Information about Climate Transition Risk and Bank Lending

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Abstract

I provide novel empirical evidence for the positive impact of banks' industry specialization on their pricing of borrowers' climate transition risk. This impact varies across geographies and different types of transition risk. I also show that banks under-react to a global shock relevant for energy-intensive firms, which leads to lower lending rates for browner firms, especially during periods of high aggregate financial stress. Interpreting banks' industry specialization as a source of heterogeneity in costs of private information acquisition and given the under-reaction to the global shock, I build a theoretical model with competitive lending, costly information acquisition, and non-Bayesian belief updates by banks about borrowers' transition risk. Specialized banks can better distinguish between differently exposed borrowers relative to non-specialized banks. When banks under-react to public information about transition risk, the optimal level of private information acquisition increases, but interest rate differentials between more and less exposed borrowers decline in favor of more exposed borrowers. This effect is more pronounced during periods of poor borrower quality, as in financial stress periods. These results imply that to reduce green firms' financing costs, it is crucial to lower banks' cost of acquiring information about firms' climate change exposure through standardized firm-level disclosures and comprehensive climate-stress testing guidelines, even when there is high-quality public information and communication about decarbonization.

Keywords: Information and Knowledge; Beliefs, Banks, Sustainability

JEL Codes: D82, G21, Q54, Q55

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1. Introduction

The risks posed by climate change to society and the economy have become increasingly apparent in recent years. Climate transition risk arises from technological or policy uncertainty associated with the possible transition to a low-carbon economy. This transition may result in losses if carbon-intensive assets are revalued or technological shocks render carbon-intensive operations unproductive. However, evidence suggests that most banks do not incorporate transition-risk considerations into their loan pricing decisions and have not slowed the pace of lending to high-emission firms or fossil-fuel projects (Kirsch et al. 2021). Climate stress-testing studies conducted for the banking industry show that banks are meaningfully exposed to climate transition policies—especially shocks that entail a sudden increase in carbon prices—through credit risk and market risk channels (Acharya et al. 2023; Jung et al. 2023).

This paper takes an information-centric approach to understanding how banks price corporate exposure to climate transition risk. I answer two central questions: First, do banks charge higher lending rates to firms more exposed to transition risks, and is this effect stronger for loans made by banks specialized in the borrower's industry? Second, can the cost of acquiring information about borrowers' industry exposure and banks' response to public signals about transition risk explain the interest rate differentials between more and less exposed firms?

I first answer these questions empirically and then propose an analytical framework to further understand the empirical findings. I use syndicated lending data for non-financial firms across multiple countries and leverage emission intensity data and forward-looking measures of firms' policy and technological transition risks estimated from public companies' earnings calls by Sautner et al. (2023) as proxies for transition risk exposure to understand the relationship between firm-level transition risk and lending contracts. To examine the potential effects of heterogeneity in policy efforts to drive sustainable activities, I perform separate analyses for firms headquartered in the U.S. and those headquartered in the E.U.

I find no evidence that higher emission intensity is associated with a higher lending rate (all-in-spread-drawn (bps)). However, I find that higher forward-looking exposure to climate regulations is associated with a lower lending rate on average for firms headquartered in the E.U. Interestingly, I observe the opposite effect for firms in the U.S., where higher climate regulatory exposure is associated with a higher lending rate. I do not observe any significant effects associated with higher exposure to green technologies.

Without mandated and standardized information disclosure of exposure to climate transition risks, it is challenging for banks to acquire information about their borrowers' sustainable activities (or lack thereof). However, banks specialized in lending to specific industries might have an informational advantage over non-specialized banks. I find that while, on average, banks specializing in the borrower's industry charge a higher lending rate for firms with high emission intensity. Furthermore, I find evidence that specialized banks charge a higher interest rate to E.U. firms exposed negatively to climate regulations.However, I do not find similar effects for U.S. firms.

In the absence of global carbon pricing, I use oil supply news shocks as a proxy for public signals about shocks from disorderly transition risk to further examine whether banks specialized in the borrower's industry incorporate market signals of a firm's vulnerability to fossil-fuel shocks and exposure to overall transition risk. After I incorporate oil supply news shocks in the empirical analysis, the evidence showing that specialized banks charge higher lending rates to more exposed firms becomes mixed. Across the sample, I see high-emission-intensity firms facing higher lending rates from specialized banks after an oil supply news shock, albeit with a two- to three- quarter lag. For E.U. firms alone, I do not find these effects for firms with high emission intensity or negative regulatory exposure. Interestingly, I find evidence that specialized banks charge lower lending rates to E.U. firms negatively exposed to green technological development after an oil supply news shock.

I find some evidence that specialized banks charge U.S. firms with high emission intensity higher interest rates on average one quarter after an oil supply news shock. While I find evidence that specialized banks charge lower rates to U.S. firms negatively exposed to climate regulations one quarter after an oil supply news shock, the direction of this association reverses two quarters after the news shock, at which point specialized banks charge a higher rate to those U.S. firms facing more negative regulatory exposure. In contrast to the evidence for E.U. firms negatively exposed to green technology-related developments, I find evidence that U.S. firms negatively exposed to green technological developments are charged a higher interest rate by specialized banks two quarters after an oil supply news shock.

In a nutshell, the empirical results show that while specialized banks might be better equipped to incorporate certain aspects of firm-level transition risk in lending contracts, global oil supply news shocks that might affect energy-intensive firms similarly as disorderly transition shocks (via jumps to carbon prices) are not necessarily priced in by specialized banks when lending to negatively exposed firms or are priced in after a significant lag.

To understand the empirical results, it is important to answer the aforementioned second question. Climate stress tests piloted by central banks and regulatory authorities have noted that lenders face significant information gaps in identifying their transition risk exposure, predominantly due to a lack of standardization (EBA 2021) and a lack of comprehensive frameworks to estimate borrowers' emissions and transition risk management (FRB 2024). Information frictions related to transition risk are further exacerbated by the fact that climate risk is characterized by deep uncertainties. Models that are not forward-looking and focus more on the past emission performance of firms will not comprehensively capture these risks (Monasterolo 2020).

I incorporate non-Bayesian updating in response to costless public information in a model of costly screening of two borrowers differentially exposed to climate transition risk. Both borrowers are similar in all aspects and do not have any default risk; the key difference between them is the probability of their projects' success. Borrowers more exposed to transition risk have lower expected project profitability given a potential transition risk shock[1].

Previous research on financial intermediaries has shown how lower screening costs and better monitoring reduce uncertainty about the ex-ante qualities of borrowers, thus positively affecting aggregate investment (Gertler and Bernanke 1989; Holmstrom and Tirole 1997; Levine 2005). However, screening is costly and imperfect, and heterogeneous screening capacities across lenders in a perfectly competitive environment can result in informational advantages for the screening lender. To incorporate bank specialization in the borrower's industry as a source of informational advantage, I consider two banks - (i) specialized (informed: acquires costly private information about the borrowers' quality) and (ii) unspecialized (uninformed: does not acquire any private information due to prohibitively high information acquisition costs).

The changing dynamics of transition risk caused by the development of energy-efficient technologies, scientific evidence, or frequent weather events should ideally lead lenders to update

[1]One possible source of heterogeneity among entrepreneurs could emerge from the use of energy in production functions, where an aggregated "energy input" is a convex combination of energy from fossil fuels and that from renewable sources (Hassler et al. 2016). A transition shock could be a carbon tax, leading to a decline in the per-unit return on physical capital for a carbon intensive firm. In a transition scenario involving a policy shift towards energy efficiency, a firm with lower levels of energy-efficient technology would receive smaller returns from an "energy-efficient technology" shock than a more energy-efficient firm (Hassler et al. 2012). The lenders' payoff from financing these firms' investment projects would then be adversely affected. The recent TFCD report by Citibank has shown a high exposure to transition risk arising from funding oil & gas projects and automobile manufacturers (*Finance for a climate-resilient future* 2012).

their loan repayment expectations for more exposed borrowers. However, neglecting relevant information while updating expectations is a major concern when assessing climate risk. Belief updates regarding climate change can be slow, influenced by model uncertainty, weather shocks, or policy responses, making it difficult for expectations to converge to the true distribution of risks (Kelly and Kolstad 1999; Kelly and Tan 2015). Moreover, backward-looking expectations could severely underestimate the tail risks related to climate change (Bolton et al. 2020). At the same time, the nature of belief updating by the lenders could also be a critical determinant of the difference in the loan-contract terms and hence the aggregate credit supply to green firms[2] [3]

I incorporate this feature of climate-change related expectation formation into the model by allowing the banks to symmetrically update their beliefs in response to informative and costless yet imperfect public information about the quality of the borrower. The structure of the updating process is based on Epstein (2006), where the lenders' updated beliefs are linear combination of their "priors" (i.e., their beliefs before receiving public signals) and the Bayesian posterior after they observe the public signal about transition risk exposure. This structure of belief formation is "accuracy-motivated", i.e. the lender evaluates new information so that their updated beliefs accurately estimate the true distribution[4]. The "prior" beliefs play no role in the evaluation of the new information. However, the subjective posterior beliefs may be affected by how the lender weighs their Bayesian posterior relative to their prior beliefs. Consequently, there are three possible outcomes from updating: (i) no update, (ii) learning in the direction of the new information, and (iii) learning in the direction opposite to the new information (Druckman and McGrath 2019). I focus on the first two outcomes, and examine the effect on the interest rate differentials between borrowers if lenders underreact to public information.

My first theoretical result compares the expected interest rates charged after the lenders receive public and private signals about borrower quality. As the lenders' underreaction (and therefore the

[2]Research on climate risk perception employs surveys and secondary data, highlighting evidence for partial alignment with Bayesian learning and the representativeness heuristic, with individuals assigning more weight to prior beliefs amidst higher uncertainty relating to information about climate change (Cameron 2005; Deryugina 2013). Using a county-year panel from the Yale Climate Beliefs survey, I provide empirical evidence that after controlling for county-level demographics, median household income, and political beliefs, perceptions about exposure to damages from global warming increase after individuals witness a state-level 'Billion-Dollar Disaster'. However, these perceptions are still strongly anchored to 'prior' beliefs or beliefs recorded six years before the billion-dollar disaster (Appendix C).

[3]The representativeness heuristic emphasizes the overweighting of recent observations during belief formation (Kahneman and Tversky 1972). This bias is linked to Bayesian learning and diagnostic expectations, which explain business cycles (Baley and Veldkamp 2021; Bianchi et al. 2021) and pre-crisis market behavior (Krishnamurthy and Li 2020). Investors often underreact to initial negative signals but overestimate downturn risks after persistent bad news (Bordalo et al. 2018; Gennaioli et al. 2015).A similar mechanism - the neglect of risk - could be the reason that climate risk is underpriced by the financial markets, as noted by central banks worldwide (NGFS 2019).

[4]As opposed to "directed motivation" where the individual updates their beliefs to arrive at a pre-determined concluion, which may be influenced by their "prior" beliefs.

weight they give their prior beliefs) increases, at any given level of information acquisition, the expected interest rate differential decreases in favor of more exposed borrowers. The decline in this differential is sharper for higher quality public information. Furthermore, the expected interest rate charged to a borrower given a signal indicating low transition risk exposure from both private and public information sources is lower than that charged to a borrower given a signal related to high exposure from either information source. Borrowers who are the subject of high exposure signals (or low-quality signals) from both sources are charged a considerably higher interest rate.

My second theoretical result examines how the degree of underreaction impacts the optimal level of private information acquisition. Given a public signal of medium to high informativeness, the informed lender is somewhat dependent on public information. As lender underreaction increases, the informed lender's dependence on private information increases, increasing their informational advantage in equilibrium. However, when the probability of success for an average borrower is high, the increase in optimal private information acquisition with an increase in underreaction is smaller, implying that public information is better incorporated in lending decisions during times of higher credit quality.

My third theoretical result examines the implications of the association between borrower quality and private information acquisition on the interest rate differentials between more and less exposed borrowers. The reliance on private information acquisition is high given poor average borrower quality. Therefore, as underreaction increases, there is a sharp decrease in the interest rate differentials between more and less exposed firms despite high-quality public information. This effect becomes weaker as average borrower quality improves and the threshold of underreaction, beyond which interest rate differentials decline, increases. This implies that, during periods of poor average borrower quality, even a minor increase in underreaction can result in a sharp decline in the interest rate differential between more and less exposed borrowers. This result has important implications for the pricing of transition risk exposure during periods of high financial stress in the economy.

I test this result empirically for U.S. and E.U. firms by incorporating economy-wide financial stress measures one quarter before the lending contract is originated to examine whether high aggregate financial stress preceding the loan contract results in banks charging lower interest rates to negatively exposed firms. As a measure of financial stress, I use the Financial Stress Index (FSI) by the Office of Financial Research (OFR) (Bejarano 2023) for the U.S., and I use the Country-Level

Indicator of Financial Stress (CLIFS) (Duprey et al. 2017) for the E.U.

I find that U.S. firms with high emission intensity and negative exposure to climate regulations and green technological developments are charged relatively lower interest rates by specialized banks four quarters after an oil supply news shock if the contract is originated after a period of high financial stress. I find the same effect for E.U. firms, albeit only for firms with high emission intensity and negative exposure to green technologies. Moreover, this effect is noticeable within one to two quarters after an oil supply news shock. This empirical finding validates the above theoretical result.

The above results highlight how, during periods of high financial stress, the pricing of transition risk might be even weaker, obstructing decarbonization financing by keeping the cost of debt high for more energy-efficient or green firms. Underreaction to public information increases dependence on private information, which is influenced by the marginal cost of private information acquisition. These results have relevant policy implications. Standardized climate disclosure frameworks and climate transition stress tests would provide lenders with a better understanding of their borrower's emissions and trajectory towards decarbonization, lowering information costs for lenders and supporting green transition financing even during episodes of high financial stress.

Related Literature: This paper engages with and expands upon two distinct strands of literature. First, I examine the extent to which climate transition risk considerations play a role in corporate bank lending decisions. The main channels of transition risk can be summarized into (i) policies such as carbon taxes or changes in financial regulations that drive emission reductions, (ii) technological developments that increase the costs of fossil-fuel extraction or decrease those of renewable energy generation (iii) behavioral changes among agents in financial markets or in the adoption of green behaviors (Dikau and Volz 2018; Monasterolo 2020; Semieniuk et al. 2021).

There has recently been substantial expansion in empirical research on the degree to which the lending rates charged by banks are associated with the environmental concerns linked to a borrower, either because of an adverse climate-related or ESG incident or high carbon emission intensity. Both these factors represent a reputational risk or firm exposure to environmental policies that would have an adverse impact on the profitability of emission-heavy firms (Hrazdil et al. 2020; Ehlers et al. 2021; Ivanov et al. 2023)[5].

[5]Environmental, Social, and Governance – ESG criteria are used to inform investors about the degree to which a firm is environmentally and socially conscious and its governance is transparent and accountable.

While not necessarily focused on pricing decisions, some studies have also discussed the salience of public events that strengthen willingness to decarbonize, such as the Paris Agreement and COP21, to the credit allocation between carbon-intensive and non-carbon-intensive firms (Delis et al. 2019; Reghezza et al. 2021). There is also increasing focus on the exposure of firms to disruptions in green technology and on how banking concentration and bank exposure to negatively exposed firms play a role in credit reallocation between firms positively and negatively exposed to green technological developments (Degryse et al. 2020; Mueller and Sfrappini 2022).

While the aforementioned empirical studies are relevant because they document the empirical facts regarding changes in bank behavior given an increase in climate change policy discussions, they do not necessarily identify all the channels through which transition risk might affect banks' lending decisions. Unlike default lending information, which is verifiable by both the borrower and the lender, information on firms' exposure to climate risk is not and therefore comes under the category of 'soft' or 'subjective' information (Liberti and Petersen 2019).

I add to the empirical literature on the pricing of transition risk by examining the role of bank specialization in the borrower's industry as a source of informational advantage when pricing borrower exposure to both the regulatory and the technological aspects of transition risk. Bank specialization provides a marginal improvement in information acquisition in an environment where standardized emission and sustainability disclosures are not the norm. Furthermore, I incorporate oil supply news shocks as global shocks relevant to all firms, regardless of the state of environmental policies in country in which they are headquartered. Álvarez-Román et al. (2024) take a similar approach to understand the association between credit allocation and physical risks. They examine firm-level credit allocation after wildfires in Spain and show that local banks leverage their geographical proximity to firms as soft information, which allows them to decrease credit to the firms by lesser extent than the more diversified nonlocal banks.

I also build upon the literature on competitive information acquisition by lenders. Theoretical frameworks of lending decisions by competitive banks with heterogeneous information acquisition capacities highlight how a reduction in the costs or uncertainty associated with information acquisition benefit high-quality borrowers through lower interest rates (Hauswald and Marquez 2003; Karapetyan and Stacescu 2014; Banerjee 2005).

I extend the existing theoretical frameworks by highlighting the impact of underreaction to public signals on private information acquisition and the potential failure of lenders to incorporate relevant public information about exposure to green technologies and policies during times of high credit risk. The theoretical model provides a tractable framework to show how public information creates interest-rate differentials between less and more exposed firms provided banks choose to update their beliefs about climate risk. Thus, the model highlights two critical mechanisms through which banks can effectively price climate risk in lending contracts – (i) information acquisition and (ii) accuracy-motivated belief updates given the availability of new information.

The rest of the paper is structured as follows: Section 2 discusses the empirical framework and results to motivate the theoretical framework for information acquisition and underreaction to public information. Section 3 describes the setup of the theoretical model and the equilibrium of the lending game in the second period with non-Bayesian updating. Finally, Section 4 concludes.

2. Empirical evidence: The role of bank specialization in pricing firm-level transition risks in loan contracts

2.1. Data

I rely on three data sources: (i) syndicated loan data from Dealscan (ii) Scope 1 and 2 carbon emission intensity from Trucost and (iii) Green technology-related exposure, and climate regulation exposure from Sautner et al. (2023) for the periods 2010 - 2022 respectively[6]. I restrict the analysis to loans made by banks and borrowers in the non-financial sector for whom I find firm annual balance-sheet variables in Compustat[7]. I exclude loans not made by the lead arranger. The resultant sample consists of 59,630 loan-level observations with emissions data across 2,031 firms in 64 countries and 65,633 loan-level observations with climate risk measures across 2,106 firms in 64 countries. A detailed explanation of the sample composition is in Table 1

To measure the effect of climate risk exposure on loan pricing, I use the All-In-Spread-Drawn (AISD) variable from Dealscan. AISD measures the amount paid by the borrower over LIBOR for each dollar drawn down, with the annual (or facility) fee paid to the lender(s). I control for loan amount, tenor maturity, collateral requirements and presence of covenants in the loan contract.

[6] I merge loan-level data with climate risk measures from Sautner et al. (2023) by first combining the Dealscan sample with the Chava and Roberts (2008) Dealscan-Compustat link and then using the merged sample to link to the Sautner et al. (2023) firms using gvkey as an identifier. I merge loan-level data with firm-level emissions data in Trucost in two steps. I first do an exact merge using the borrowers' gvkey and company name using the Dealscan-Compustat link. I use multi-variable fuzzy matching techniques for the unmatched firms by approximately matching borrower name and borrower parent name in Dealscan to entity names in Dealscan.

[7] I distinguish between bank and non-bank lenders using the classification in the existing literature (Aldasoro et al. 2023; Elliott et al. 2021).

Firm-level controls from Compustat include log of total assets in US dollars, leverage ratio, ratio of capital expenditure to total assets, and ratio of EBITDA to total assets. Summary statistics for loan- and firm-level variables for the entire sample are in Table 2.

