirect air pollutant costs as a percentage of revenue	0.59	0.24	1.11
ghg emissions impact (%)	The value of direct and indirect GHG emissions as a percentage of revenue	1.53	0.58	3.02
waste impact (%)	The dollar value impact of the direct and indirect waste generation by the company as a percentage of revenue	0.09	0.05	0.20
Dealscan	**definition**	**mean**	**median**	**standard deviation**
All-in-spread	The amount the borrower pays in basis points over LIBOR for each dollar drawn down including the annual fees	224.67	187.5	160.82
Deal size	Total amount that the deal has received commitments for (in USD)	440.2	1149.39	2519.97
Maturity	How long (in months) the facility will be active from the signing date to the expiration date	55.47	60	38.93
Covenant	Dummy indicator whether or not the facility has financial or net worth covenants	0.21	0	0.41
Secured	Dummy indicator whether or not the facility is secured or collateral is held against the loan	0.38	0	0.49
Non-bank presence	Dummy indicator whether or not the facility has non-bank participants or lead arrangers (*e.g.*, corporation, finance company, investment firm, insurance company and mutual fund)	0.39	0	0.49
Compustat	**definition**	**mean**	**median**	**standard deviation**
Log(Total Assets)	The Natural Logarithm of Total Assets	5.63	5.77	2.85
Log(Total Debt)	The Natural Logarithm of Total Debt	3.18	2.43	3.14
Log(Cash)	The Natural Logarithm of Total Cash	3.11	2.94	2.28
Ebitda/Assets	Earnings Before Interest Divided by Total Assets	-1.47	0.05	39.88

Table 2: **Sensitivity of Loan Rates to Total Environmental Impact**

This table reports the sensitivity of the loan rates to the environmental impact of the borrowers at the loan facility level. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), log(cash) and ebitda/assets. Deal controls include deal size and maturity, the secured and covenant status, and non-bank participation. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

	no controls	with borrower controls	with borrower and deal controls	no controls	with borrower controls	with borrower and deal controls	no controls	with borrower controls	with borrower and deal controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
total impact	0.555***	0.456***	0.248**						
	(0.129)	(0.143)	(0.116)						
direct impact				0.866***	0.444**	0.280*			
				(0.143)	(0.187)	(0.152)			
indirect impact							-0.665	1.630**	0.244
							(0.429)	(0.824)	(0.705)
N	31055	8658	8638	31055	8658	8638	31055	8658	8638
R^2	0.40	0.47	0.60	0.40	0.46	0.60	0.39	0.46	0.60
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Deal controls	No	No	Yes	No	No	Yes	No	No	Yes

Table 3: **Sensitivity of Loan Rates to Different Types of Environmental Impact**

This table reports the sensitivity of the loan rates to the different types of environmental impact of the borrowers at the loan facility level. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), log(cash) and ebitda/assets. Deal controls include deal size and maturity, the secured and covenant status, and non-bank participation. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

	no controls	with borrower controls	with borrower and deal controls	no controls	with borrower controls	with borrower and deal controls	no controls	with borrower controls	with borrower and deal controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
natural resources total impact	5.110***	4.128***	2.462***						
	(0.471)	(0.706)	(0.624)						
water total impact				0.294	1.723***	1.440**			
				(0.358)	(0.527)	(0.580)			
land and water total impact							-2.731	16.25***	23.25***
							(2.342)	(5.760)	(5.037)
N	31055	8658	8638	31055	8658	8638	31055	8658	8638
R^2	0.40	0.47	0.60	0.39	0.47	0.60	0.39	0.47	0.60
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Deal controls	No	No	Yes	No	No	Yes	No	No	Yes

	no controls	with borrower controls	with borrower and deal controls	no controls	with borrower controls	with borrower and deal controls	no controls	with borrower controls	with borrower and deal controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
air pollutants total impact	-0.385	-1.202	-0.948						
	(1.115)	(1.859)	(1.225)						
ghg emissions total impact				0.979***	0.839	0.492			
				(0.325)	(0.513)	(0.299)			
waste total impact							-19.53***	-27.88***	-20.70***
							(2.725)	(6.046)	(4.794)
N	31055	8658	8638	31055	8658	8638	31055	8658	8638
R^2	0.39	0.46	0.60	0.39	0.46	0.60	0.40	0.47	0.60
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Deal controls	No	No	Yes	No	No	Yes	No	No	Yes