2.1.1. Measures of transition risk exposure

Trucost provides detailed information on Greenhouse Gas (GHG) emissions for a vast selection of firms. I use Scope 1 and Scope 2 GHG emission intensity (measured in metric tonnes per USD) for the fiscal year previous to the year of the lending contract[8]. Tables 3 summarizes the lending terms and balance-sheet variables for firms with emissions above and below the median emissions. The average AISD for firms with scope 1 and 2 emission intensity greater than the median emission intensity are lower than the sample average, implying that high emission firms are not necessarily facing higher lending rates than the rest of the sample, nor are they receiving a smaller credit amount.

Data on emissions and emission intensity are backward-looking measures of transition risk exposure, available only for a limited set of companies. They could potentially be a noisy measure of risk considering the presence of 'climate enabler' firms which might have higher emissions to support the transition to a greener economy. Sautner et al. (2023) provide a comprehensive alternative by constructing time-varying measures of firm exposure to climate change using transcripts of quarterly earnings conference calls of publicly-listed firms. They distinguish between exposure to and the sentiment and uncertainty associated with physical events, regulatory shocks, and opportunities arising from developments in renewable energy and green infrastructure in the transcripts of the conference calls, as well as the analyst Q&A sessions. Table 4 shows the descriptive statistics for lending terms and balance-sheet variables for the firms with negative exposure to technological developments related to climate transition in the year of the lending contract, and Table 5 shows the descriptive statistics for firms with negative exposure to climate regulations.

Similar to high emission firms, firms with negative regulatory and technological exposure do not

[8]Scope 1 Greenhouse Gas (GHG) Emissions are direct emissions from sources owned or controlled by the entity. Scope 2 GHG emissions are emissions from generation of purchased electricty used by the entity for operations/productions. I refrain from using estimated Scope 3 GHG emissions because of the noise in estimates from third-party providers. Emission intensity is calculated as the amount of emissions (measured in CO2 equivalent units) per unit of the entity's revenue (which indirectly measures the entity's scale of output). Emission intensity is a better measure of carbon efficiency of a firm since it accounts for output-emission relationship, and provides more information about the carbon efficiency of the entity than absolute emissions. It is important to note that a decrease in emissions intensity does not necessarily translate in reduction in overall emissions.

face a higher average lending rate relative to the sample. However, firms with negative exposure to climate-related technologies face a higher average lending rate than firms with negative exposure to climate-related regulations or firms with higher emissions. Firms with higher emissions also have higher negative exposure to climate-related regulations relative to the rest of the sample.

2.1.2. Bank specialization and informational advantage

In order to reduce the probability of selecting high-risk borrowers, banks theoretically rely on multiple sources of screening and monitoring to acquire information about their borrowers. Recent literature discusses specialization of the bank in lending to a particular industry as a source of information acquisition, possible through repeated lending to individual borrowers as well as repeated lending to certain industries to gain an understanding of the performance and profit margins of an average firm in that industry (Paravisini et al. 2023; Blickle et al. 2023; Giometti and Pietrosanti 2022). Bank specialization in their borrowers' industries can therefore be associated with lower information acquisition costs, given the high cost of shifting businesses from the industry the bank specializes in, to an industry within which the bank is not specialized.

I construct a measure of bank specialization, $X_{b,s}$ in a particular industry s (across SIC2 industry classification) at time t as the ratio of total lending by the bank to industry s at time t to total lending by the bank at time t (Paravisini et al. 2023). I further restrict the specialization measure to a categorical variable, such that if the bank's degree of specialization for industry s at time t is in the fourth quantile of the specialization measures across all banks for industry s at time t, then the bank specialization indicator is set to one, $X_{b,s} = 1$. This categorization allows a clean distinction between banks with greater informational advantage with lending to a specific industry, while also allowing a bank to be specialized in multiple industries and multiple banks to be specialized in an industry at the same time. Table 6 summarizes lending contracts and borrower balance-sheet details for loans made by banks specialized in the borrower's industry.

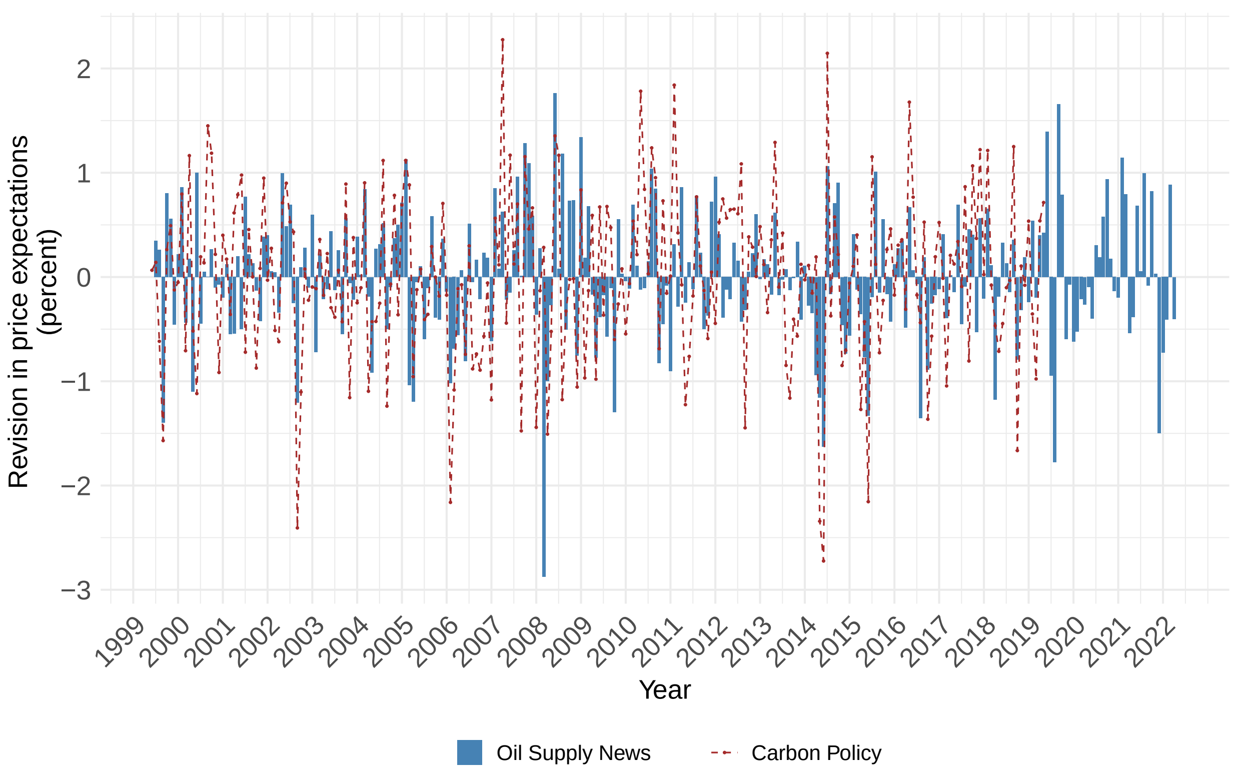
2.1.3. Response of specializing banks to an oil supply news shock

While firm-specific environmental disclosures provide an estimate of the firm's exposure to transition risk, shocks to aggregate transition risk provide a publically available dimension of information based on which lenders can adjust their expectations of firms' profitability. However, most news about transition risk is country or industry-specific, and usually centers around regulatory shocks.

An informative public signal should be related to all aspects of transition risks[9]. Transition risk shocks are often defined as a disorderly jump in carbon prices.

In the absence of carbon pricing mechanisms in most countries, I use the oil supply news shock series from Känzig (2021) as a proxy for public signals about possible transition risk exposure. The estimated oil supply news shocks are associated with changes in oil supply expectations, which further leads to a significant increase in oil prices, and therefore, energy prices. While these shocks are not associated with financial or economic uncertainty, by affecting energy prices they also present significant implications for the profitability of energy-intensive firms. Figure 1 shows how the movement in the oil supply news shock series moves with periods of significant volatility in the oil and gas market, along with the movements in carbon policy shocks as estimated in Känzig (2023).

FIGURE 1. Oil supply news shocks



Source: Oil supply news shock (Känzig 2021); Carbon policy shock series (Känzig 2023)
Note: Carbon policy shocks are estimated using changes in the EUA futures prices in windows around carbon regulatory events associated with higher energy prices.

[9]The Paris Agreement led landmark shift in public attention to climate change. However, it did not lay down specific guidelines for financial institutions regarding the path to financing of decarbonization-friendly projects

2.2. Empirical specification

To examine whether banks price firms' transition risk exposure as reflected in their Scope 1 and Scope 2 emission intensity from the previous year, as well as forward-looking exposure to risks from climate policies, and climate-related technological developments, I estimate the following regression:

$$
\begin{aligned}
& AISD_{f,b,t} = \alpha + \underbrace{\beta_{risk}}_{>0}(risk)_{f,t} + \beta_{spec}X_{b,s,t-1} + \beta_{news_i}Shock_{t-i}+ \\
(1) \quad & \underbrace{\beta_{risk,spec_{t-1}}}_{>0}X_{b,s,t-1} \times (risk)_{f,t} + \beta_{spec_{t-1},news_i}X_{b,s,t-1} \times Shock_{t-i}+ \\
& \underbrace{\beta_{risk,spec_{t-1},news_i}}_{>0}X_{b,s,t-1} \times (risk)_{f,t} \times Shock_{t-i}+ \\
& \delta_f + \delta_{b,t} + \delta_{j,t} + \beta_f X_{f,t} + \beta_l X_{f,b,t} + \epsilon_{f,b,t}
\end{aligned}
$$

where AISD is the All-in-spread-drawn charged to firm f by bank b in year t. $\delta_{b,t}$ controls for bank-year fixed effects, δ_f controls for borrower fixed effects, and $\delta_{j,t}$ controls for industry-year fixed effects. $X_{b,s}$ is the specialization indicator described in section 2.1.2. News shock$_{t-i}$ is the mean value of oil supply news shock i quarters before the loan contract was originated. $X_{f,b,t}$ and $X_{f,t}$ include loan-level controls and firm-level controls (as described in section 2.1) respectively.

If banks perceive the transition risk exposure variables as a reliable component of borrower's overall risk exposure, $\beta_{risk_i} > 0$ will be positive. If however, that is not the case, and only the specialized banks are differentially pricing-in transition risk for more exposed firms, $\beta_{risk,spec_{t-1}}$ will be > 0. If there is an additional effect of shocks to oil markets increasing awareness about detrimental effects of potential disorderly transition risk realizations, especially by banks that are already specialized in the borrowers' industry, we will also observe $\beta_{risk,spec_{t-1},news_i}$ to be positive[10].

2.3. Results

Table 7 reports the estimation results for equation 1 with scope 1 and 2 GHG emission intensity (in million metric ton per USD) as a measure of exposure to transition risk without taking news shocks into account. I find that firms with higher emission intensity in the year preceding the loan contract

[10] Results of the above estimation for credit line loans vs. term loans, as well as for non-amended loans are in progress. Estimations for the effect of emissions and risk measures on other terms of the contract, such as loan amount, collateral requirements, and covenants are currently underway.

face a 0.06 bps increase in lending rates on average if the lender is specialized in the borrower's industry. Tables 8 and 9 report the estimation results for equation 1 with categorical variables such that (i) I[relative frequency of negative tone words associated with climate regulations > 0] = 1 and (ii) I[relative frequency of negative tone words associated with climate-related technological opportunities > 0] = 1. I do not find any significant effects associated with negative regulatory exposure or green technology-related exposure.

I split the sample between for E.U. firms and U.S. firms. There has been a consistent effort towards sustainability disclosure and decarbonization policies in the E.U. in the past decade. Along with the recent Sustainable Finance Disclosure Regulation (SFDR), the Non-Financial Reporting Directive (NFRD) adopted in 2014 required certain large companies to disclose non-financial information regarding environmental, social, and employee-related issues. This was further supplemented with the Guidelines on Reporting Climate-Related Information in 2019, and the E.U. Sustainable Taxonomy which provided detailed standardized guidelines on identifying sustainable economic activity.

In the same period, the U.S. climate policy suffered major upheavals. Between 2016 - 2022, major orders aimed at emission reduction were subjected to rollbacks or reviews. The administration under President Trump also withdrew from the Paris Climate Agreement. Starting 2021, under the Biden administration, U.S. re-joined the Paris Agreement, and the Inflation Reduction Act (2022) set out provisions to increase investment in decarbonization technologies such as renewable energy generation, clean transportation, and energy-efficient retrofits. However, the state of climate-related disclosures is still in a nascent stage, with the SEC finally adopting the Climate-Related Disclosure rules in 2024.

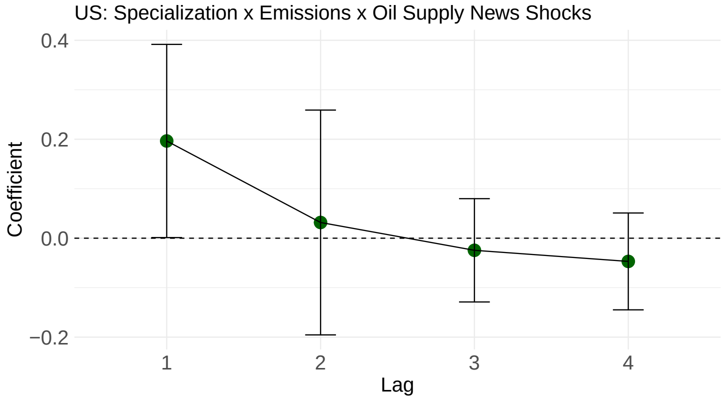
Keeping the above differences in mind, lenders and investors would face fewer frictions incorporating transition risk exposure in their financing decisions for E.U. firms, relative to U.S. firms. I do not find strong evidence supporting this hypothesis. While there is no significant association between high firm-level emission intensity and negative exposure to green technological developments, and interest rates charged, I find that on an average U.S. firms with negative regulatory exposure face higher lending rates (by 11.70 bps) whereas E.U. firms with negative regulatory exposure face lower lending rates (by 20 - 37 bps) relative to firms with non-negative regulatory exposure. However, I find a role for specialized banks in pricing negative regulatory exposure for E.U. firms. E.U. firms with negative climate-regulatory exposure face higher rates by 27.24 bps for loans made by banks specialized in the firms' industries. I do not find similar effects for U.S. firms.

Tables 10, 13, and 16 present results for estimation of equation 1 with scope 1 and 2 GHG emission intensity after taking into account oil supply news shocks lagged i quarters before the loan contract was originated. Across the entire sample, I find evidence for specialized banks charging firms with high emission intensity higher rates by 0.16 - 0.19 bps 2-4 quarters after a positive oil supply news shock. However, I find the opposite effect 1 quarter after the news shock. I do not find any effects of high emission intensity E.U. firms being charged higher rates by specialized banks after an oil supply news shock. However, I find evidence of higher rates being charged to high emission intensity US firms by specialized banks for a quarter after the oil supply news shock (Figure 2).

Tables 11, 14, and 17 present results for estimation of equation 1 with negative forward-looking climate-regulatory exposure after taking into account oil supply news shocks lagged i quarters before the loan contract was originated. I find no evidence for specialized banks charging firms with negative regulatory exposure higher rates after a positive oil supply news shock across the complete sample. Despite finding higher average rates being charged by specialized banks for negatively exposed E.U. firms, I find no differential effects after oil supply news shocks.charged higher rates by specialized banks after an oil supply news shock. For U.S. firms, I find negatively exposed firms being charged lower rates on average by specialized banks a quarter after the oil supply news shock. This effect reverses two quarters after the news shock, with specialized banks charging negatively exposed U.S. firms higher rates by 98.83 bps (Figure 3).

Tables 12, 15, and 18 present results for estimation of equation 1 with negative forward-looking green-technology exposure after taking into account oil supply news shocks lagged i quarters before the loan contract was originated. Across the whole sample, I find evidence for specialized banks charging negative exposed firms lower lending rates by 67.31 bps, but only 3 quarters after the oil supply news shock. I find similar effects for E.U. firms. E.U. firms negatively exposed to green technologies are charged lower rates on average by 55.18 bps by specialized banks with a lag of two quarters after the oil supply news shock. On the other hand, I find that negatively exposed U.S. firms are charged higher rates by specialized banks by 46.39 bps with a two quarter lag after the oil supply news shock (Figure 4).

FIGURE 2. Effect of bank specialization on interest rates after oil supply news shock (Emission Intensity)



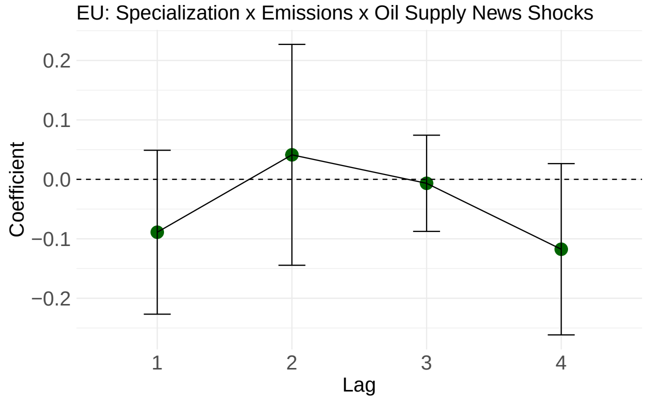
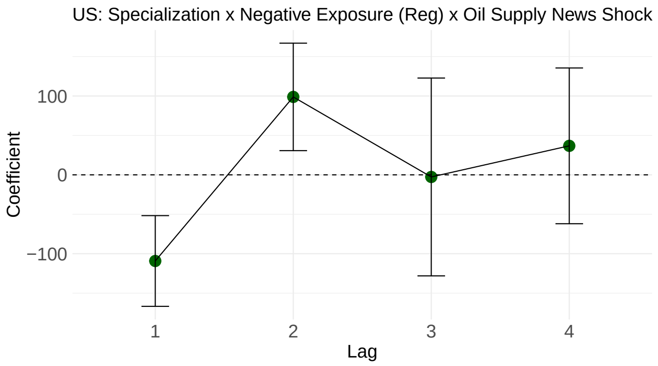


FIGURE 3. Effect of bank specialization on interest rates after oil supply news shock (Negative Exposure - Regulatory)



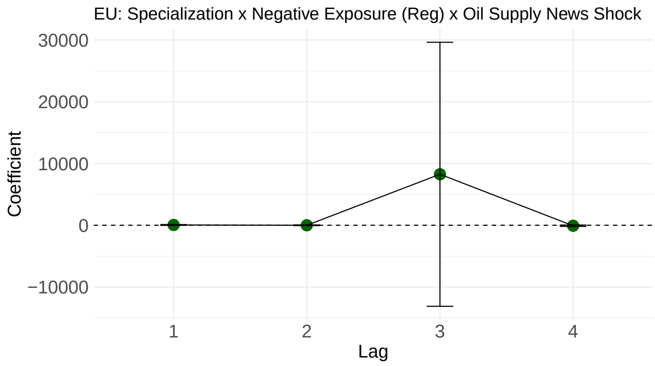
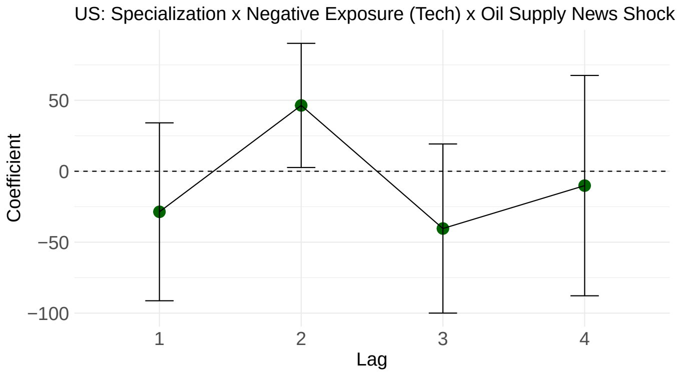
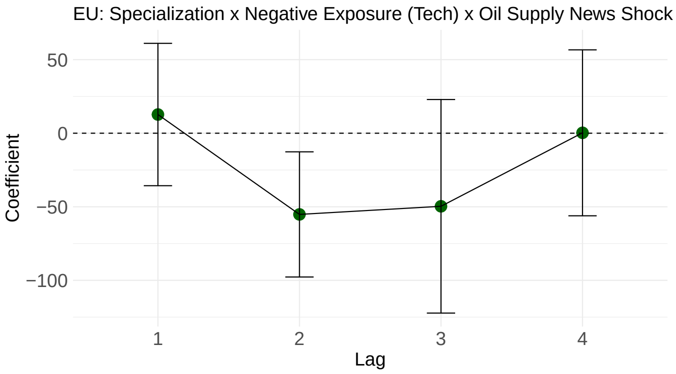


FIGURE 4. Effect of bank specialization on interest rates after oil supply news shock (Negative Exposure - Technological)





The results from the empirical analysis highlight two mechanisms that might explain the banking sector's role in pricing corporates' transition risk exposure:

a. Firms' location and banks' specialization in certain industries can explain whether banks are pricing in transition risk.

b. Despite oil supply news shocks being relevant for energy prices and overall economic activity, even specialized banks either do not incorporate these shocks in lending decisions towards firms more exposed to transition risk, or respond with a significant lag.

3. A model of imperfect screening and belief updates

To understand the role of bank specialization, and the under-reaction to observable oil supply news shocks that are relevant for emission-intensive firms, I incorporate costless public information in a model of competitive lending where one bank can acquire costly and imperfect private information about firms' transition risk exposure (Specialized) and the other bank faces prohibitively high information acquisition costs, and therefore, cannot acquire private information about its borrowers (Un-Specialized).

3.1. Borrowers

The environment consists of 2 types of entrepreneurs who belong to a type $j \in H, L$, where the L-type borrowers are more exposed to climate transition risk than the H-type entrepreneurs. The mass of the entrepreneurs is public with the proportion of an H-entrepreneur = λ. Both entrepreneurs require an initial investment of 1 unit of capital and cannot use any other source of financing. As such, the model does not have an equity market[11].

The probability of success for a project also varies across entrepreneur types. Each entrepreneur has a successful project with a probability $p_j; j \in \{h, l\}$ and terminal cash-flow R, and an unsuccessful project with probability $1 - p_j$ and no terminal returns. I assume that $p_h > p_l$ and $p_l R < 1 < p_h R$, so that L-type borrowers are not-creditworthy, if their type was observable. However, the average borrower is creditworthy under imperfect information such that: $\bar{p}R > 1; \quad \text{where}\, \bar{p} = \lambda p_h + (1-\lambda)\, p_l$.

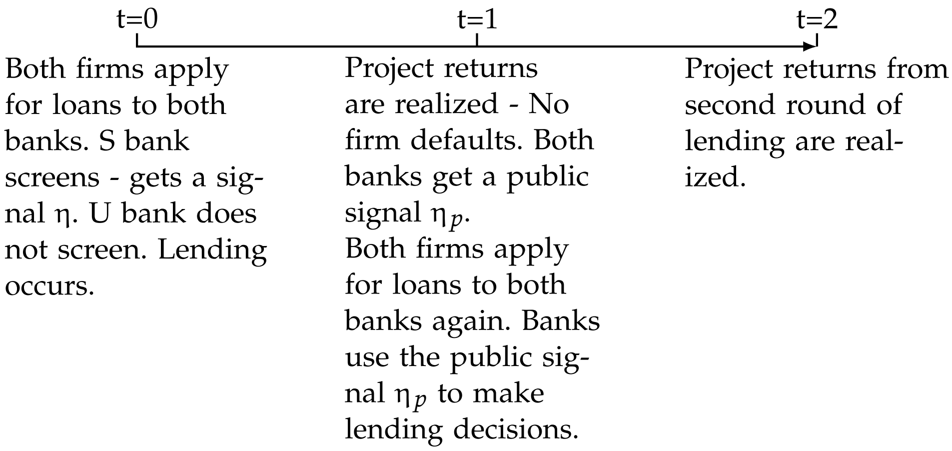
3.2. Banks

There are two banks, 'S' (Specialized) and 'U' (Un-specialized), which compete for firms in the market for loans. The former conducts a screening process for the borrowers, and the latter does not. The quality of information acquired by the S bank is endogenous. Banks do not observe if the entrepreneur is an H-type. The screening process is not endogenized, i.e., I assume that

[11] The debt-equity financing decision can also be affected by lending being affected by climate risk beliefs. This model does not focus on that component.

the screening decision of the I bank is exogenously determined. For simplicity, I set the lending decision to be unsecured. Every equilibrium decision comprises of an equilibrium interest rate r.

FIGURE 5. Timeline of the lending process



The S-bank conducts a screening process for a borrower's first-time application, which yields a signal $\eta \in \{l, h\}$. The results of the screening process cannot be observed by the U-bank, and hence, there are no information spillovers. In the context of climate risk, screening could pertain to looking at the firm's production history, GHG emissions, and investments in energy-efficiency. The signal is imperfect, i.e., it reveals the correct type of the borrower with probability ϕ (precision of the signal), but informative:

$$Pr(\eta = h|H) = Pr(\eta = l|L) = \phi \geq \frac{1}{2}$$

$$Pr(\eta = h|L) = Pr(\eta = l|H) = 1 - \phi$$

There is an increasing and convex cost to screening: $C(\phi) = \frac{(\phi-0.5)^2}{2}$, which implies that the optimal level of screening will depend on the parameters of the model. Thus, this becomes a problem of information acquisition in a perfectly competitive market. Since there are no information spillovers from screening, the screening bank has an informational advantage over the non-screening banks. In the second round of lending starting in period $t = 1$, the informed firm can choose not to screen again since it already has an informative signal about the climate-risk related creditworthiness of the borrowers. I assume that after the returns from projects are realized in $t = 1$, none of the firms have defaulted[12].

However, an informative public signal (η_p) about transition risk appears in period $t = 1$, which both

[12] This is a simplifying assumption to abstract from the information generated from the distinction of a defaulting and non-defaulting firms.

banks observe. This signal could be a geo-political event that positively shocks energy prices,an adverse weather event that triggers discussions about policy solutions to climate change and global warming, or it could be the release of new information about the development of a new technology that is climate-friendly. This signal is imperfect but informative, independent of the precision of the signal from screening, and is costless to observe.

$$Pr(\eta_p = h_p|H) = Pr(\eta_p = l_p|L) = \phi_p \geq \frac{1}{2}$$

$$Pr(\eta_p = h_p|L) = Pr(\eta_p = l_p|H) = 1 - \phi_p$$

If the types of the borrowers were perfectly observed, then under the setup of the model, the L-entrepreneur would not receive a loan from either of the banks. However, both banks would compete for the H-type, and in a Bertrand-like repeated undercutting, both banks will charge equilibrium the same interest rate r to the H-type, which would be equal to their break-even interest rate:

$$p_h r - 1 = 0 \Rightarrow r = \frac{1}{p_h}$$

The effect of imperfect information can be easily surmised from the above information - as the known probability with which a borrower can be deemed H or L decreases, the equilibrium interest rate increases, driving out the H-entrepreneurs away from the borrower pool. This is the standard adverse selection result. Under perfect competition, and no bank having an informational advantage over the other, the average probability of success of a borrower would be $\bar{p}$ as defined above, and the equilibrium interest rate would be $\bar{r} = \frac{1}{\bar{r}}$. Each bank would make zero profits by bidding this interest rate.

After observing the screening results, the S-bank updates its beliefs about the borrowers. The posterior probabilities for each type are:

$$P(type = H|\eta = h) = \frac{\lambda\phi}{\phi\lambda + (1-\phi)(1-\lambda)} = H$$

$$P(type = L|\eta = h) = \frac{(1-\lambda)(1-\phi)}{\phi\lambda + (1-\phi)(1-\lambda)} = 1 - H$$

$$P(type = L|\eta = l) = \frac{\phi(1-\lambda)}{\phi(1-\lambda) + (1-\phi)\lambda} = L$$

$$P(type = H|\eta = l) = \frac{\lambda(1-\phi)}{\phi(1-\lambda)+(1-\phi)\lambda} = 1 - L$$

The corresponding probabilities of success for a project on observing the signal η are:

$$p(h) = P(Returns = R|\eta = h) = Hp_h + (1-H)p_l$$

$$p(l) = P(Returns = R|\eta = l) = (1-L)p_h + Lp_l$$

Upon observing the public signal $\eta_p \in \{l_p, h_p\}$, both banks update the probabilities of the borrower being successful. However, there is the possibility of inertia in learning about transition risks by banks[13]. Consistent with (Epstein et al. 2010) and (Cripps 2018), the posterior success probabilities as the a linear combination of the beliefs the banks had in period $t = 1$ and the Bayesian posterior. This inertia is captured by the parameter $\mu \in [0, 1]$, such that $\mu = 0$ is consistent with strict Bayesian updating and $\mu = 1$ corresponds to no update.

The success probabilities used by the S-bank to calculate the breakeven interest rates for the different groups of borrowers are as follows:

- $p(hh_p) = \mu p(h) + (1-\mu)\left[\frac{\lambda\phi\phi_p p_h + (1-\lambda)(1-\phi)(1-\phi_p)p_l}{\lambda\phi\phi_p + (1-\lambda)(1-\phi)(1-\phi_p)}\right]$
- $p(lh_p) = \mu p(l) + (1-\mu)\left[\frac{\lambda(1-\phi)\phi_p p_h + (1-\lambda)\phi(1-\phi_p)p_l}{\lambda(1-\phi)\phi_p + (1-\lambda)\phi(1-\phi_p)}\right]$
- $p(hl_p) = \mu p(h) + (1-\mu)\left[\frac{\lambda\phi(1-\phi_p)p_h + (1-\lambda)(1-\phi)\phi_p p_l}{\lambda\phi(1-\phi_p) + (1-\lambda)(1-\phi)\phi_p}\right]$
- $p(ll_p) = \mu p(l) + (1-\mu)\left[\frac{\lambda(1-\phi)(1-\phi_p)p_h + (1-\lambda)\phi\phi_p p_l}{\lambda(1-\phi)(1-\phi_p) + (1-\lambda)\phi\phi_p}\right]$

The U-bank does not conduct screening but observes the public signal, on the basis of which it updates its beliefs about the borrowers' types, similar to the update process of the S-bank:

- $p(h_p) = P(Returns = R|\eta = h_p) = \mu[\lambda p_h + (1-\lambda)p_l] + (1-\mu)\left[\frac{\lambda\phi_p p_h + (1-\lambda)(1-\phi_p)p_l}{\lambda\phi_p + (1-\lambda)(1-\phi_p)}\right]$
- $p(l_p) = P(Returns = R|\eta = l_p) = \mu[\lambda p_h + (1-\lambda)p_l] + (1-\mu)\left[\frac{\lambda(1-\phi_p)p_h + (1-\lambda)\phi_p p_l}{(1-\lambda)\phi_p + \lambda(1-\phi_p)}\right]$

[13] In Appendix C, I provide empirical evidence for how beliefs about exposure to damages from climate change amongst individuals might update after witnessing a major state-level disaster, while still being strongly anchored to their beliefs in the past.

3.2.1. Second period

Since the S-bank observes two distinct signals in periods 0 and 1, it can distinguish between four different types of borrowers based on the signals, and the respective ex-ante profits are as follows[14]:

$$\pi_I^{hh_p} = (p(hh_p)r - 1)(1 - F_U^{h_p}(r))$$

$$\pi_I^{hl_p} = (p(hl_p)r - 1)(1 - F_U^{l_p}(r))$$

$$\pi_I^{lh_p} = (p(lh_p)r - 1)(1 - F_U^{h_p}(r))$$

$$\pi_I^{ll_p} = (p(ll_p)r - 1)(1 - F_U^{l_p}(r))$$

where $F_U^j(r)$ is the cumulative density function for the U-bank's interest rate after observing the public signal j.

Similarly, the expected profits for the U-bank, given that it cannot observe the signal from screening by the S-bank, are:

$$\pi_U^{h_p} = Pr(\eta = h, \eta_p = h_p)(p(hh_p)r - 1)(1 - F_S^{hh_p}(r)) + Pr(\eta = l, \eta_p = h_p)(p(lh_p)r - 1)(1 - F_S^{lh_p}(r))$$

$$\pi_U^{l_p} = Pr(\eta = h, \eta_p = l_p)(p(hl_p)r - 1)(1 - F_S^{hl_p}(r)) + Pr(\eta = l, \eta_p = l_p)(p(ll_p)r - 1)(1 - F_S^{ll_p}(r))$$

where $F_S^j(r)$ are the S-bank's interest rate bidding distribution for $j = hh_p, lh_p, hl_p, ll_p$

I assume that the informativeness level of ϕ is such that the borrower with signals l, l_p is not credit-worthy, i.e. $p(ll_p(\bar{\phi}))R < 1$. Consistent with the standard result for competition under asymmetric information, the U-bank does not make positive expected profits with simultaneous bidding, since it does not have any informational advantage over the S-bank, even after observing the public signal Engelbrecht-Wiggans et al. (1983). Thus, the U-bank will break even in equilibrium.

Proposition 1: *The competition between the S-bank and the U-bank has a mixed strategy equilibrium for borrowers facing both types of public signals. The common support for interest rates for borrowers facing* $\eta_p = h_p$ *is* $[\bar{r}_{h_p}, \bar{r}_{lh_p})$*, and the common support for borrowers facing* $\eta_p = l_p$ *is* $[\bar{r}_{l_p}, R)$*. The S-bank does not bid for borrowers facing the signals* (l, l_p)

Proof: For borrowers facing public signal $\eta_p = h_p$, the breakeven interest rate for the U-bank is

[14] Since both η and η_p are informative, $p(hh_p) > p(h_p) > p(hl_p) and p(hl_p) > p(l_p) > p(ll_p)$

$r_U^{h_p} = \bar{r}_{h_p} = \frac{1}{p(h_p)}$. At this interest rate, the U-bank is able to capture the h_p borrowers for sure. The S-bank has informational advantage and can distinguish between hh_p and lh_p borrowers. Charging $\bar{r}_{h_p}$ to the hh_p borrowers, the S-bank makes positive profits since $\bar{r}_{h_p} p(hh_p) - 1 = \frac{p(hh_p)}{p(h_p)} - 1 > 0$, and hence, it has no reason to charge below this interest rate. However, for the lh_p borrower is $\bar{r}_{lh_p} = \frac{1}{p(lh_p)} > \bar{r}_{h_p}$. With repeated undercutting, the S-bank charges $\bar{r}_{lh_p}$ in pure-strategy, and makes zero profits.

By definition of $\bar{\phi}$, the S-bank does not lend to the ll_p borrower. The U-bank captures any l_p borrower at the breakeven interest rate $\bar{r}_{l_p} = \frac{1}{p(l_p)}$, and to maintain the borrower's participation constraint, it will not charge any borrower more than R. Since, $\bar{r}_{hl_p} = \frac{1}{p(hl_p)} < \bar{r}_{l_p}$, the S-bank will make positive profits by charging $\bar{r}_{l_p}$. So, the lower bound for the support for interest rate charged to the l_p borrower is $\bar{r}_{l_p}$[15].

Since $\bar{r}_{h_p} < \bar{r}_{lh_p} < \bar{r}_{lh_p} \forall \quad \phi_p \geq \frac{1}{2}$, the distribution of the expected interest rates for a borrower facing a public signal h_p lies to the left of the distribution of expected interest rates for a borrower facing a public signal l_p, such that there is no overlap between the two distributions. This implies that the expected interest rate paid by a borrower facing h, h_p signals will be lower than any borrower facing a public signal l_p.

3.3. Cumulative distribution functions for interest rates

Equilibrium profits for both banks must be the same for any r in the common support derived in Proposition 1 for the banks to not deviate. Consequently, using the profit functions conditional on public signals defined above:

- From the S-bank's expected profits conditional on observing the public signal h_p for a borrower:

$$
\begin{aligned}
(p(hh_p)\bar{r}_{h_p} - 1) &= (p(hh_p)r - 1)(1 - F_U^{h_p}(r))^{16} \\
\Rightarrow F_U^{h_p}(r) &= 1 - \frac{p(hh_p)\bar{r}_{h_p} - 1}{p(hh_p)r - 1}
\end{aligned}
$$

- From the U-bank's expected profits conditional on observing the public signal h_p for a borrower:

$$
\begin{aligned}
P(\eta = h|\eta_p = h_p)(p(hh_p)r - 1)(1 - F_S^{hh_p}(r)) + Pr(\eta = l|\eta_p = h_p)(p(lh_p)r - 1) &= 0^{17} \\
\Rightarrow F_S^{hh_p}(r) = 1 - \frac{1 - p(lh_p)r}{p(hh_p)r - 1} \cdot \frac{Pr(\eta = l|\eta_p = h_p)}{P(\eta = h|\eta_p = h_p)}
\end{aligned}
$$

[15] A separate case for when the screening is informative enough is when the S-bank lends to the ll_p borrower. Results for this case are currently in progress

- From the S-bank's expected profits conditional on observing the public signal l_p for a borrower:

$$\begin{aligned}(p(hl_p)\bar{r}_{l_p} - 1) &= (p(hl_p)r - 1)(1 - F_U^{l_p}(r))^{18} \\ \Rightarrow F_U^{l_p}(r) &= 1 - \frac{p(hl_p)\bar{r}_{l_p} - 1}{p(hl_p)r - 1}\end{aligned}$$

- From the U-bank's expected profits conditional on observing the public signal l_p for a borrower:

$$\begin{aligned}P(\eta = h|\eta_p = l_p)(p(hl_p)r - 1)(1 - F_I^{hl_p}(r)) + Pr(\eta = l|\eta_p = l_p)(p(ll_p)r - 1) &= 0^{19} \\ \Rightarrow F_I^{hl_p}(r) &= 1 - \frac{1 - p(ll_p)r}{p(hl_p)r - 1} \cdot \frac{Pr(\eta = l|\eta_p = l_p)}{Pr(\eta = h|\eta_p = l_p)}\end{aligned}$$

3.4. Expected interest rates

The interest rate paid by a borrower on a loan will be the $min\{r_S, r_U\}$, where r_S is the interest rate offered by the screening bank and r_U is the interest rate offered by the non-screening bank. In order to compare the effect of belief updates on the interest rates, I calculate the expected interest rates for borrower group j where $j \in \{hh_p, lh_p, lh_p, ll_p\}$, i.e.

$$E\left[min\{r_S^j, r_U^j\}\right] = \int_{lower\_bound}^{upper\_bound} rdF(r); \text{where} F(r) = F_S^j(r) + F_U^j(r) - F_S^j(r)F_U^j(r)$$

The distribution function for the minimum interest rate is derived as above since $F_S(r)$ and $F_U(r)$ are independent as both banks bid simultaneously. The distribution function for expected interest rates for all the groups are:

- $F^{hh_p}(r) = F_S^{hh_p}(r) + F_U^{h_p}(r) - F_S^{hh_p}(r)F_U^{h_p}(r) \quad \text{where} \quad r \in [\bar{r}_{h_p}, \bar{r}_{lh_p})$
- $F^{lh_p}(r) = F_U^{h_p}(r) \quad \text{where} \quad r \in [\bar{r}_{h_p}, \bar{r}_{lh_p})$
- $F^{hl_p}(r) = F_S^{hl_p}(r) + F_U^{l_p}(r) - F_S^{hl_p}(r)F_U^{l_p}(r) \quad \text{where} \quad r \in [\bar{r}_{l_p}, R)$
- $F^{ll_p}(r) = F_U^{l_p}(r) \quad \text{where} \quad r \in [\bar{r}_{l_p}, R)$

Proposition 2: *Conditional on any private signal η from the screening process in the first period, the expected interest rate will be higher for borrowers who receive a low public signal in the second period, i.e. $E\left[r_{ll_p}\right] > E\left[r_{lh_p}\right]$ and $E\left[r_{hl_p}\right] > E\left[r_{hh_p}\right]$. The interest rate differentials at a given level of ϕ and ϕ_p decrease as the under-reaction (i.e. μ) increases.*

Proof: Given the structure of the distribution functions for interest rates for different borrower groups, for borrowers who received a low signal from private screening conducted by the S-bank in the first period:

$$\begin{aligned}
&F_{lh_p}(r) = 1 - \left[\frac{(p(hh_p)\bar{r}_{h_p} - 1)}{(p(hh_p)r - 1)}\right] \\
&F_{ll_p}(r) = 1 - \left[\frac{(p(hl_p)\bar{r}_{l_p} - 1)}{(p(hl_p)r - 1)}\right] \\
&\Rightarrow E\left[r_{ll_p}\right] - E\left[r_{lh_p}\right] = \int_{\bar{r}_{l_p}}^{R} rdF_{ll_p}(r) - \int_{\bar{r}_{h_p}}^{\bar{r}_{lh_p}} rdF_{lh_p}(r) \\
&= \int_{\bar{r}_{l_p}}^{R} \frac{p(hl_p)\bar{r}_{l_p} - 1)p_{hl_p}}{(p(hl_p)r - 1)^2} rdr - \int_{\bar{r}_{h_p}}^{(\bar{r}_{lh_p}} \frac{(p(hh_p)\bar{r}_{h_p} - 1)p_{hh_p}}{(p(hh_p)r - 1)^2} rdr \\
&\text{which is } > 0 \quad \forall \quad \phi, \phi_p \geq \frac{1}{2} \quad \text{and} \quad \mu \in [0, 1]
\end{aligned}$$

Similarly, for borrowers who received a high signal from private screening conducted by the S-bank in the first period:

$$\begin{aligned}
&F_{hh_p}(r) = 1 - \left[\frac{(1 - p(lh_p)r)(p(hh_p)\bar{r}_{h_p} - 1)}{(p(hh_p)r - 1)^2}\right]\left[\frac{Pr(\eta = l|\eta_p = h_p)}{Pr(\eta = h|\eta_p = h_p)}\right] \\
&F_{hl_p}(r) = 1 - \left[\frac{(1 - p(ll_p)r)(p(hl_p)\bar{r}_{l_p} - 1)}{(p(hl_p)r - 1)^2}\right]\left[\frac{Pr(\eta = l|\eta_p = l_p)}{Pr(\eta = h|\eta_p = l_p)}\right] \\
&\Rightarrow E\left[r_{hl_p}\right] - E\left[r_{hh_p}\right] = \int_{\bar{r}_{l_p}}^{R} rdF_{hl_p}(r) - \int_{\bar{r}_{h_p}}^{\bar{r}_{lh_p}} rdF_{lh_p}(r) \\
&\text{which is } > 0 \quad \forall \quad \phi, \phi_p \geq \frac{1}{2} \quad \text{and} \quad \mu \in [0, 1]
\end{aligned}$$

The detailed proof of Proposition 2 is presented in Appendix B. The relationship of interest rate differentials with μ varies with different levels of informativeness of the private screening signal ϕ. When screening is highly informative, ignoring a highly informative public signal would imply interest rate differentials are in favor of borrowers with public signal pointing to l_p (Figure 6). Moreover, the decline in interest rate differentials with increasing under-reaction (or increasing μ) is less sharper when the informativeness of the public signals decreases, since the information loss due to the under-reaction is smaller (Figure 7).

FIGURE 6. Expected interest rate differential (High informativeness of screening)

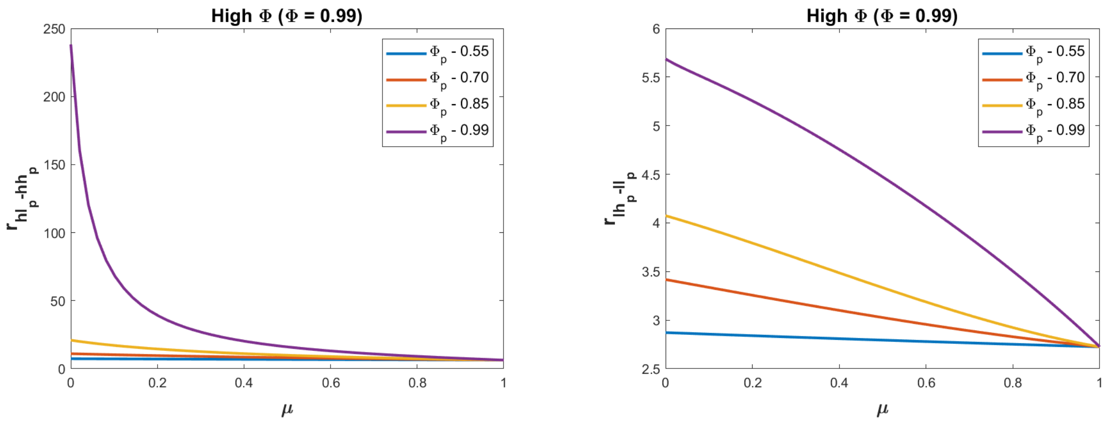


FIGURE 7. Expected interest rate differential (Medium informativeness of screening)

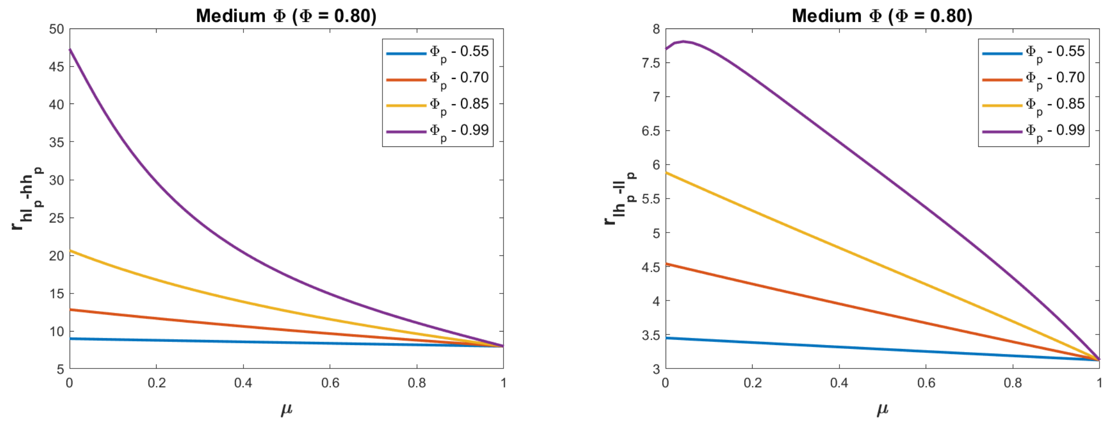
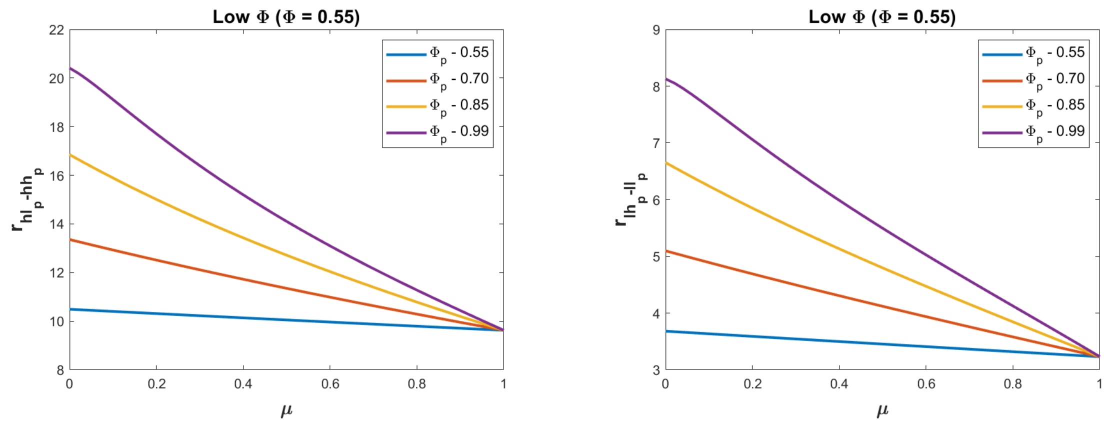


FIGURE 8. Expected interest rate differential (Low informativeness of screening)



For $\lambda = 0.4$, $p_h = 0.3$, $p_l = 0.1$

Proposition 2 provides a mechanism to understand the emerging empirical literature on pricing of carbon risk and adverse climate events in lending contracts. An informative public signal about transition risk provides an additional tool to (partially) resolve imperfect information in a perfectly competitive banking environment. I test these results in Section 2.

3.5. Expected second-period profits for the screening bank

The S-bank makes zero profits on borrowers facing signals (l, h_p), and does not bid for borrowers facing signals (l, l_p). Substituting for the cumulative distribution functions for interest rates bidded by the uninformed bank, the expected profits for the informed bank in the second period are:

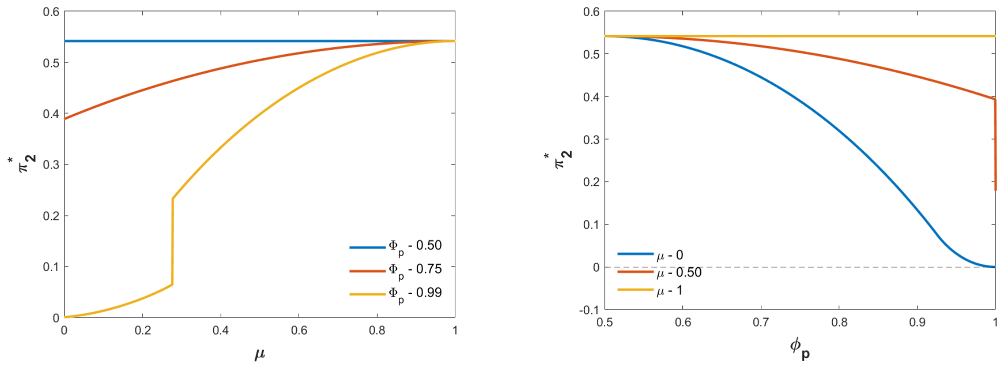
$$
\begin{aligned}
\pi_S &= P(\eta = h, \eta_p = h_p)(p(hh_p)\bar{r}_{h_p} - 1) + P(\eta = h, \eta_p = l_p)(p(hl_p)\bar{r}_{l_p} - 1) - \frac{(\phi - 0.5)^2}{2} \\
&= \left[\lambda\phi\phi_p + (1-\lambda)(1-\phi)(1-\phi_p)\right] \cdot \left[\frac{\lambda\phi\phi_p p_h + (1-\lambda)(1-\phi)(1-\phi_p)p_l}{\lambda\phi\phi_p + (1-\lambda)(1-\phi)(1-\phi_p)}\bar{r}_{h_p} - 1\right] \\
&+ \left[\lambda(1-\phi)\phi_p + (1-\lambda)\phi(1-\phi_p)\right] \cdot \left[\frac{\lambda\phi(1-\phi_p)p_h + (1-\lambda)(1-\phi)\phi_p p_l}{\lambda\phi(1-\phi_p) + (1-\lambda)(1-\phi)\phi_p}\bar{r}_{l_p} - 1\right] - \frac{(\phi - 0.5)^2}{2}
\end{aligned}
$$

The second-period gross profits (and hence, the informational advantage) of the screening bank are not linearly increasing in ϕ, and depend on the the precision strength of the public signal ϕ_p and the level of under-reaction μ. Maximum profits of the informed bank increase as μ increases because it has a stronger informational advantage over the uninformed bank, now that the latter is not taking advantage of a costless and informative signal anymore. Keeping all other parameters constant, maximum profits decrease with ϕ_p.

Moreover, this decrease is sharper when μ is smaller, or, when banks' updates are Bayesian (Figure 9). This could again be attributed to informational advantage. With more informative public signals, the uninformed bank can update its beliefs about success probabilities of the borrower - which in a perfectly competitve market would act in lowering the equilibrium interest rates, thereby lowering the profits. The update in success probabilities is greater when the banks are Bayesian, and thus the competition resulting from the public signal would be stronger.

FIGURE 9. Optimal profits for the screening bank

A. With ϕ_p B. With μ



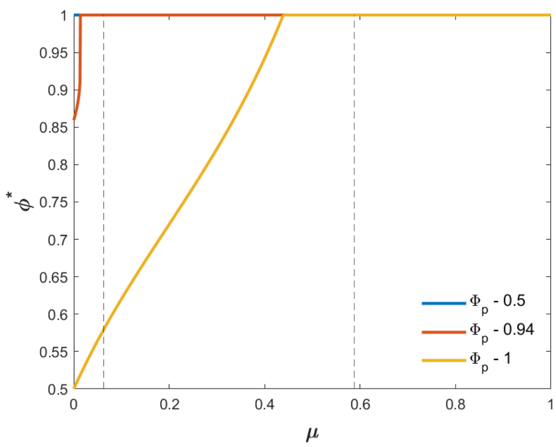
For $\lambda = 0.4$, $p_h = 0.3$, $p_l = 0.1$

3.6. Optimal private information acquisition (ϕ^*)

Proposition 3: *The informed lender facing* λ, p_h, p_l *optimally chooses* ϕ^* *by maximizing* π_2^* *such that (i)* $\forall\ \phi_p\ \exists\ \bar{\mu} \in [0, 1]$ *for which* $\phi^*(\phi_p, \mu > \bar{\mu}) = 1$ *and (ii)* $\forall\ \phi_p > 0.5$, ϕ^* *increases non-monotically with* $\mu \in [0, \bar{\mu}]$.

The profit maximizing level of information acquisition by the informed bank - ϕ^* non-linearly increases with μ with sufficiently high quality of public information ϕ (Figure 10). This result is aligned with the literature on the crowding out effects of public information, specifically theoretical work that shows that more informative public signals crowd out the acquisition of private information (Colombo et al. 2014). However, the under-reaction parameter adds another dimension to this analysis in this model of convex information costs and non-linear profits. While private information acquisition is lower for more informative public signals, this effect only holds true if the lender is sufficiently Bayesian. After a certain threshold of μ is crossed, the lenders under-react to the public information enough for the informed lender to depend on private information acquisition to achieve the profit maximizing informational advantage over the uninformed lender.

FIGURE 10. Optimal level of screening



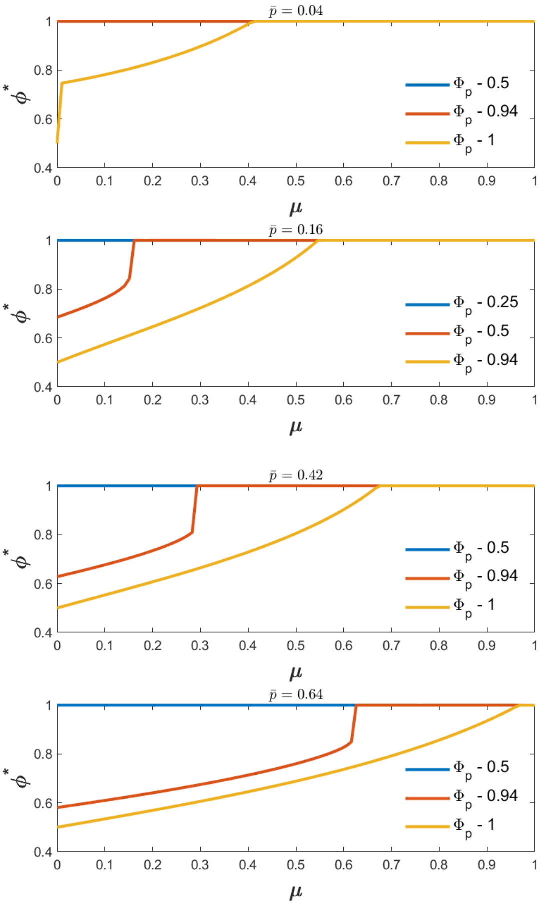
For $\lambda = 0.4$, $p_h = 0.3$, $p_l = 0.1$

3.7. Private information acquisition and average project quality

The crowding out effect of public information on private information also varies with the average borrower quality in the economy (Figure 11). As the probability of success of the average borrower ($\bar{p} = \lambda p_h + (1 - \lambda) p_l$) increases, private information acquisition at high levels of informativeness of public information increases if the lenders are sufficiently Bayesian (i.e. $\mu < \bar{\mu}$). This implies a greater dependence of the lender on private information during higher average credit risk in the economy.

This 'state-dependence' of private information acquisition is further affected by the under-reaction of the lenders. With greater average success probability of a borrower, the threshold of under-reaction after which the lender depends only on private information acquisition (despite a higher precision of public information) increases, implying a greater incorporation of public information in optimal decisions for under-reaction under a threshold $\bar{\mu}$.

FIGURE 11. Optimal private information acquisition with average borrower quality



Consequently, there is an impact on interest rate differentials. In states of poor average borrower quality, the threshold of under-reaction under which the lender relies on both public and private information reduces. As the average borrower quality increases, the crowding out effects of public information on private information become apparent, in that the screening lender's incentives to acquire private information reduce. Under a certain threshold of under-reaction, this crowding-out effect steadily reduces as under-reaction increases, implying that the level of private information acquired increases to approach perfect quality. The interest rate differential between more and less exposed borrowers increases even with increasing under-reaction due to increasing private information.

Beyond that threshold, the interest rate differential again declines with under-reaction (Figures 12 and 13). This implies that for low $\bar{p}$, even small levels of under-reaction to an informative public signal can result in a lower interest rate differential between more and less exposed borrowers. This mechanism is especially relevant for understanding the dynamics of bank financing of green technologies in times of higher average credit or liquidity risk in the economy.