Table 4: **Environmental Footprint and Lender Capitalization**

This table reports the sensitivity of the loan rates to the different levels of the lender capitalization at the loan facility level. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), log(cash) and ebitda/assets. Deal controls include deal size and maturity, the secured and covenant status, and non-bank participation. Weak capitalization takes one for a lender if the capitalization or equity to assets ratio is lesser then the country median in any given year. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

	banks with weak capitalization	banks with high capitalization	banks with weak capitalization	banks with high capitalization
	(1)	(2)	(3)	(4)
total impact	0.462**	-0.0334		
	(0.191)	(0.152)		
direct impact			0.554**	-0.0539
			(0.255)	(0.190)
N	4312	4322	4312	4322
R^2	0.56	0.64	0.56	0.64
Lender × Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes

Table 5: **Borrower Heterogeneity by Biodiversity Risk**

This table studies the role of biodiversity risk on the sensitivity of the loan rates to the environmental impact of the borrowers at the loan facility level. Biodiversity risk is the rank of the borrower state in the Nature Serve on the basis of the extinction risk of its local biodiversity. Count, regulation, and negative are the bio-diversity measures from Giglio et al. (2023). Count is an indicator variable that takes one if the firm has mentioned biodiversity at least twice in its 10-K statements, and regulation is one if at least one of these sentences is about regulation, and zero otherwise. Negative is the number of negative biodiversity sentences minus the number of positive biodiversity sentences in the 10-K filings. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), log(cash) and ebitda/assets. Deal controls include deal size and maturity, the secured and covenant status, and non-bank participation. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
total impact	0.128	0.275**	0.258**	0.264**				
	(0.207)	(0.116)	(0.117)	(0.116)				
biodiversity risk	0.292***				0.302***			
	(0.104)				(0.101)			
total impact × *biodiversity risk*	0.0147*							
	(0.00783)							
count		33.98***				36.68***		
		(11.89)				(10.66)		
total impact × *count*		-3.026**						
		(1.273)						
regulation			12.13				12.45**	
			(9.175)				(6.092)	
total impact × *regulation*			-3.659***					
			(1.234)					
negative				20.34***				26.45***
				(6.134)				(7.776)
total impact × *negative*				-3.492**				
				(6.134)				
direct impact					-0.00263	0.553***	0.546***	0.548***
					(0.243)	(0.138)	(0.138)	(0.138)
direct impact × *biodiversity risk*					0.0215**			
					(0.00939)			
direct impact × *count*						-8.833***		
						(1.569)		
direct impact × *regulation*							-6.776***	
							(1.121)	
direct impact × *negative*								-13.02***
								(1.894)
N	8639	8638	8638	8638	8639	8690	8690	8690
R^2	0.57	0.60	0.60	0.60	0.57	0.57	0.57	0.57
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: **Borrower Heterogeneity: The Role of Personal Beliefs**

This table studies the role of personal beliefs on the sensitivity of the loan rates to the environmental impact of the borrowers at the loan facility level. In Panel A, climate denier (believer) state takes the value of one if the borrower is in a state with a low (high) percentage of individuals who think that global warming will harm them personally a moderate amount/a great deal based on the Yale Survey data. In Panel B, climate denier (believer) state takes the value of one if the borrower is in a state with a low (high) percentage of individuals who agree that they have personally experienced the effects of global warming based on the Yale Survey data. The bottom of the table provides information about fixed effects. The borrower controls include log(assets), log(total debt), log(cash) and ebitda/assets. Deal controls include deal size and maturity, the secured and covenant status, and non-bank participation. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

	climate denier state	climate believer state	all states	climate denier state	climate believer state	all states
	(1)	(2)	(3)	(4)	(5)	(6)
total impact	-0.110	0.973***	1.069***			
	(0.282)	(0.253)	(0.191)			
total impact × climate denier (personal harm)			-1.306***			
			(0.326)			
direct impact				-0.121	0.885***	1.038***
				(0.298)	(0.290)	(0.203)
direct impact × climate denier (personal harm)						-1.305***
						(0.335)
climate denier (personal harm)			1.532			-1.244
			(3.261)			(2.966)
N	1369	3650	5261	1369	3650	5261
R^2	0.65	0.55	0.51	0.65	0.54	0.51
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes

	climate denier state	climate believer state	all states	climate denier state	climate believer state	all states
	(1)	(2)	(3)	(4)	(5)	(6)
total impact	-0.0911	0.883***	1.067***			
	(0.248)	(0.275)	(0.193)			
total impact × climate denier (personal experience)			-1.116***			
			(0.301)			
direct impact				-0.261	0.848***	1.095***
				(0.249)	(0.324)	(0.205)
direct impact × climate denier (personal experience)						-1.369***
						(0.320)
climate denier (personal experience)			6.923**			5.249*
			(3.249)			(2.993)
N	1536	3473	5261	1536	3473	5261
R^2	0.63	0.56	0.51	0.63	0.56	0.51
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: **Extreme Weather Events**

This table studies the differential sensitivity of loan rates and amounts to the environmental impact of the borrowers at times of extreme weather events. $POST[0,1]$ is a dummy variable that takes one for the borrowers located in the affected states during the year of the extreme weather event. $POST[1,2]$ and $POST[2,3]$ are indicators that are one after the first and second year after the extreme weather event, respectively. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), log(cash) and ebitda/assets. Deal controls include deal size and maturity, the secured and covenant status, and non-bank participation. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$POST[0,1]$	18.41***	17.13***	21.27***	21.06***	23.83***	16.22***	16.47***	18.08***
	(4.138)	(4.035)	(3.912)	(3.837)	(3.922)	(4.007)	(4.222)	(3.742)
$POST[1,2]$	8.669*	7.925*	7.253*	11.00**	8.783*	5.747	7.204	6.923
	(4.687)	(4.064)	(3.912)	(5.198)	(4.813)	(4.470)	(4.433)	(4.314)
$POST[2,3]$	1.034	1.264	0.890	2.131	-1.464	0.172	1.007	-1.056
	(5.698)	(5.200)	(5.445)	(5.917)	(5.966)	(5.460)	(5.470)	(5.563)
total impact	0.273**							
	(0.127)							
total impact × $POST[0,1]$	0.0323							
	(0.432)							
total impact × $POST[1,2]$	-0.380							
	(0.521)							
total impact × $POST[2,3]$	-0.129							
	(0.194)							
natural resources impact			2.545***					
			(0.614)					
natural resources impact × $POST[0,1]$			-8.489***					
			(2.033)					
natural resources impact × $POST[1,2]$			1.480					
			(4.968)					
natural resources impact × $POST[2,3]$			-2.076					
			(3.407)					
water impact				1.822***				
				(0.691)				
water impact × $POST[0,1]$				-3.808				
				(2.585)				
water impact × $POST[1,2]$				-4.584				
				(3.679)				
water impact × $POST[2,3]$				-1.315				
				(0.863)				
land and water impact					24.38***			
					(5.443)			
land and water impact × $POST[0,1]$					-44.80***			
					(10.47)			
land and water impact × $POST[1,2]$					2.117			
					(13.27)			
land and water impact × $POST[2,3]$					0.359			
					(6.234)			
air pollutants impact						-1.604		
						(1.404)		
air pollutants impact × $POST[0,1]$						3.729*		
						(2.061)		
air pollutants impact × $POST[1,2]$						2.022		
						(2.228)		
air pollutants impact× $POST[2,3]$						1.102		
						(1.460)		
ghg emissions impact							0.314	
							(0.336)	
ghg emissions impact × $POST[0,1]$							0.787	
							(0.599)	
ghg emissions impact× $POST[1,2]$							0.169	
							(0.702)	
ghg emissions impact × $POST[2,3]$							-0.0679	
							(0.456)	
waste impact							-20.60***	
							(4.854)	
waste impact × $POST[0,1]$							6.726	
							(16.60)	
waste impact × $POST[1,2]$							-6.892	
							(9.997)	
waste impact × $POST[2,3]$							10.86	
							(9.134)	
N	8638	8638	8638	8638	8638	8638	8638	8638
R^2	0.60	0.60	0.60	0.60	0.60	0.60	0.60	0.60
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: **Paris Agreement Withdrawal and Environmental Footprint**

This table studies the differential sensitivity of loan rates and amounts to the environmental impact of the borrowers at times of extreme weather events. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), and ebitda/assets. The lender controls include log(assets), capitalization, and return on assets. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