FIGURE 12. Interest rate differential and average borrower quality (for borrowers with η = *h*)

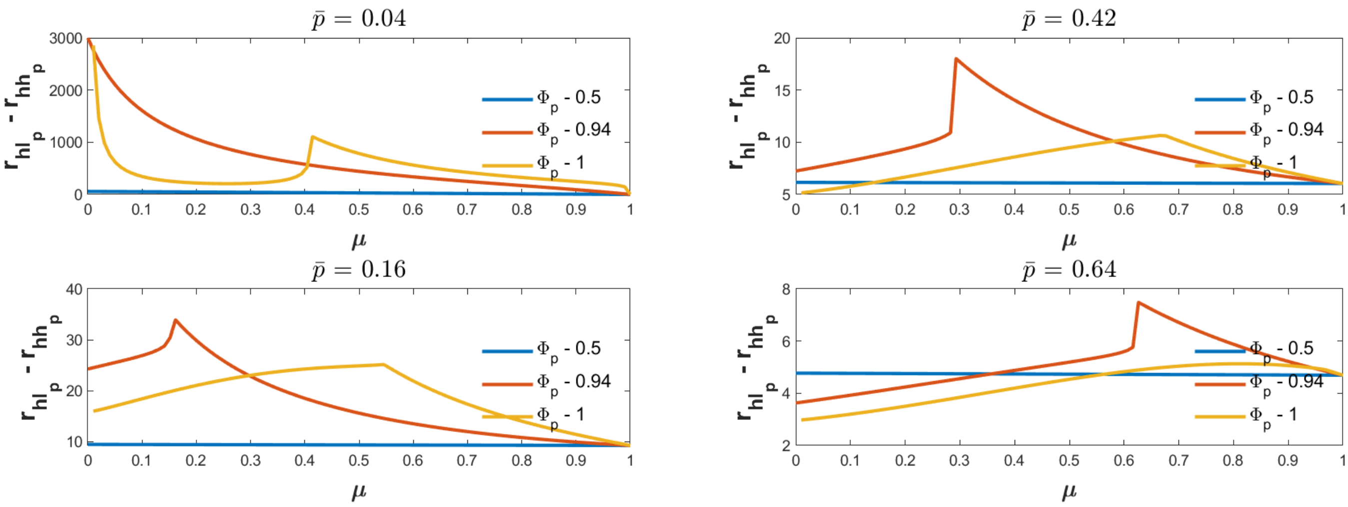
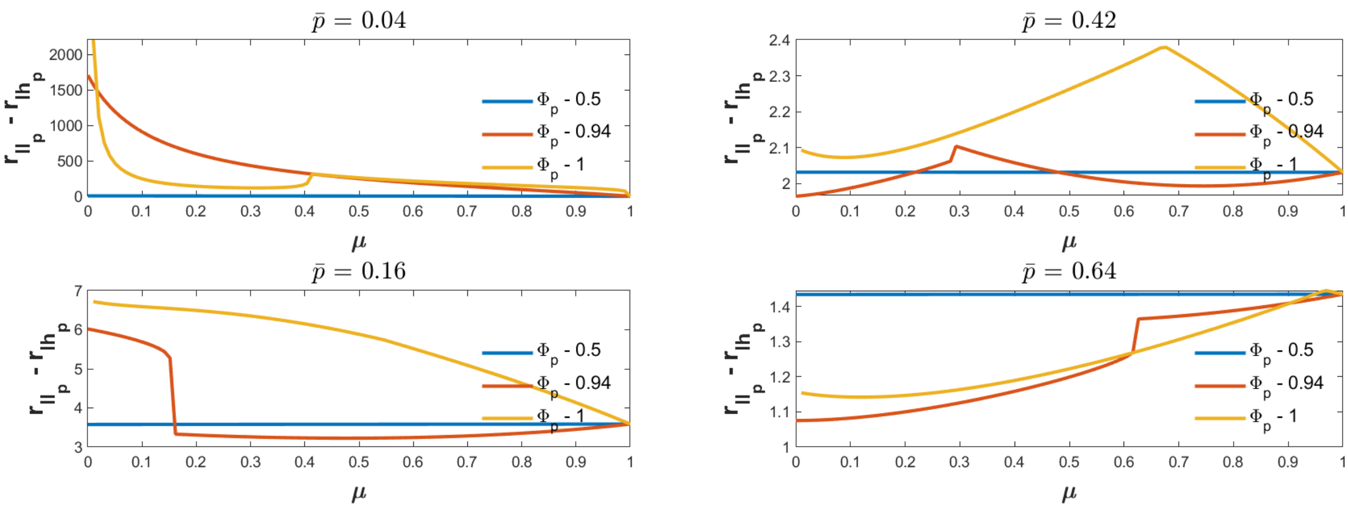


FIGURE 13. Interest rate differential and average borrower quality (for borrowers with η = *l*)



3.7.1. Empirical analysis of pricing of transition risk after periods of aggregate financial stress

To examine whether banks price firms' transition risk exposure as reflected in their Scope 1 and Scope 2 emission intensity, as well as forward-looking exposure to risks from climate policies, and climate-related technological developments from the previous year in periods after financial stress episodes, I estimate the following regression:

$$AISD_{f,b,t} = \alpha + \underbrace{\beta_{risk}}_{>0}(risk)_{f,t} + \beta_{spec}Specialization_{b,s,t-1} + \beta_{news_i}NewsShock_{t-i} + \beta_{fs}FinancialStressIndicator_{t-j}$$

$$+ \underbrace{\beta_{risk,spec_{t-1}}}_{>0} Specialization_{b,s,t-1} \times (risk)_{f,t} + \beta_{spec_{t-1},news_i}Specialization_{b,s,t-1} \times NewsShock_{t-i}+$$

$$\underbrace{\beta_{risk,spec_{t-1},news_i}}_{>0} Specialization_{b,s,t-1} \times (risk)_{f,t} \times NewsShock_{t-i}+$$

$$\beta_{risk,fs,spec,news_i}(risk)_{f,t} \times Specialization_{b,s,t-1} \times FinancialStressIndicator_{t-j} \times NewsShock_{t-i}+$$

$$\delta_f + \delta_{b,t} + \delta_{j,t} + \beta_f X_{f,t} + \beta_l X_{f,b,t} + \epsilon_{f,b,t}$$

where $\delta_{b,t}$ controls for bank-year fixed effects, δ_f controls for borrower fixed effects, and $\delta_{j,t}$ controls for industry-year fixed effects. $Specialization_{b,s,t-1}$ is a dummy variable whose value $(= 1, 0)$ depends on whether the bank is 'specialized' in the industry the borrower belongs to in the year before the lending contract was initiated. News shock$_{t-i}$ is the mean value of oil supply news shock i quarters before the loan contract was originated. $X_{f,b,t}$ and $X_{f,t}$ include loan-level and firm-level controls respectively. Financial Stress Indicator$_{t-j}$ is the measure of overall financial stress 1 quarter before the contract was initiated.

I use the OFR Financial Stress Index for the U.S. (Bejarano 2023). The OFR FSI for the U.S. uses 26-33 financial market variables that are correlated with some form of financial stress. For the E.U., I use the Country-Level Index of Financial Stress (CLIFS) for the country that firm has headquarters in (Duprey et al. 2017). The CLIFS indicators include 6 market-based measures of financial stress across equity markets, credit markets and foreign exchange markets. Each of these indicators are able to identify period of high financial market stress with significant explanatory power. For the U.S. I find high emission intensity as well as negative regulatory and green techonological exposure being charged relatively lower interest rates on average for 2-4 quarters after an oil supply news shock for contracts initiated after a quarter of a period of high financial stress (Tables 22, 23, and 24). For E.U. firms, I find evidence for high emission intensity and negative exposure to green technologies being charged lower lending rates on average for contracts initiated after a quarter of a period of high financial stress, a quarter after an oil supply news shock (Tables 19, 20, and 21).

FIGURE 14. Effect of bank specialization on interest rates after oil supply news shock a quarter after increased financial stress (Emission Intensity)

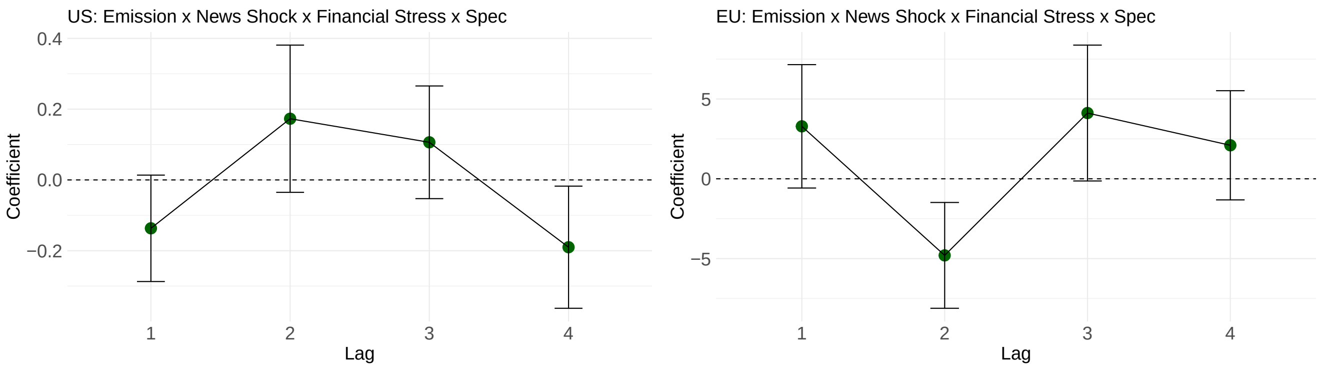


FIGURE 15. Effect of bank specialization on interest rates after oil supply news shock a quarter after increased financial stress (Negative Exposure - Regulatory)

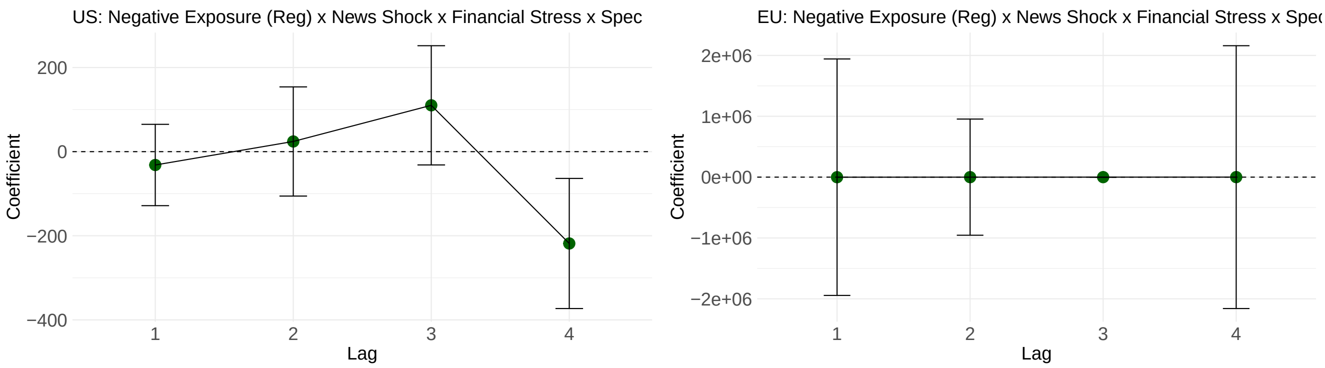
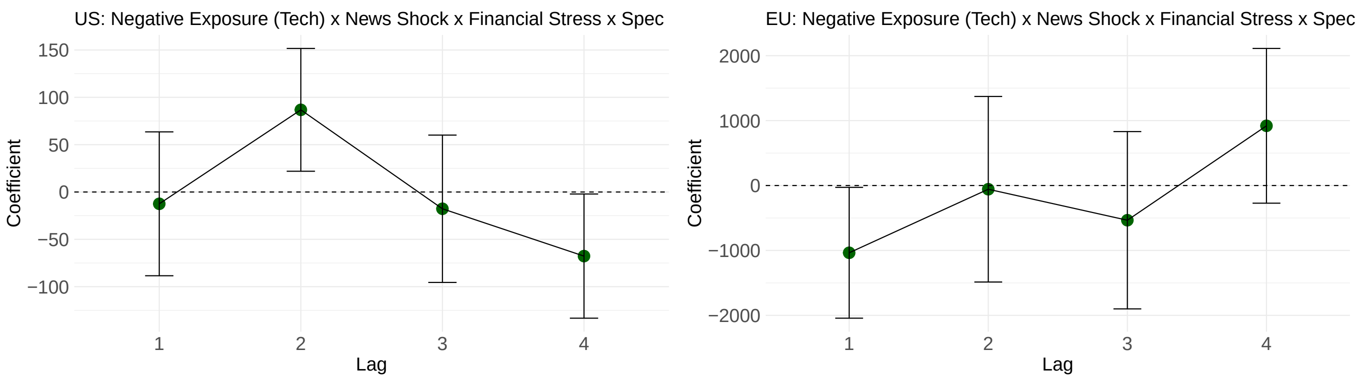


FIGURE 16. Effect of bank specialization on interest rates after oil supply news shock a quarter after increased financial stress (Negative Exposure - Technological)



The above empirical analysis confirms the theoretical results, and shows that periods of high financial stress can reduce the amount of relevant public information that even the specialized lenders incorporate in their lending decisions. This leads to an equilibrium where the effects of under-reaction are sharper and more exposed borrowers end up with more favorable lending rates than the less exposed borrowers. This has significant consequences for financing of decarbonization investments during periods of financial stress, with the cost of debt for more green and energy efficient firms not reflecting their lower exposure to transition risks.

4. Conclusion

In this paper, I show how banks' reaction to public information about transition risk can lead to interest rate differentials in favor of firms facing a unfavorable public signal about their climate risk exposure, conditional on the signal provided by the screening. The interest rate differential further decreases in the favor of negatively exposed firms as the degree of under-reaction increases. I also discuss the effects of non-Bayesian updating on the effort made by the screening bank in acquiring information about the firms during the initial screening process.

Empirical analysis using syndicated loan data shows the role banks' specialization in the industry of the borrower plays in pricing both regulatory and technological aspects of transition risk. However, this effect does not increase after an oil-supply news shock that increases the volatility in the oil and gas markets. The mechanisms described in this paper and potential empirical tests of these mechanisms can also provide the moments necessary to analyze the interaction between bank lending and a shift in the financing of 'green' projects. These questions are imperative for understanding the impact of climate change on the financial sector's stability and the changing composition of aggregate investment and production. The theoretical results also highlight the importance of lowering the costs of information acquisition related to climate change exposure of firms to allow for interest rate differentials to move in favor of greener firms.

A. Descriptive statistics for loan pricing analysis

TABLE 1. Observations by year, country, and major industry group

Year	N	Country	N	Industry	N
2010	8996	Argentina	1	Aerospace and Defense	1473
2011	9809	Australia	1964	Agriculture	410
2012	8708	Austria	71	Automotive	3678
2013	8839	Belgium	213	Beverage, Food, and Tobacco Processing	3580
2014	10938	Bermuda	934	Broadcasting	2042
2015	7678	Brazil	266	Business Services	3024
2016	6331	Canada	2191	Chemicals, Plastics & Rubber	3220
2017	5861	Cayman Islands	183	Construction	2333
2018	6419	Chile	29	General Manufacturing	9039
2019	4188	China	337	Healthcare	6810
2020	2144	Colombia	33	Hotel & Gaming	1437
2021	2674	Czech Republic	19	Leisure and Entertainment	1750
2022	1847	Denmark	99	Media	1733
		Finland	103	Mining	3025
		France	1231	Oil and Gas	8255
		Germany	2215	Paper & Packaging	1478
		Gibraltar	4	Real Estate	59
		Greece	101	Restaurants	811
		Hong Kong	159	Retail & Supermarkets	3451
		Hungary	82	Services	2211
		Iceland	10	Shipping	1036
		India	137	Technology	7273
		Ireland	910	Telecommunications	3100
		Israel	232	Textiles and Apparel	1372
		Italy	566	Transportation	2443
		Japan	245	Utilities	6291
		Kazakhstan	34	Wholesale	3098
		Luxembourg	622		
		Macao	138		
		Malaysia	3		
		Mauritius	30		
		Mexico	316		
		Monaco	75		
		Netherlands	982		
		New Zealand	57		
		Nigeria	53		
		Norway	215		
		Pakistan	4		
		Panama	5		
		Papua New Guinea	17		
		Peru	1		
		Philippines	15		
		Poland	49		
		Portugal	74		
		Qatar	14		
		Romania	20		
		Russian Federation	449		
		Singapore	308		
		South Africa	240		
		South Korea	17		
		Spain	1683		
		Sweden	221		
		Switzerland	1650		
		Taiwan	680		
		Thailand	13		
		Turkey	80		
		Ukraine	17		
		United Arab Emirates	35		
		United Kingdom	4150		
		United States	59821		
		Virgin Islands (British)	9		

TABLE 2. Summary statistics - Syndicated bank loans 2010 - 2022

Variable	Mean	Median	Standard Deviation	Max	Min
AISD (bps)	197.406	175	87.500	340	117.431
Log (Total Assets)	9.128	8.915	7.120	11.364	1.700
Leverage Ratio	0.393	0.367	0.173	0.627	0.206
CapexTotal Assets	0.353	0.263	0.053	0.785	0.288
EBITDATotal Assets	11.317	10.342	5.303	18.879	7.751
Log (Tranche Amount)	6.476	6.515	4.942	8.006	1.280
Maturity	51.585	60	19	72	20.327

Variable	Yes (Percentage)	No (Percentage)
Negative Regulatory Exposure	7.782	92.218
Negative Technological Exposure	20.589	79.411
Collateralized	42.246	57.754
Covenants	38.992	61.008
Lender Specialization	1.688	98.312

TABLE 3. Summary statistics - Syndicated bank loans for firms with high Scope 1 and 2 emission intensity (above median)

Variable	Mean	Median	Standard Deviation	Max	Min
AISD (bps)	184.076	150	60	325	119.576
Log (Total Assets)	10.051	9.845	7.666	12.757	2.101
Leverage Ratio	0.357	0.338	0.155	0.562	0.186
CapexTotal Assets	0.502	0.474	0.176	0.858	0.261
EBITDATotal Assets	10.039	9.517	4.279	17.280	7.827
Log (Tranche Amount)	6.664	6.620	4.828	8.517	1.528
Maturity	52.347	60	13	73	34.769

Variable	Yes (Percentage)	No (Percentage)
Collateralized	26.548	73.452
Covenants	19.780	80.220

TABLE 4. Summary statistics - Syndicated bank loans for firms with negative technological exposure

Variable	Mean	Median	Standard Deviation	Max	Min
AISD (bps)	166.679	150	45	300	109.374
Log (Total Assets)	10.070	10.193	8.224	11.819	1.552
Leverage Ratio	0.326	0.314	0.173	0.521	0.136
CapexTotal Assets	0.500	0.503	0.141	0.829	0.262
EBITDATotal Assets	8.839	8.410	4.110	15.357	6.804
Log (Tranche Amount)	6.857	6.908	5.011	8.517	1.425
Maturity	49.782	60	12	61	24.768

Variable	Yes (Percentage)	No (Percentage)
Negative Regulatory Exposure	22.621	77.379
Secured	25.734	74.266
Covenants	25.414	74.859
specialization_dum_lag1	1.686	98.314

TABLE 5. Summary statistics - Syndicated bank loans for firms with negative regulatory exposure

Variable	Mean	Median	Standard Deviation	Max	Min
AISD (bps)	166.679	150	45	300	109.374
Log (Total Assets)	10.070	10.193	8.224	11.819	1.552
Leverage Ratio	0.326	0.314	0.173	0.521	0.136
CapexTotal Assets	0.500	0.503	0.141	0.829	0.262
EBITDATotal Assets	8.839	8.410	4.110	15.357	6.804
Log (Tranche Amount)	6.857	6.908	5.011	8.517	1.425
Maturity	49.782	60	12	61	24.768
Variable	Yes (Percentage)	No (Percentage)			
Negative Technological Exposure	64.769	35.231			
Collateralized	19.892	80.108			
Covenants	23.513	76.487			
Lender Specialization	1.454	98.546			