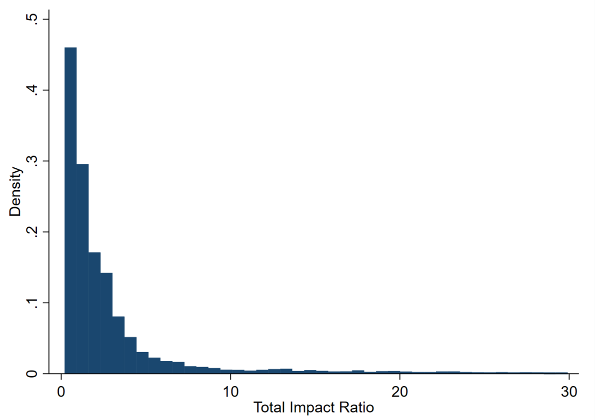
	(1)	(2)	(3)	(4)
total impact	0.431***	0.392***	1.113***	1.132***
	(0.153)	(0.132)	(0.193)	(0.194)
deregulation	-11.55***	-12.85***	-12.45**	-8.329
	(4.442)	(4.632)	(5.071)	(5.264)
total impact × *deregulation*	2.634***	2.536***	1.320**	0.573
	(0.741)	(0.631)	(0.623)	(0.465)
no-lawsuit-state	-1.884			
	(2.198)			
deregulation × *no-lawsuit-state*	28.69***			
	(4.911)			
total impact × *no-lawsuit-state*	0.253			
	(0.219)			
total impact × *deregulation* × *no-lawsuit-state*	-4.913***			
	(0.719)			
republican-state		-9.529***		
		(3.015)		
deregulation × *republican-state*		38.98***		
		(5.877)		
total impact × *republican state*		0.455**		
		(0.212)		
total impact × *deregulation* × *republican state*		-5.373***		
		(0.568)		
climate denier (personal harm)			-1.367	
			(3.059)	
deregulation × *climate denier (personal harm)*			16.06**	
			(7.685)	
total impact × *climate denier (personal harm)*			-0.677***	
			(0.254)	
total impact × *deregulation* × *climate denier (personal harm)*			-3.353***	
			(0.826)	
climate denier (personal experience)				5.199*
				(2.941)
deregulation × *climate denier (personal experience)*				7.640
				(7.015)
total impact × *climate denier (personal experience)*				-0.518**
				(0.258)
total impact × *deregulation* × *climate denier (personal experience)*				-2.548***
				(0.624)
N	8690	8690	5261	5261
R^2	0.57	0.57	0.51	0.51
Lender × Year FE	Yes	Yes	Yes	Yes
State FE	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes

Table 9: **Paris Agreement Withdrawal and Environmental Footprint**

This table studies the differential sensitivity of loan rates and amounts to the environmental impact of the borrowers at times of extreme weather events. The bottom of the table provides information about fixed effects, and the level of clustering. The borrower controls include log(assets), log(total debt), and ebitda/assets. The lender controls include log(assets), capitalization, and return on assets. Standard errors correct for clustering at the lender-level, and are reported in parentheses. ***, ** and * indicate statistical difference from zero at the 1%, 5% and 10% levels, respectively.

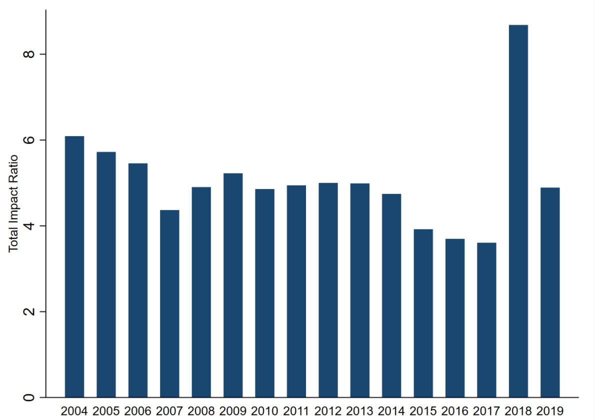
	(1)	(2)	(3)	(4)	(5)	(6)
deregulation	-1.396	-6.717	-5.289	-12.08***	-18.15***	-1.245
	(4.758)	(4.704)	(4.883)	(4.123)	(5.149)	(5.586)
no-lawsuit-state	-0.248	-5.899***	-7.820***	4.716	1.833	0.215
	(2.275)	(2.268)	(2.812)	(3.135)	(2.353)	(2.801)
deregulation × *no-lawsuit-state*	12.17**	17.74***	17.11***	27.13***	29.04***	15.14***
	(5.641)	(5.780)	(5.610)	(6.654)	(5.446)	(5.537)
natural resources impact	2.967***					
	(0.697)					
natural resources impact × *deregulation*	-5.219***					
	(1.203)					
natural resources impact × *no-lawsuit-state*	1.475					
	(1.191)					
natural resources impact × *deregulation* × *no-lawsuit-state*	-6.583					
	(6.722)					
water impact		-1.431***				
		(0.493)				
water impact × *deregulation*		4.030***				
		(0.801)				
water impact × *no-lawsuit-state*		5.543***				
		(1.261)				
water impact × *deregulation* × *no-lawsuit-state*		-3.887				
		(4.454)				
land and water impact			-3.814			
			(3.754)			
land and water impact × *deregulation*			16.04***			
			(3.717)			
land and water impact × *no-lawsuit-state*			42.00***			
			(12.12)			
land and water impact × *deregulation* × *no-lawsuit-state*			-23.97**			
			(10.38)			
air pollutants impact				3.207		
				(2.152)		
air pollutants impact × *deregulation*				-5.905**		
				(2.603)		
air pollutants impact × *no-lawsuit-state*				-5.878***		
				(2.153)		
air pollutants impact × *deregulation* × *no-lawsuit-state*				-8.303***		
				(2.808)		
ghg emissions impact					0.975**	
					(0.401)	
ghg emissions impact × *deregulation*					13.51***	
					(3.207)	
ghg emissions impact × *no-lawsuit-state*					-0.701*	
					(0.421)	
ghg emissions impact × *deregulation* × *no-lawsuit-state*					-16.03***	
					(3.130)	
waste impact						0.351
						(7.106)
waste impact × *deregulation*						-13.47
						(28.27)
waste impact × *no-lawsuit-state*						-1.247
						(7.422)
waste impact × *deregulation* × *no-lawsuit-state*						-15.21
						(28.65)
N	8690	8690	8690	5261	8690	8690
R^2	0.57	0.57	0.58	0.51	0.57	0.57
Lender × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	No
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower controls	Yes	Yes	Yes	Yes	Yes	Yes
Deal controls	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: **Total Environmental Impact as a Percentage of Revenue (%)**



The graph displays the distribution of the environmental impact of the U.S. firms based on the Trucost total environmental impact measure.

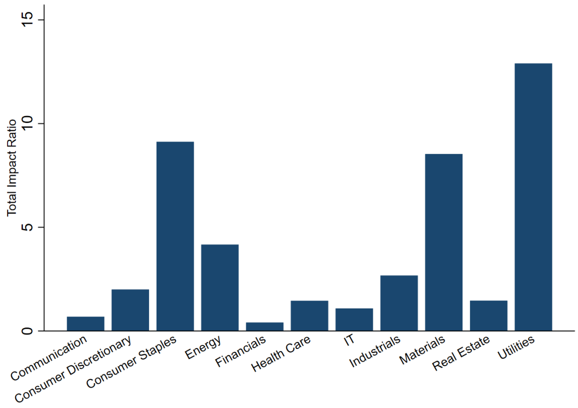
Figure 2: **The Yearly Average Total Environmental Impact**



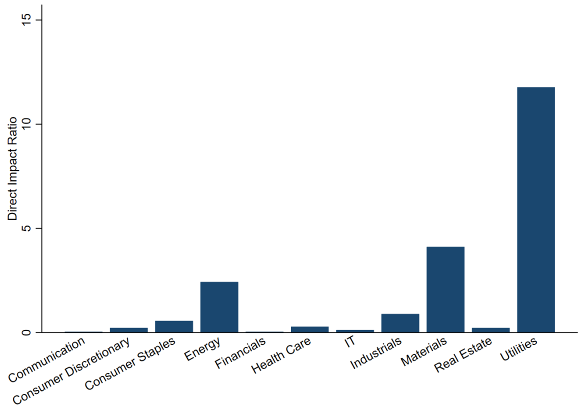
The graph presents the yearly average of the total environmental impact of the U.S. firms during the sample period 2004-2019.

Figure 3: **Impact Ratios by Different Sectors**

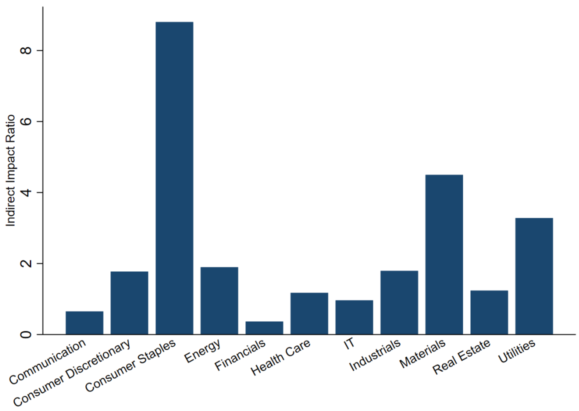
This graph presents the total, direct, and indirect impact ratios for different sectors during our sample period 2004-2019.