TABLE 6. Summary statistics - Syndicated bank loans 2010 - 2022 by banks specialized in the borrower's industry

Variable	Mean	Median	Standard Deviation	Max	Min
AISD (bps)	191.358	162.500	80	325	113.701
Log (Total Assets)	9.575	9.209	7.289	12.457	2.343
Leverage Ratio	0.352	0.332	0.153	0.583	0.176
CapexTotal Assets	0.327	0.241	0.042	0.753	0.269
EBITDATotal Assets	10.221	9.810	4.480	18.817	9.156
Log (Tranche Amount)	6.406	6.397	4.463	8.091	1.591
Maturity	50.841	60	12	70	36.479
Variable	Yes (Percentage)	No (Percentage)			
Negative Regulatory Exposure	5.846	94.154			
Negative Technological Exposure	15.766	84.234			
Collateralized	27.635	72.365			
Covenants	22.764	77.236			

TABLE 7. Regression of AISD (bps) on Emission Intensity

	All-in-spread-drawn (bps)					
	All	All	EU	EU	US	US
Scope 1 and 2 Emission Intensity$_{t-1}$	0.00	0.00	-0.01	0.01	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)
Specialization$_{t-1}$	-6.22	-6.86	-7.44	-13.72	8.99	7.63
	(5.37)	(5.19)	(10.47)	(8.77)	(5.92)	(5.50)
Emission Intensity$_{t-1}$ × Specialization$_{t-1}$	0.06*	0.05	-0.01	-0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)
Firm-level controls	✓	✓	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓	✓	✓
R^2	0.73	0.76	0.82	0.87	0.67	0.71
N	59,630	59,630	10,459	10,459	35,678	35,678
Borrower F.E.	✓	✓	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓	✓	✓
Industry-Year F.E.		✓		✓		✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022. I estimate if firms with higher emission intensity face higher lending rates, and whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks. The dependent variable is All-in-spread-drawn (bps). Columns 1 and 2 report results for all firms, columns 3 and 4 report results for lending contracts made for E.U. firms, and columns 5 and 6 report results for lending contracts made for firms headquartered in the U.S.Borrower and Lender-Year fixed effects are included across all specifications, while columns 2, 4, and 6 are estimations with SIC 2-digit industry-year fixed effects as well. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 8. Regression of AISD (bps) on Negative Regulatory Exposure

	All-in-spread-drawn (bps)					
	All	All	EU	EU	US	US
Reg. Sentiment$_{t-1}$	0.27	3.33	-20.37*	-37.24*	5.81	11.70*
	(4.70)	(5.60)	(10.00)	(15.44)	(4.82)	(5.64)
Specialization$_{t-1}$	2.86	2.38	-3.63	-10.41*	1.57	-0.50
	(4.38)	(3.81)	(10.46)	(5.11)	(5.13)	(4.23)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$	2.17	-16.10	9.20	27.24**	-3.89	-29.25
	(13.32)	(13.49)	(14.27)	(10.37)	(23.34)	(19.60)
Firm-level controls	✓	✓	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓	✓	✓
R^2	0.70	0.73	0.85	0.88	0.66	0.69
N	65,633	65,633	9,023	9,023	48,113	48,113
Borrower F.E.	✓	✓	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓	✓	✓
Industry-Year F.E.		✓		✓		✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022. I estimate if firms with negative exposure to climate policies and regulations face higher lending rates, and whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks. The dependent variable is All-in-spread-drawn (bps). Columns 1 and 2 report results for all firms, columns 3 and 4 report results for lending contracts made for E.U. firms, and columns 5 and 6 report results for lending contracts made for firms headquartered in the U.S.Borrower and Lender-Year fixed effects are included across all specifications, while columns 2, 4, and 6 are estimations with SIC 2-digit industry-year fixed effects as well. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 9. Regression of AISD (bps) on Negative Technological Exposure

	All-in-spread-drawn (bps)					
	All	All	EU	EU	US	US
Tech. Sentiment$_{t-1}$	-1.01	-2.28	-6.71	29.69	-3.00	-1.29
	(4.26)	(4.75)	(12.63)	(17.53)	(5.24)	(5.50)
Specialization$_{t-1}$	0.14	-1.05	-9.49	-12.30	-0.47	-2.54
	(4.55)	(3.86)	(13.13)	(6.46)	(5.56)	(4.59)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$	16.45	14.28	16.48	6.14	14.49	7.33
	(10.45)	(9.65)	(17.70)	(6.75)	(10.43)	(8.17)
Firm-level controls	✓	✓	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓	✓	✓
R^2	0.70	0.73	0.84	0.88	0.66	0.69
N	65,633	65,633	9,023	9,023	48,113	48,113
Borrower F.E.	✓	✓	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓	✓	✓
Industry-Year F.E.		✓		✓		✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022. I estimate if firms with negative exposure to green technology-related developments face higher lending rates, and whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks. The dependent variable is All-in-spread-drawn (bps). Columns 1 and 2 report results for all firms, columns 3 and 4 report results for lending contracts made for E.U. firms, and columns 5 and 6 report results for lending contracts made for firms headquartered in the U.S.Borrower and Lender-Year fixed effects are included across all specifications, while columns 2, 4, and 6 are estimations with SIC 2-digit industry-year fixed effects as well. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 10. Regression of AISD (bps) on Emission Intensity and Oil Supply News Shocks (All)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Scope 1 and 2 emissions$_{t-1}$	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Specialization$_{t-1}$	-4.32	-0.78	-6.78	-7.95
	(3.96)	(3.25)	(4.57)	(4.18)
Emissions$_{t-1}$ × Specialization$_{t-1}$	0.05**	0.03***	0.05*	0.07***
	(0.01)	(0.01)	(0.02)	(0.01)
Oil Supply News Shock$_{t-1}$	5.05			
	(7.55)			
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.01			
	(0.00)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	27.43*			
	(13.41)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.25***			
	(0.06)			
Oil Supply News Shock$_{t-2}$		2.99		
		(6.33)		
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.00		
		(0.00)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-11.29		
		(10.10)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.16***		
		(0.02)		
Oil Supply News Shock$_{t-3}$			-14.72	
			(7.55)	
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.00	
			(0.00)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			6.73	
			(16.43)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-0.08	
			(0.06)	
Oil Supply News Shock$_{t-4}$				2.29
				(6.29)
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.00
				(0.00)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-12.05
				(13.14)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.19***
				(0.04)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.77	0.77	0.77	0.77
N	59,630	59,630	59,630	59,630
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for the entire sample. I estimate if firms with higher emission intensity face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 11. Regression of AISD (bps) on Negative Regulatory Exposure and Oil Supply News Shocks (All)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Reg. Sentiment$_{t-1}$	3.57	2.42	4.21	3.15
	(5.67)	(5.60)	(5.43)	(5.57)
Specialization$_{t-1}$	2.76	3.91	2.39	2.42
	(3.61)	(3.87)	(3.66)	(3.82)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$	-15.19	-22.08	-17.74	-15.95
	(14.25)	(14.05)	(13.79)	(13.73)
Oil Supply News Shock$_{t-1}$	-1.75			
	(6.83)			
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-6.69			
	(13.29)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	7.76			
	(14.04)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-33.73			
	(35.92)			
Oil Supply News Shock$_{t-2}$		3.13		
		(6.53)		
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		29.55		
		(16.12)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		19.98		
		(15.59)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		34.15		
		(40.17)		
Oil Supply News Shock$_{t-3}$			-18.22*	
			(7.12)	
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-21.24	
			(15.16)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-3.50	
			(9.97)	
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-23.59	
			(67.82)	
Oil Supply News Shock$_{t-4}$				3.29
				(5.64)
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-5.86
				(16.19)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				11.55
				(14.94)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-8.58
				(45.99)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.73	0.73	0.73	0.73
N	65,633	65,633	65,633	65,633
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for the entire sample. I estimate if firms with negative climate regulatory exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 12. Regression of AISD (bps) on Negative Technological Exposure and Oil Supply News Shocks (All)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Tech. Sentiment$_{t-1}$	-2.21	-2.25	-1.96	-2.10
	(4.70)	(4.77)	(4.70)	(4.72)
Specialization$_{t-1}$	-0.71	-0.99	-0.83	-1.10
	(3.70)	(3.51)	(3.73)	(3.96)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$	14.24	15.35	13.56	14.17
	(9.83)	(10.08)	(9.33)	(9.77)
Oil Supply News Shock$_{t-1}$	-3.21			
	(7.60)			
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	2.92			
	(10.97)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	6.30			
	(14.52)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-22.52			
	(30.35)			
Oil Supply News Shock$_{t-2}$		8.53		
		(7.32)		
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-9.46		
		(12.17)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		2.59		
		(12.40)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		82.26		
		(43.11)		
Oil Supply News Shock$_{t-3}$			-23.79**	
			(7.79)	
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			16.72	
			(11.95)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			4.76	
			(10.70)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-67.31*	
			(27.73)	
Oil Supply News Shock$_{t-4}$				1.44
				(5.92)
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				5.12
				(11.32)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				5.48
				(15.73)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				30.78
				(35.51)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.73	0.73	0.73	0.73
N	65,633	65,633	65,633	65,633
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for the entire sample. I estimate if firms with negative green technology-related exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 13. Regression of AISD (bps) on Emission Intensity and Oil Supply News Shocks (EU)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Scope 1 and 2 emissions$_{t-1}$	0.00	0.01	0.01*	0.00
	(0.01)	(0.00)	(0.00)	(0.01)
Specialization$_{t-1}$	-15.49	-14.23	-14.03	-13.68
	(8.41)	(8.52)	(8.63)	(8.72)
Emissions$_{t-1}$ × Specialization$_{t-1}$	0.00	0.00	0.00	0.01
	(0.02)	(0.03)	(0.02)	(0.02)
Oil Supply News Shock$_{t-1}$	27.37			
	(29.11)			
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.05			
	(0.03)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	36.45			
	(28.23)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.09			
	(0.07)			
Oil Supply News Shock$_{t-2}$		-35.46		
		(35.38)		
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.01		
		(0.06)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.92		
		(34.75)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.04		
		(0.09)		
Oil Supply News Shock$_{t-3}$			-30.10	
			(34.06)	
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.10*	
			(0.05)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-11.60	
			(24.42)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-0.01	
			(0.04)	
Oil Supply News Shock$_{t-4}$				-14.26
				(24.68)
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.05
				(0.06)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-16.41
				(22.21)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.12
				(0.07)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.87	0.87	0.87	0.87
N	10,459	10,459	10,459	10,459
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with higher emission intensity face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 14. Regression of AISD (bps) on Negative Regulatory Exposure and Oil Supply News Shocks (EU)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Reg. Sentiment$_{t-1}$	-36.60*	-38.51*	-37.85*	-41.04**
	(15.19)	(15.74)	(14.74)	(15.07)
Specialization$_{t-1}$	-10.17*	-10.64*	-9.24	-9.36
	(5.07)	(4.85)	(4.88)	(4.82)
Oil Supply News Shock$_{t-1}$	18.34			
	(19.82)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$	31.30***	36.13*	1,610.89	25.62***
	(8.52)	(15.77)	(2,087.82)	(6.94)
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-44.91			
	(25.17)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	7.01			
	(17.23)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	45.47			
	(32.91)			
Oil Supply News Shock$_{t-2}$		-12.21		
		(33.38)		
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		37.89		
		(38.65)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		25.77		
		(16.02)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-5.11		
		(25.85)		
Oil Supply News Shock$_{t-3}$			-27.97	
			(33.11)	
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-16.06	
			(38.99)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			23.03	
			(18.77)	
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			8,250.76	
			(10,858.19)	
Oil Supply News Shock$_{t-4}$				-29.22
				(22.49)
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				62.52
				(37.42)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-24.38
				(18.03)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-79.55
				(55.21)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.88	0.88	0.88	0.88
N	9,023	9,023	9,023	9,023
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with negative climate regulatory exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 15. Regression of AISD (bps) on Negative Technological Exposure and Oil Supply News Shocks (EU)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Tech. Sentiment$_{t-1}$	29.37	27.55	27.48	32.23*
	(17.13)	(16.38)	(17.71)	(16.02)
Specialization$_{t-1}$	-12.81*	-14.34*	-10.52	-11.81
	(6.51)	(6.13)	(6.61)	(6.22)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$	7.00	5.95	3.34	7.89
	(7.24)	(6.50)	(7.51)	(6.43)
Oil Supply News Shock$_{t-1}$	17.75			
	(22.52)			
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-8.57			
	(29.25)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	6.70			
	(18.90)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	12.70			
	(24.57)			
Oil Supply News Shock$_{t-2}$		-5.25		
		(35.53)		
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-32.48		
		(34.85)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		33.60*		
		(16.82)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-55.18*		
		(21.61)		
Oil Supply News Shock$_{t-3}$			-23.24	
			(36.91)	
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-16.61	
			(32.95)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			47.02	
			(35.43)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-49.67	
			(36.87)	
Oil Supply News Shock$_{t-4}$				-16.02
				(25.91)
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-34.56
				(40.93)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-24.99
				(25.33)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.27
				(28.65)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.88	0.88	0.88	0.88
N	9,023	9,023	9,023	9,023
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with negative green technology-related exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 16. Regression of AISD (bps) on Emission Intensity and Oil Supply News Shocks (US)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Scope 1 and 2 emissions$_{t-1}$	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Specialization$_{t-1}$	7.02	8.67	6.82	8.53
	(5.29)	(4.59)	(4.96)	(5.58)
Emissions$_{t-1}$ × Specialization$_{t-1}$	-0.02	-0.01	-0.02	-0.01
	(0.01)	(0.02)	(0.02)	(0.01)
Oil Supply News Shock$_{t-1}$	-10.39			
	(11.48)			
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-1}$	0.00			
	(0.00)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-32.95			
	(17.29)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	0.20*			
	(0.10)			
Oil Supply News Shock$_{t-2}$		8.87		
		(8.80)		
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.00		
		(0.00)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		8.65		
		(18.86)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.03		
		(0.12)		
Oil Supply News Shock$_{t-3}$			-11.11	
			(10.12)	
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.00	
			(0.00)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-20.11	
			(17.51)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-0.02	
			(0.05)	
Oil Supply News Shock$_{t-4}$				1.07
				(7.56)
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.00
				(0.00)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				48.74*
				(24.22)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.05
				(0.05)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.71	0.71	0.71	0.71
N	35,678	35,678	35,678	35,678
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the U.S. I estimate if firms with higher emission intensity face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 17. Regression of AISD (bps) on Negative Regulatory Exposure and Oil Supply News Shocks (US)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Reg. Sentiment$_{t-1}$	11.59*	10.28	11.81*	10.84
	(5.66)	(5.67)	(5.59)	(5.58)
Specialization$_{t-1}$	0.14	0.31	-0.65	-0.41
	(4.05)	(3.85)	(4.09)	(4.22)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$	-49.72**	-41.57*	-29.17	-35.07
	(16.62)	(16.13)	(19.02)	(22.40)
Oil Supply News Shock$_{t-1}$	-13.15			
	(7.99)			
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-6.21			
	(14.41)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	15.44			
	(15.59)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-109.23***			
	(29.33)			
Oil Supply News Shock$_{t-2}$		11.02		
		(7.55)		
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		17.69		
		(17.37)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		4.56		
		(14.24)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		98.83**		
		(34.74)		
Oil Supply News Shock$_{t-3}$			-13.23	
			(7.51)	
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-12.11	
			(15.47)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-12.57	
			(11.25)	
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-2.68	
			(63.95)	
Oil Supply News Shock$_{t-4}$				1.96
				(5.81)
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-17.49
				(20.60)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				20.62
				(17.83)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				36.78
				(50.35)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.69	0.69	0.69	0.69
N	48,113	48,113	48,113	48,113
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with negative climate regulatory exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 18. Regression of AISD (bps) on Negative Technological Exposure and Oil Supply News Shocks (US)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Tech. Sentiment$_{t-1}$	-0.59	-1.55	-1.48	-1.08
	(5.32)	(5.52)	(5.42)	(5.49)
Specialization$_{t-1}$	-1.83	-2.22	-2.53	-2.26
	(4.43)	(4.12)	(4.45)	(4.67)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$	5.97	6.56	7.38	6.07
	(7.93)	(7.48)	(8.08)	(8.22)
Oil Supply News Shock$_{t-1}$	-17.60*			
	(8.74)			
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	12.70			
	(12.84)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	12.67			
	(16.75)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-28.58			
	(31.96)			
Oil Supply News Shock$_{t-2}$		15.66		
		(8.04)		
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-6.81		
		(15.07)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		2.60		
		(15.40)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		46.39*		
		(22.30)		
Oil Supply News Shock$_{t-3}$			-19.67*	
			(7.83)	
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			28.33	
			(14.80)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-8.11	
			(11.88)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-40.36	
			(30.38)	
Oil Supply News Shock$_{t-4}$				-1.29
				(6.22)
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				6.67
				(13.65)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				21.74
				(19.06)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-10.12
				(39.58)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.69	0.69	0.69	0.69
N	48,113	48,113	48,113	48,113
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the U.S. I estimate if firms with negative green technology-related exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect is stronger 1 - 4 quarters after an oil supply news shock. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