(a) Total Environmental Impact as a percentage of revenue (%)

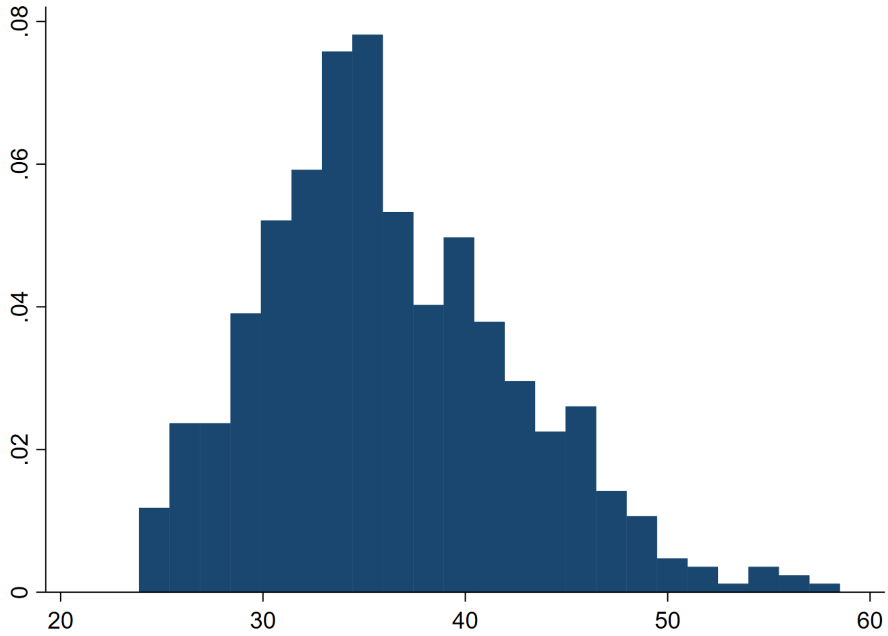


(b) Direct Environmental Impact as a percentage of revenue (%)

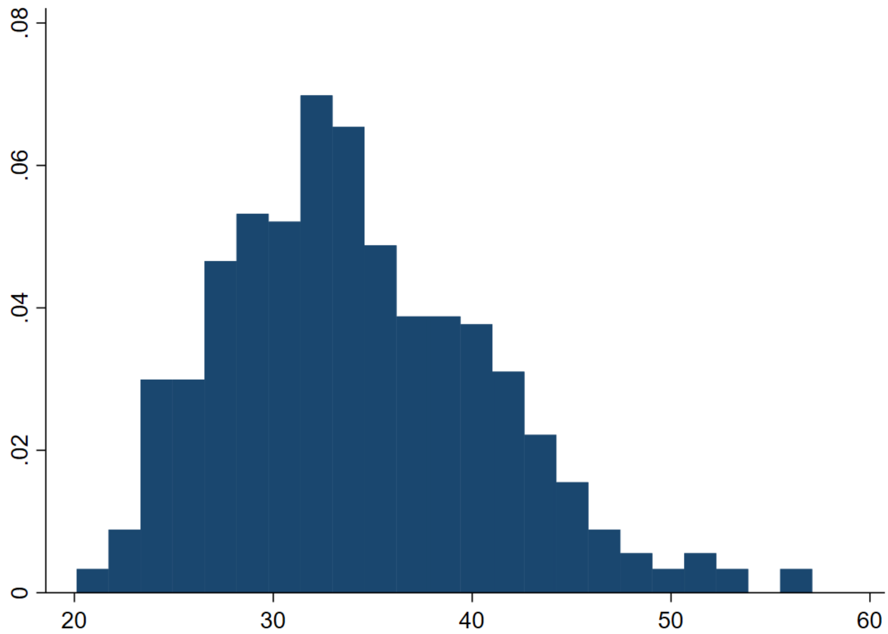


(c) Indirect Environmental Impact as a percentage of revenue (%)

Figure 4: **Distribution of Climate Change Denial across the U.S. States**

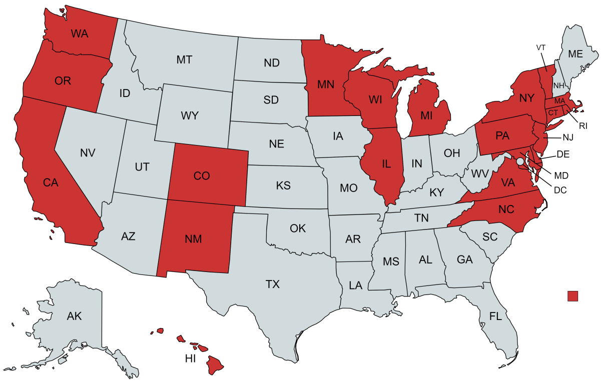


(a) Distribution of climate change denial based on personal harm
This graph presents the average estimated percentage who think global warming will harm them personally a moderate amount/a great deal in the Yale Climate Opinion Survey

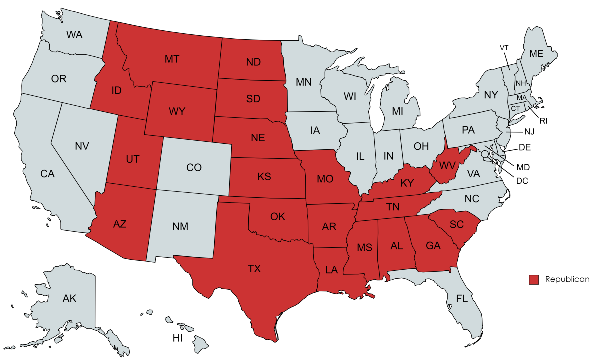


(b) Distribution of Climate Change Denial based on Personal Experience
This graph presents the average estimated percentage who somewhat/strongly agree that they have personally experienced the effects of global warming in the Yale Climate Opinion Survey

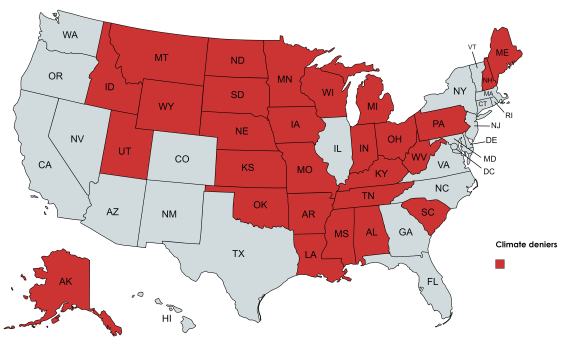
Figure 5: **States that are Climate Change Deniers and Trump Challengers**



(a) States that challenged the Trump-era Environmental Deregulation
This graph presents the states that appealed the Trump withdrawal from the Paris Agreement and sued the government in the court

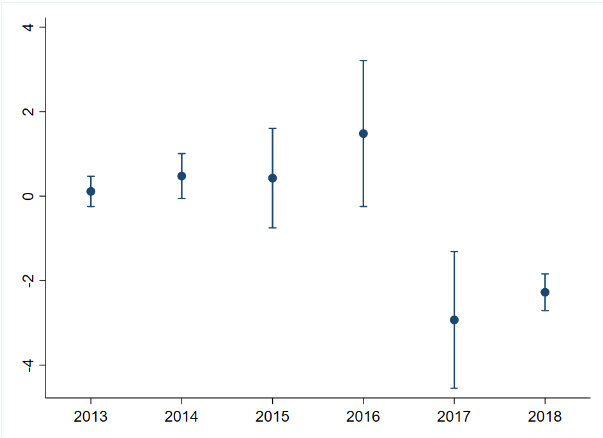


(b) Republican States
This graph presents the states that have consistently voted as Republican in our sample period

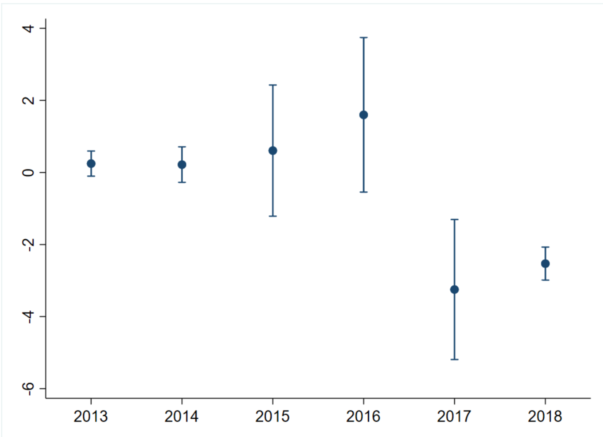


(c) States classified as Climate Deniers based on Personal Harm
This graph presents the states that are classified as climate deniers based on personal harm, *i.e.* with a lower proportion of the public who believes that global warming will harm them personally than the country median in 2016