Note: This table reports estimates from the regression specification given in equation 3.7.1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with higher emission intensity face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect changes 1 - 4 quarters after an oil supply news shock after a period of high financial stress. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 19. Regression of AISD (bps) on Emission Intensity and Oil Supply News Shocks after periods of financial stress (EU)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Scope 1 and 2 emissions$_{t-1}$	0.00	0.01	0.01*	0.01
	(0.01)	(0.00)	(0.00)	(0.01)
Specialization$_{t-1}$	-13.07	0.39	-16.34	-20.87
	(16.62)	(18.68)	(21.12)	(21.70)
Financial Stress$_{t-1}$	-99.96	-88.66	-90.30	-77.47
	(53.85)	(50.16)	(60.33)	(52.37)
Oil Supply News Shock$_{t-1}$	24.63			
	(39.34)			
Emissions$_{t-1}$ × Specialization$_{t-1}$	-0.09	-0.07	0.00	0.04
	(0.07)	(0.08)	(0.06)	(0.08)
Specialization$_{t-1}$ × Financial Stress$_{t-1}$	-13.98	-116.10	-3.03	63.21
	(149.38)	(174.72)	(179.63)	(179.01)
Scope 1 and 2 emissions$_{t-1}$ × Financial Stress$_{t-1}$	0.02	-0.02	0.03	-0.01
	(0.08)	(0.05)	(0.04)	(0.04)
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.05			
	(0.04)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	12.49			
	(82.05)			
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	14.68			
	(156.58)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$	0.67	0.56	0.13	-0.18
	(0.63)	(0.63)	(0.53)	(0.63)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.64*			
	(0.31)			
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	345.79			
	(680.29)			
Emissions$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.02			
	(0.11)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	3.29			
	(1.97)			
Oil Supply News Shock$_{t-2}$		-28.56		
		(43.37)		
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.06		
		(0.07)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-184.40		
		(98.88)		
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-107.93		
		(189.94)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.63**		
		(0.22)		
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		1,594.21*		
		(742.46)		
Emissions$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-0.27		
		(0.24)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-4.80**		
		(1.69)		
Oil Supply News Shock$_{t-3}$			-30.11	
			(38.50)	
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.11	
			(0.06)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			79.05	
			(65.73)	
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			57.02	
			(143.02)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-0.58	
			(0.30)	
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-741.07	
			(566.20)	
Emissions$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-0.15	
			(0.19)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			4.12	
			(2.17)	
Oil Supply News Shock$_{t-4}$				-2.39
				(28.05)
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.01
				(0.06)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				4.43
				(60.24)
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-93.79
				(159.94)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.30
				(0.16)
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-328.09
				(606.68)
Emissions$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.42
				(0.25)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				2.10
				(1.74)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.87	0.87	0.87	0.87
N	10,376	10,376	10,376	10,376
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 3.7.1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with negative climate regulatory exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect changes 1 - 4 quarters after an oil supply news shock after a period of high financial stress. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 20. Regression of AISD (bps) on Negative Regulatory Exposure and Oil Supply News Shocks after periods of financial stress (EU)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Reg. Sentiment$_{t-1}$	-34.78	-43.08	-43.21*	-40.87*
	(22.13)	(22.81)	(20.72)	(20.66)
Specialization$_{t-1}$	-2.59	-5.64	-4.96	-5.97
	(9.48)	(8.75)	(9.41)	(8.60)
Financial Stress$_{t-1}$	78.67	47.20	78.30	60.72
	(49.25)	(50.66)	(59.05)	(55.12)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$	4.57	23.03	126.21	-16.27
	(99,597.49)	(19,592.21)	(60,066.95)	(116,836.24)
Specialization$_{t-1}$ × Financial Stress$_{t-1}$	-84.77	-43.12	-67.05	-27.64
	(91.84)	(83.95)	(94.51)	(71.53)
Reg. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$	79.52	65.52	65.61	21.27
	(142.41)	(118.32)	(99.20)	(108.28)
Oil Supply News Shock$_{t-1}$	39.52			
	(28.57)			
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-126.54			
	(66.46)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-30.58			
	(50.04)			
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-131.20			
	(83.59)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$	270.77	356.21	-154.12	419.80
	(1,007,026.17)	(478,738.51)	(6,877.10)	(1,137,720.69)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	170.03			
	(146,642.43)			
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	331.93			
	(366.25)			
Reg. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	914.27			
	(671.92)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-1,043.31			
	(987,296.89)			
Oil Supply News Shock$_{t-2}$		-14.16		
		(41.81)		
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		35.87		
		(62.75)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-44.76		
		(50.20)		
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		39.88		
		(192.18)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		65.99		
		(86,513.56)		
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		618.83		
		(496.94)		
Reg. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		26.56		
		(416.43)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-327.14		
		(485,048.22)		
Oil Supply News Shock$_{t-3}$			-59.48	
			(46.11)	
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-52.34	
			(60.12)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			54.97	
			(46.70)	
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			214.38	
			(144.77)	
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			440.22	
			(316,070.78)	
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-296.14	
			(330.86)	
Reg. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			443.05	
			(470.84)	
Oil Supply News Shock$_{t-4}$				-23.67
				(26.10)
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				97.32
				(52.11)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.77
				(37.63)
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-63.63
				(169.10)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-186.52
				(224,136.22)
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-255.09
				(341.20)
Reg. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-413.88
				(307.10)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				255.17
				(1,097,259.77)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.89	0.89	0.89	0.89
N	8,947	8,947	8,947	8,947
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 3.7.1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the E.U. I estimate if firms with negative green technology-related exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect changes 1 - 4 quarters after an oil supply news shock after a period of high financial stress. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 21. Regression of AISD (bps) on Negative Technological Exposure and Oil Supply News Shocks after periods of financial stress (EU)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Tech. Sentiment$_{t-1}$	46.66*	44.40*	42.25*	48.07**
	(18.06)	(18.50)	(18.95)	(16.06)
Specialization$_{t-1}$	3.75	-5.28	0.28	-2.59
	(15.04)	(13.96)	(14.07)	(14.11)
Financial Stress$_{t-1}$	163.75*	125.04	154.75*	142.28*
	(67.46)	(66.50)	(74.12)	(63.27)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$	-2.12	-6.69	-16.03	-1.14
	(19.17)	(18.29)	(20.93)	(16.78)
Specialization$_{t-1}$ × Financial Stress$_{t-1}$	-150.86	-77.85	-102.77	-54.70
	(134.43)	(119.32)	(124.84)	(107.99)
Tech. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$	-185.34*	-157.84*	-183.84*	-169.81*
	(81.85)	(76.33)	(74.00)	(76.04)
Oil Supply News Shock$_{t-1}$	27.47			
	(29.48)			
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	18.10			
	(54.63)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-44.41			
	(51.39)			
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-8.27			
	(118.96)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$	102.80	128.30	223.82	70.83
	(192.85)	(170.72)	(216.39)	(139.90)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	145.71*			
	(65.31)			
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	406.49			
	(402.55)			
Tech. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-165.10			
	(195.21)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-1,035.89*			
	(511.80)			
Oil Supply News Shock$_{t-2}$		-21.73		
		(43.24)		
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-3.01		
		(41.40)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-19.63		
		(64.44)		
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		237.26		
		(267.75)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-41.30		
		(79.25)		
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		457.42		
		(603.11)		
Tech. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-329.15		
		(304.96)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-57.26		
		(725.88)		
Oil Supply News Shock$_{t-3}$			-48.80	
			(46.77)	
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-35.75	
			(45.46)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-12.62	
			(51.94)	
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			151.25	
			(178.64)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			27.92	
			(69.59)	
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			503.45	
			(600.22)	
Tech. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			119.76	
			(224.03)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-534.59	
			(693.65)	
Oil Supply News Shock$_{t-4}$				-0.50
				(28.00)
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-87.48*
				(41.89)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				25.82
				(56.46)
Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-269.11
				(204.95)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-98.84
				(67.92)
Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-522.47
				(527.24)
Tech. Sentiment$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				703.80*
				(308.30)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Financial Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				919.41
				(605.38)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.89	0.89	0.89	0.89
N	8,947	8,947	8,947	8,947
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 3.7.1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the U.S. I estimate if firms with higher emission intensity face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect changes 1 - 4 quarters after an oil supply news shock after a period of high financial stress. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 22. Regression of AISD (bps) on Emission Intensity and Oil Supply News Shocks after periods of financial stress (US)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Scope 1 and 2 emissions$_{t-1}$	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Specialization$_{t-1}$	17.63	16.73*	17.45	21.09*
	(10.07)	(7.91)	(12.70)	(9.91)
Fin. Stress$_{t-1}$	-7.14	-2.10	-4.40	-4.40
	(5.07)	(4.52)	(4.64)	(4.41)
Emissions$_{t-1}$ × Specialization$_{t-1}$	-0.04	-0.03	-0.03	-0.05
	(0.02)	(0.02)	(0.03)	(0.03)
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$	10.84	9.71	13.04	12.54*
	(6.49)	(5.38)	(8.81)	(6.34)
Scope 1 and 2 emissions$_{t-1}$ × Fin. Stress$_{t-1}$	0.00	0.00*	0.00*	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Oil Supply News Shock$_{t-1}$	-21.68			
	(12.72)			
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-1}$	0.00			
	(0.01)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-5.03			
	(17.31)			
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-17.44			
	(11.19)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$	-0.01	-0.02	-0.01	-0.02
	(0.02)	(0.02)	(0.03)	(0.02)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	0.10			
	(0.09)			
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	28.68			
	(18.96)			
Emissions$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.01			
	(0.00)			
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-0.14			
	(0.08)			
Oil Supply News Shock$_{t-2}$		-9.57		
		(12.98)		
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-0.02		
		(0.01)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-59.09		
		(34.24)		
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-26.01*		
		(11.80)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.16		
		(0.12)		
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-77.10**		
		(27.04)		
Emissions$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-0.02*		
		(0.01)		
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		0.17		
		(0.11)		
Oil Supply News Shock$_{t-3}$			10.58	
			(14.73)	
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.00	
			(0.01)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-43.26	
			(44.42)	
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			26.87*	
			(11.07)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.10	
			(0.09)	
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-16.24	
			(31.03)	
Emissions$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.00	
			(0.00)	
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			0.11	
			(0.08)	
Oil Supply News Shock$_{t-4}$				5.77
				(12.76)
Emissions$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.00
				(0.01)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				107.11*
				(47.75)
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				5.96
				(11.24)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.29*
				(0.13)
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				50.33
				(29.48)
Emissions$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				0.00
				(0.01)
Emissions$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-0.19*
				(0.09)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.71	0.71	0.71	0.71
N	35,583	35,583	35,583	35,583
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 3.7.1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the U.S. I estimate if firms with negative climate regulatory exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect changes 1 - 4 quarters after an oil supply news shock after a period of high financial stress. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 23. Regression of AISD (bps) on Negative Regulatory Exposure and Oil Supply News Shocks after periods of financial stress (US)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Reg. Sentiment$_{t-1}$	10.39	10.00	10.30	13.54*
	(6.26)	(6.20)	(6.13)	(5.90)
Specialization$_{t-1}$	2.79	2.03	2.13	0.58
	(5.49)	(5.54)	(6.18)	(5.16)
Fin. Stress$_{t-1}$	-3.15	0.10	-1.94	-1.82
	(4.18)	(3.98)	(4.14)	(3.77)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$	-44.12*	-20.69	-44.06	46.36
	(18.45)	(17.55)	(47.49)	(26.88)
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$	3.50	3.03	3.88	1.59
	(3.89)	(4.27)	(4.24)	(3.48)
Reg. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$	-1.06	1.15	-1.66	1.71
	(5.25)	(5.26)	(5.20)	(4.73)
Oil Supply News Shock$_{t-1}$	-15.60			
	(8.85)			
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-9.68			
	(15.08)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	20.65			
	(16.49)			
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-1.99			
	(9.89)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$	6.91	16.16	2.38	67.29***
	(12.37)	(13.54)	(31.61)	(18.67)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-118.23**			
	(44.07)			
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	5.26			
	(12.63)			
Reg. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-8.05			
	(18.78)			
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-31.76			
	(49.28)			
Oil Supply News Shock$_{t-2}$		-12.39		
		(11.39)		
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-2}$		1.34		
		(25.31)		
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-14.99		
		(25.54)		
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-32.61**		
		(11.51)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		98.50		
		(81.37)		
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-23.22		
		(19.77)		
Reg. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-11.87		
		(25.08)		
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		24.16		
		(66.16)		
Oil Supply News Shock$_{t-3}$			-1.23	
			(11.72)	
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-1.08	
			(16.60)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-23.00	
			(20.08)	
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			15.77	
			(9.96)	
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			102.95	
			(110.73)	
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-12.59	
			(16.20)	
Reg. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			22.84	
			(15.14)	
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			110.12	
			(72.25)	
Oil Supply News Shock$_{t-4}$				11.68
				(10.07)
Reg. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-57.37**
				(19.59)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				33.03
				(30.12)
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				12.96
				(10.60)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-291.34*
				(115.91)
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				13.74
				(19.53)
Reg. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-55.94*
				(21.81)
Reg. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-218.35**
				(78.84)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.69	0.70	0.69	0.69
N	47,950	47,950	47,950	47,950
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

Note: This table reports estimates from the regression specification given in equation 3.7.1 estimated syndicated loan-level data for 2010-2022 for firms headquartered in the U.S. I estimate if firms with negative green technology-related exposure face higher lending rates, whether banks specializing in the borrower's industry charge higher rates relative to non-specializing banks, and whether this effect changes 1 - 4 quarters after an oil supply news shock after a period of high financial stress. The dependent variable is All-in-spread-drawn (bps). Borrower, Lender-Year, and SIC 2-digit industry-year fixed effects are included across all specifications. Firm-level controls include log of total assets of the borrower in US dollars, leverage ratio, ratio of capital expenditure to total assets, and the ratio of EBITDA to total assets. Loan-level controls include the maturity of the contract, whether the contract is secured, whether the contract has any covenants, and the log of the loan amount. Standard errors are clustered at the borrower level, and are reported in parentheses. The significance of coefficient estimates is indicated by *** for $p < 0.001$, ** for $p < 0.01$, * for $p < 0.05$.

TABLE 24. Regression of AISD (bps) on Negative Technological Exposure and Oil Supply News Shocks after periods of financial stress (US)

	All_In_Spread_Drawn_bps			
	(1)	(2)	(3)	(4)
Tech. Sentiment$_{t-1}$	-2.36	-3.81	-2.96	-2.96
	(5.92)	(5.64)	(6.42)	(5.57)
Specialization$_{t-1}$	3.71	3.65	1.92	2.02
	(6.05)	(6.06)	(6.53)	(5.86)
Fin. Stress$_{t-1}$	-2.58	0.86	-1.31	-1.04
	(4.53)	(4.14)	(4.52)	(3.98)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$	-6.55	-2.63	12.15	5.07
	(13.13)	(9.26)	(13.68)	(10.54)
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$	7.17	8.49	6.51	5.48
	(4.29)	(4.76)	(4.62)	(3.78)
Tech. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$	-2.90	-3.92	-3.21	-3.30
	(5.29)	(4.95)	(5.19)	(4.78)
Oil Supply News Shock$_{t-1}$	-19.47*			
	(9.52)			
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-1}$	8.46			
	(13.90)			
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	20.89			
	(17.44)			
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-1.90			
	(11.17)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$	-13.97	-8.71	2.70	-3.72
	(9.88)	(7.48)	(11.05)	(7.82)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-49.04			
	(32.22)			
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	8.70			
	(14.30)			
Tech. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-3.07			
	(14.97)			
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-1}$	-12.46			
	(38.74)			
Oil Supply News Shock$_{t-2}$		-16.48		
		(12.95)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-2}$		121.89***		
		(35.72)		
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		-44.24*		
		(22.45)		
Tech. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		35.28		
		(19.18)		
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-2}$		86.79**		
		(33.07)		
Oil Supply News Shock$_{t-3}$			-6.35	
			(12.58)	
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-3}$			25.71	
			(18.79)	
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-14.62	
			(20.01)	
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			17.77	
			(11.10)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-62.15	
			(61.50)	
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-7.27	
			(16.63)	
Tech. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-2.74	
			(18.07)	
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-3}$			-17.72	
			(39.68)	
Oil Supply News Shock$_{t-4}$				6.64
				(11.37)
Tech. Sentiment$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-3.85
				(17.50)
Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				43.38
				(34.57)
Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				10.56
				(11.67)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-77.47
				(48.78)
Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				24.37
				(23.92)
Tech. Sentiment$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-15.53
				(16.31)
Tech. Sentiment$_{t-1}$ × Specialization$_{t-1}$ × Fin. Stress$_{t-1}$ × Oil Supply News Shock$_{t-4}$				-67.70*
				(33.44)
Firm-level controls	✓	✓	✓	✓
Loan-level controls	✓	✓	✓	✓
R^2	0.69	0.70	0.69	0.69
N	47,950	47,950	47,950	47,950
Borrower F.E.	✓	✓	✓	✓
Lender-Year F.E.	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓

B. Proposition 2: Proof

For borrowers who received a low signal from private screening conducted by the S-bank in the first period:

$$F_{lh_p}(r) = 1 - \left[\frac{(p(hh_p)\bar{r}_{h_p} - 1)}{(p(hh_p)r - 1)} \right]$$

$$F_{ll_p}(r) = 1 - \left[\frac{(p(hl_p)\bar{r}_{l_p} - 1)}{(p(hl_p)r - 1)} \right]$$

$$\Rightarrow E\left[r_{ll_p}\right] - E\left[r_{lh_p}\right] = \int_{\bar{r}_{l_p}}^{R} rdF_{ll_p}(r) - \int_{\bar{r}_{h_p}}^{\bar{r}_{lh_p}} rdF_{lh_p}(r)$$

$$= \int_{\bar{r}_{l_p}}^{R} \frac{p(hl_p)\bar{r}_{l_p} - 1)\, p_{hl_p}}{(p(hl_p)r - 1)^2} rdr - \int_{\bar{r}_{h_p}}^{(\bar{r}_{lh_p}} \frac{(p(hh_p)\bar{r}_{h_p} - 1)\, p_{hh_p}}{(p(hh_p)r - 1)^2} rdr$$

$$= \frac{p(hl_p)\bar{r}_{l_p} - 1}{p(hl_p)} \left[ln\left(\frac{p(hl_p)R - 1}{p(hl_p)\bar{r}_{l_p} - 1} \right) - \left(\frac{1}{p(hl_p)R - 1} - \frac{1}{p(hl_p)\bar{r}_{l_p} - 1} \right) \right]$$

$$- \frac{p(hh_p)\bar{r}_{h_p} - 1}{p(hh_p)} \left[ln\left(\frac{p(hh_p)\bar{r}_{lh_p} - 1}{p(hh_p)\bar{r}_{h_p} - 1} \right) - \left(\frac{1}{p(hh_p)\bar{r}_{lh_p} - 1} - \frac{1}{p(hl_p)\bar{r}_{h_p} - 1} \right) \right]$$

which is $> 0 \quad \forall \quad \phi, \phi_p \geq \frac{1}{2}$ and $\mu \in [0, 1]$

For borrowers who received a high signal from private screening conducted by the S-bank in the first period:

$$F_{hh_p}(r) = 1 - \left[\frac{(1 - p(lh_p)r)(p(hh_p)\bar{r}_{h_p} - 1)}{(p(hh_p)r - 1)^2} \right] \left[\frac{Pr(\eta = l|\eta_p = h_p)}{Pr(\eta = h|\eta_p = h_p)} \right]$$

$$F_{hl_p}(r) = 1 - \left[\frac{(1 - p(ll_p)r)(p(hl_p)\bar{r}_{l_p} - 1)}{(p(hl_p)r - 1)^2} \right] \left[\frac{Pr(\eta = l|\eta_p = l_p)}{Pr(\eta = h|\eta_p = l_p)} \right]$$

$$\Rightarrow E\left[r_{hl_p}\right] - E\left[r_{hh_p}\right] = \int_{\bar{r}_{l_p}}^{R} rdF_{hl_p}(r) - \int_{\bar{r}_{h_p}}^{\bar{r}_{lh_p}} rdF_{lh_p}(r)$$

$$= \int_{\bar{r}_{h_p}}^{\bar{r}_{lh_p}} r \left[\frac{(p(hh_p)\bar{r}_{h_p} - 1)}{(p(hh_p)r - 1)^2} \left((1 - 2\frac{Pr(\eta = l|\eta_p = h_p)}{Pr(\eta = h|\eta_p = h_p)}) p(hh_p) + \frac{Pr(\eta = l|\eta_p = h_p)}{Pr(\eta = h|\eta_p = h_p)} p(lh_p) \left(p(hh_p)r + 1 \right) \right) \right] dr$$