Figure 6: **Test for Pre-Trends**



This graph presents the dynamic regression coefficients λ_{year} from the augmented specification $Loan\ Rate_{ijt} = \beta \times Impact_{ijt} + \sum_{year} \delta_{year} \times no\text{-}lawsuit\text{-}state \times I_{year} + \sum_{year} \lambda_{year} \times Impact_{ijt} \times no\text{-}lawsuit\text{-}state \times I_{year} + \alpha \times X_{it-1} + \gamma \times Z_{ijt} + \eta_{j \times t} + \epsilon_{ijt}$ where the year ranges from 2013 to 2018.



This graph presents the regression coefficients λ_{year} from the augmented specification $Loan\ Rate_{ijt} = \beta \times Impact_{ijt} + \sum_{year} \delta_{year} \times republican\text{-}state \times I_{year} + \sum_{year} \lambda_{year} \times Impact_{ijt} \times republican\text{-}state \times I_{year} + \alpha \times X_{it-1} + \gamma \times Z_{ijt} + \eta_{j \times t} + \epsilon_{ijt}$ where the year ranges from 2013 to 2018.

Table 10: **States with Extreme Weather Events**

This table reports the states that reported extreme weather events during the study period.

State	*Year*
Alabama	1993
Alabama	1997
Alabama	2018
Alaska	2008
Arizona	1994
Arkansas	2015
California	2017
Connecticut	1995
Connecticut	2013
Delaware	2016
Delaware	2009
Delaware	2010
Georgia	1993
Georgia	1994
Hawaii	2018
Illinois	2019
Illinois	1996
Illinois	2015
Indiana	1994
Indiana	2004
Iowa	1996
Iowa	1998
Kansas	2009
Kansas	2010
Kansas	2019
Kentucky	1994
Kentucky	1997
Kentucky	2021
Maine	1996
Maine	2009
Maryland	1993
Maryland	2018
Massachusetts	1996
Massachusetts	1997
Michigan	2019
Minnesota	1994
Minnesota	1996
Minnesota	2007
Montana	2003
Nebraska	2003
Nebraska	2006
Nevada	1994
Nevada	1996
Nevada	2004
New Hampshire	1996
New Jersey	2011
New Mexico	1994
New York	2014
North Carolina	1993
North Carolina	2018
Ohio	1995
Ohio	1996
Oklahoma	2011
Oregon	2006
Oregon	2021
Pennsylvania	2010
Puerto Rico	1996
South Carolina	2012
South Carolina	1999
South Carolina	2018
South Dakota	1998
South Dakota	2006
South Dakota	2007
South Dakota	2010
Tennessee	1993
Tennessee	2021
Texas	1994
Texas	2021
Utah	2021
Vermont	1995
Vermont	1999
Vermont	2009
Virginia	1994
Virginia	1996
Virginia	1999
Virginia	2018
Washington	1994
Washington	2021
West Virginia	1998
West Virginia	2010
West Virginia	2018
Wisconsin	1996

Table 11: **States and Cities that Sued the Trump Government for the Paris Agreement Withdrawal**

This table reports the states and cities that sued the Trump government in the District of Columbia Circuit after the Paris Agreement withdrawal.

States that Sued Trump
New York
California
Colorado
Connecticut
Delaware
Hawaii
Illinois
Maine
Maryland
Massachusetts
Michigan
Minnesota
New Jersey
New Mexico
North Carolina
Oregon
Pennsylvania
Rhode Island
Vermont
Virginia
Washington
Wisconsin
Washington, D.C.
Cities that sued Trump
Boulder
Los Angeles
Chicago
New York
Philadelphia
South Miami

Table 12: **Republican States**

This table presents the states that consistently voted for the Republican party in the presidential elections during the sample period.

Alabama
Arizona
Arkansas
Georgia
Idaho
Kansas
Kentucky
Louisiana
Missouri
Mississippi
Montana
Nebraska
North Dakota
Oklahoma
South Carolina
South Dakota
Tennessee
Texas
Utah
West Virginia
Wyoming

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