Substituting $Pr(\eta = l|\eta_p = h_p)$ and $Pr(\eta = h|\eta_p = h_p)$ as 'c' and 'd' respectively (for the compactness of expressions) and Substituting $Pr(\eta = l|\eta_p = l_p)$ and $Pr(\eta = h|\eta_p = l_p)$ as 'a' and 'b' respectively (for the compactness of expressions), we get

$$
\begin{aligned}
E\left[r_{hl_p}\right] - E\left[r_{hh_p}\right] &= \left[\frac{\left(p(hl_p)\bar{r}_{l_p} - 1\right)\left(p(hl_p) + \frac{a}{b}p(ll_p)\right) + \frac{a}{b}\left(p(hl_p) - p(ll_p)\right)}{p(hl_p)^2}\right] ln\left(\frac{p(hl_p)R - 1}{p(hl_p)\bar{r}_{l_p} - 1}\right) \\
&+ \left[\frac{\left(p(hl_p)\bar{r}_{l_p} - 1\right)\left(p(hl_p) + \frac{a}{b}\left(3p(ll_p) - 2p(hl_p)\right)\right) + \frac{a}{b}\left(p(hl_p) - p(ll_p)\right)}{p(hl_p)^2}\right]\left[\frac{1}{p(hl_p)\bar{r}_{l_p} - 1} - \frac{1}{p(hl_p)R - 1}\right] \\
&+ \left[\frac{a}{b}\frac{\left(p(hl_p)\bar{r}_{l_p} - 1\right)\left(p(ll_p) - p(hl_p)\right)}{p(hl_p)^2}\right]\left[\frac{1}{\left(p(hl_p)\bar{r}_{l_p} - 1\right)^2} - \frac{1}{\left(p(hl_p)R - 1\right)^2}\right] \\
&- \left[\frac{\left(p(hh_p)\bar{r}_{h_p} - 1\right)\left(p(hh_p) + \frac{c}{d}p(lh_p)\right) + \frac{c}{d}\left(p(hh_p) - p(lh_p)\right)}{p(hh_p)^2}\right] ln\left(\frac{p(hh_p)\bar{r}_{lh_p} - 1}{p(hh_p)\bar{r}_{h_p} - 1}\right) \\
&- \left[\frac{\left(p(hh_p)\bar{r}_{h_p} - 1\right)\left(p(hh_p) + \frac{c}{d}\left(3p(lh_p) - 2p(hh_p)\right)\right) + \frac{c}{d}\left(p(hh_p) - p(lh_p)\right)}{p(hh_p)^2}\right] \\
&\cdot \left[\frac{1}{p(hh_p)\bar{r}_{h_p} - 1} - \frac{1}{p(hh_p)\bar{r}_{lh_p} - 1}\right] \\
&- \left[\frac{c}{d}\frac{\left(p(hh_p)\bar{r}_{h_p} - 1\right)\left(p(lh_p) - p(hh_p)\right)}{p(hh_p)^2}\right]\left[\frac{1}{\left(p(hh_p)\bar{r}_{h_p} - 1\right)^2} - \frac{1}{\left(p(hh_p)\bar{r}_{lh_p} - 1\right)^2}\right]
\end{aligned}
$$

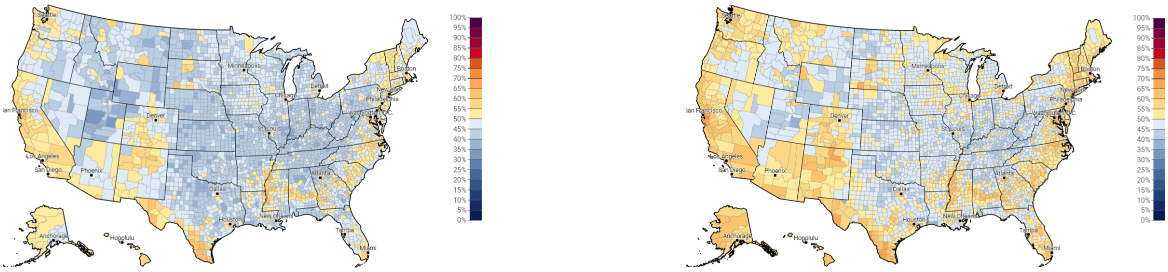
which is $> 0 \quad \forall \quad \phi, \phi_p \geq \frac{1}{2}$ and $\mu \in [0, 1]$

C. Evidence of updates in beliefs about short-term and long-term risks from climate change

C.1. Data

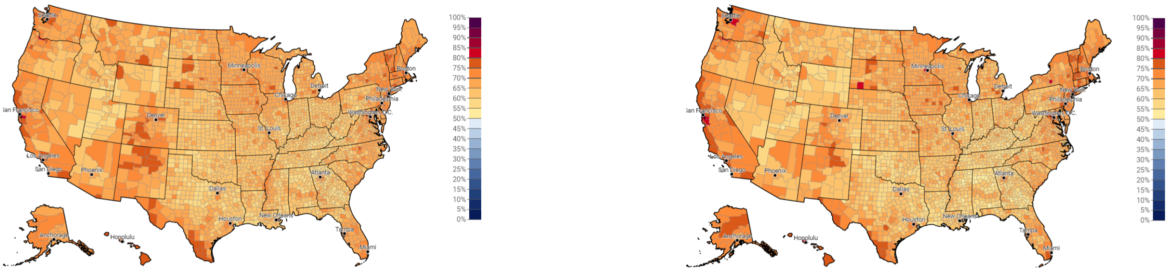
To understand if there is any under-reaction due to prior-conformity in the structure of belief updates in response to a climate event, I use county-level survey data on beliefs related to climate risk and potential damages from climate risk from **Yale Climate Beliefs** datasets (Howe et al. 2015). The estimates of county-level risk perceptions and opinions on policy are derived from a statistical model using multilevel regression with post-stratification on the national survey dataset, accounting for demographic and geographic population characteristics. I use data from the 2014 survey as an estimate of the prior beliefs. As an estimate for time-varying posterior beliefs, I use the data from the 2016, 2018, and 2020 surveys. Moreover, I also examine the changes in policy preferences to examine whether individual preferences update with major weather events, and whether the nature of this update is heterogenous across different climate policy instruments. I specifically focus on the following questions in the surveys:

a. Do you think that global warming is already harming people in the U.S. now or within ten years?
b. Do you think future generations are at risk of damage from climate change?
c. Do you support regulating CO_2 as a pollutant?
d. Do you support a policy requiring utilities to produce 20% electricity from renewable sources?



A. 2016 B. 2020

FIGURE 17. Short-term risk perceptions



A. 2016 B. 2020

FIGURE 18. Long-term risk perceptions

We can see from the maps above that the public opinion on these questions has evolved over the year, evidently in the direction of belief in climate change. For almost all of the questions on risk perception, the mean response grew between

2014 to 2020. The average percentage of people who think there are short-run risks from global warming increased from 39.67% in 2014 to 50.10% in 2020. The average percentage of people who believe there are long-run risks from global warming increased from 58.07% to 64.92%. (Table 25). Moreover, the average support for regulating CO_2 as a pollutant increased between 2014 and 2018 but declined in 2020 (Table 25).

I use the **Billion-Dollar Weather and Climate Disasters** report from NOAA[20]. The events covered in these reports account for greater than 80% of the damage that has been recorded from all U.S. weather and climate events.To examine the impact of Billion-Dollar weather events on beliefs/preferences in 2020, I used the total number of Billion Dollar events for the state to which the county belonged to for 2018 and 2019. I also control for the cumulative billion-dollar events between 2005 to 2017 to account for any long-term incorporation of information about climate change that may have resulted from more than a decade of large-scale weather-event-induced losses. From the descriptive statistics, we can see a noticeable variation in the number of these events across the states.

One of the significant caveats about using the YCM dataset is that despite the authors including census and election data into their model for accuracy, the estimated shifts in public opinion at the sub-national level between 2014 and 2020 may not only be due to opinion changes but also changes in demographics and weather anomalies that were relevant for modeling opinions about climate change.

I measure annual temperature and precipitation using the NCEI divisional data, containing quality controlled annual summaries of minimum and maximum temperature, and precipitation[21]. Annual averages are computed using equally weighted months. I calculate the difference of the maximum, minimum, and average temperature, and average precipitation from the 30 year average for the county to control for weather anomalies.

I measure demographic characteristics using the 5-year estimates from the 2019 American Community Survey 5-year estimates for county population, median household income, and percentage of people with more than 2 years of college education. For data on political affiliations, I use the MIT Election Data and Science Lab repository for official returns for the 2016 Presidential elections for all counties[22]. The dataset contains county-level vote shares for all candidates.

C.2. Methodology

I analyse the belief updating process in line with (Epstein et al. 2010) and (Cripps 2018), who present updated beliefs as a linear combination of the prior beliefs and the posterior beliefs.

$$\mu_t|x_t = (1-\lambda)\mu_0 + \lambda(\mu_t|x_t, x_{t-1}, x_{t-2}, \ldots)$$

where: μ_0 - prior belief ; $(\mu_t|x_t, x_{t-1}, x_{t-2}, \ldots)$ - Bayesian posterior on the basis of the information set available till time 't'. If there is no learning when subjected to new information, the individual's posterior beliefs are not significantly different from their prior beliefs ($\lambda = 0$). If the learning is Bayesian, then the posterior beliefs in the current period are the only determinants of the updated belief ($\lambda = 1$). In cases of non-Bayesian updating, $\lambda \in (0, 1)$.

[20] NOAA National Centers for Environmental Information (NCEI) U.S. Billion-Dollar Weather and Climate Disasters (2021). https://www.ncdc.noaa.gov/billions/, DOI: 10.25921/stkw-7w73

[21] https://www.ncei.noaa.gov/pub/data/cirs/climdiv/

[22] https://github.com/MEDSL

This parameter could represent the confidence of the agent in the news, or the strength of the priors[23]. So, $\lambda < 1$ would imply that the agent is conservative in updating their beliefs when subjected to new information, whereas $\lambda > 1$ represents 'overconfidence' in the new information received. For the purpose of estimation, I assume that if the learning is perfectly Bayesian, the posterior beliefs in the current period are a combination of posterior beliefs in the previous period and new information being generated by the number of events occurring at the state-level. Taking into account all relevant controls, this would imply that the prior beliefs have no significant effect on the current beliefs.

Using the survey data, I examine the importance of the beliefs in the previous period ($PosteriorBelief_{t-1}$ where t = 2016 & 2018), the priors ($Belief_{2014}$), and the number of billion dollar events in the intermittent period between two survey waves, in determining the beliefs about the short-run and long-run risk perceptions across 3104 counties in the United States. The event count is a a proxy for a signal about climate risks - it is imperfectly informative about the risks. I control for local geographic conditions, population, educational attainment measures, and weather anomalies to account for possible non-linearities of effects of weather on risk perceptions. Since the waves measure the estimated percentage of people that say yes to the questions mentioned in the previous section, I look at the changes between the percentages recorded in waves after 2014 as posterior beliefs, and the percentage recorded in 2014 as the prior beliefs. If the posterior beliefs formed between 2016 and 2018 are strongly determinant of the beliefs iformed between 2018 and 2020, individuals have updated their risk perceptions.

C.3. Results

C.3.1. Beliefs about Climate Risks

Table 27 presents the results from the regression of change in average short-run climate risk perceptions between 2018 and 2020 on the change in beliefs between 2018 and 2016, and the perceptions recorded in the first wave of the survey in 2014. The change in estimated percentage of people who believe that they are at risk from global warming between 2018 and 2016 is a proxy for the posterior beliefs in 't-1,' and the estimated percentage in 2014 is a proxy for the prior beliefs about short-run climate risk. In order to examine the effects of major climate-induced weather events on the update in beliefs, I check the impact of the frequency of billion-dollar weather events in 2018 and 2019, and the total number of events between 2005 and 2017, on the risk perceptions in 2020. Controlling only for state fixed effects (Specifications 1 and 2), I do not find a statistically significant effect of the recent events recorded in 2018 and 2018, or of the effect of the cumulative events recorded between 2005 and 2017 by themselves. However, these events have an interactive statistically significant positive effect for counties with higher posterior beliefs about short-run risk.

Across specifications 1 and 2, both the prior (2014 beliefs) and the previous period posterior (2018-2016 beliefs) play a statistically significant role in determining the update in beliefs between 2018 and 2020. The magnitude of the effect of the posterior beliefs is negative implying that the updated beliefs between 2020 and 2018 are growing at a slower pace, and the effect of the prior beliefs is positive. However, the effect of the posterior beliefs increases in the direction of higher short-term risk from climate change with large weather events in the recent past. This effect holds for the cumulative history of events between 2005 and 2017 as well, though the magnitude is smaller.

Controlling for the elevation, temperature, and precipitation anomalies for 2018 and 2019 (as compared to the 30-year

[23] The updating could be iterated or 'one-shot'. For the purposes of this analysis, I am considering a one-shot Bayesian posterior

county average), total population, educational attainment levels, and median household income, and the state fixed effects, does not lead to a change in the significance or the relative importance of the prior and posterior beliefs in the previous period in determining the update in beliefs between 2018 and 2019 (Specifications 3-6) [24].

However, the role of weather events become positive and statistically significant. The increase in the estimated percentage of adults between 2018 and 2020, who believe that the U.S. is at risk from climate change in the short-run, increases by 0.58-0.68 percentage points if the county belongs to a state that has experienced an additional event relative to other states in 2018 and 2019. Moreover, this effect is stronger by 0.015 percentage points in counties which have had a greater positive update about short-run risk perceptions betwene 2016 and 2018. The cumulative history of events between 2005 and 2017 has a positive, albeit smaller effect on the beliefs as well. However, as shown in specifications 4 and 6, the effect of the prior beliefs declines when the events between 2005 and 2017 are accounted for. This implies that not only do the weather events serve as a signal for individuals to update their beliefs in the direction of harm from climate change, but they also induce individuals to accord a higher weight to new information than their prior beliefs when thinking about short-term climate risk.

Examining the effect of the share of votes for the Republican party in the 2016 Presidential elections could provide evidence in favor of updating process being affected by the political beliefs of individuals in a county. However, I do not find any statistically significant effects of political beliefs on the change in short-term risk perceptions between 2018 and 2020. Table 26 presents the results from the regression of change in average long-run climate risk perceptions between 2018 and 2020 on the change in beliefs between 2018 and 2016, and the perceptions recorded in the first wave of the survey in 2014. The change in estimated percentage of people who believe that future generations are at risk from global warming between 2018 and 2016 is a proxy for the posterior beliefs in 't-1,' and the estimated percentage in 2014 is a proxy for the prior beliefs about long-run climate risk. Controlling only for state fixed effects (Specifications 1 and 2), I find a statistically significant positive effect of the recent events recorded in 2018 and 2019, and of the effect of the cumulative events recorded between 2005 and 2017 by themselves. Moreover, these events have an interactive statistically significant positive effect for counties with higher posterior beliefs about long-run risk.

Controlling for the elevation, temperature, and precipitation anomalies for 2018 and 2019 (as compared to the 30-year county average), total population, educational attainment levels, and median household income, and the state fixed effects, does not lead to a change in the significance or the relative importance of the prior and posterior beliefs in the previous period in determining the update in beliefs between 2018 and 2019 (Specifications 3-6) [25].

The increase in the estimated percentage of adults between 2018 and 2020, who believe that the U.S. is at risk from climate change in the short-run, increases by 0.56-1.08 percentage points if the county belongs to a state that has experienced an additional event relative to other states in 2018 and 2019. Moreover, this effect is stronger by 0.012 - 0.014 percentage points in counties which have had a greater positive update about short-run risk perceptions betwene 2016 and 2018. The cumulative history of events between 2005 and 2017 has a positive effect, and the magnitude of this effect is larger relative to that observed in table 27. The effect of the prior beliefs declines when the events in 2018 and

[24] Note that these results hold when weather anomalies are accounted for in a quadratic form (Specifications 5 and 6), implying that controlling for possible nonlinear effects of weather anomalies does not reduce the belief-updating role of large-scale weather events and disasters.

[25] Note that these results hold when weather anomalies are accounted for in a quadratic form (Specifications 5 and 6), implying that controlling for possible nonlinear effects of weather anomalies does not reduce the belief-updating role of large-scale weather events and disasters.

2019, as well as the events between 2005 and 2017 are accounted for. This again signals to beliefs about long-term risk being updated in presence of new information, but with the prior beliefs and the beliefs in the previous period still playing an important role. In order to distinguish the news effects of these events from the monetary damages borne by individuals, I examine the possible effects of crop and property damages from weather-induced natural disasters across the United States between 2018 and 2019. The data on damages is acquired from the SHELDUS database, and includes per capita crop damages (in 2019 dollars) and per capital property damages (in 2019) dollars. I analyze quartile-wise impact of total crop and property damages in 2018 and 2019 on the updated beliefs between 2018 and 2020.

Controlling for the elevation, temperature, and precipitation anomalies for 2018 and 2019 (as compared to the 30-year county average), total population, educational attainment levels, and median household income, and the state fixed effects, I do not find any significant effects of the crop and property damages on the change in long-run perceptions about climate risks (Table 28). However, substantial property damages (or the fourth quartile of recorded property damages) have a positive significant effect when interacted with counties that had high posterior beliefs about short-term climate risks between 2016 and 2018 (Table 29). These results could provide some hints about the kind of information individuals pay attention to while forming their expectations about the long-run and short-run risks from climate change. While the occurrence of large weather events has a stronger impact on update in beliefs about long-run risks relative to the impact on short-run risks, monetary damages seem to only affect beliefs about short-run risks. Moreover, this impact is observable only for substantial property damages, in counties which already have a greater increase in posterior beliefs about short-run risks.

C.3.2. Policy Preferences

Tables 30 and 31 present the results of regression of policy preferences on the occurrence of the billion-dollar events. Controlling for all the county-level demographics, linear and quadratic weather anomalies, as well as state-level fixed effects, the results highlight that while the policy preference for CO_2 to be regulated as a pollutant is updating over time, with the posterior changes having a positive and significant effect, the weather events have no significant impact on these preferences. However, both the recent events and the cumulative event history between 2005 and 2017 have a positive and significant effect on the change in the percentage of people who support requiring utilities to produce 20% of electricity from renewable sources, with the magnitude of effect of recent events being larger. While I do not establish the link between beliefs and preferences, my analysis provides some preliminary evidence to think about the role weather events play in updating consumer preference for renewable energy, and hence accelerate the push for transition towards clean energy.

It is also interesting to notice, that while county-level poltiical beliefs did not have a significant role in expectation formation, they impact preferences for both CO_2 regulation and renewable-energy based power sources. The impact of the share of republican votes in the 2016 general election is negative and statistically significant.

TABLE 25. Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Timing (2014)	3,104	39.67	3.50	32	37	42	56
Timing (2016)	3,104	46.24	5.04	33.34	42.75	48.85	63.68
Timing (2018)	3,104	45.21	5.17	34.11	41.58	47.94	64.09
Timing (2020)	3,104	50.10	5.38	35.86	46.17	53.03	70.69
Futuregen (2014)	3,104	58.07	4.61	47	55	61	76
Futuregen (2016)	3,104	65.37	4.51	53.58	62.17	68.05	81.83
Futuregen (2018)	3,104	65.10	4.86	52.81	61.67	67.95	82.01
Futuregen (2020)	3,104	64.92	5.16	50.10	61.26	68.00	83.01
Republican Vote Share (2016 elections)	3,104	63.33	15.59	8.40	54.49	74.93	96.03
$Events_{1819}$	3,104	5.85	3.45	1	2	8	13
$Events_{1415}$	3,104	5.11	2.70	0	3	6	11
$Events_{1617}$	3,104	6.03	4.17	0	3	8	17
Total Pop.	3,104	103,753.90	332,508.50	98	11,177.2	67,926.5	10,081,570
Pop. enrolled in college	3,104	5,781.47	20,801.40	0	298	3,157	713,939
Pop. enrolled in graduate/professional school	3,104	1,346.02	5,252.93	0	47	531	147,778
Median HH. Income	3,104	53,332.83	14,095.89	21,504	44,144.2	59,611.5	142,299
30-yr Temperature (Max) Anomaly (2016)	3,104	1.84	0.65	−0.26	1.40	2.30	3.91
30-yr Temperature (Avg) Anomaly (2016)	3,104	1.91	0.52	0.43	1.55	2.25	4.13
Precipitation (Avg) Anomaly (2016)	3,104	−0.03	0.56	−2.11	−0.32	0.30	1.84
30-yr Temperature (Min) Anomaly (2016)	3,104	1.97	0.68	−0.02	1.51	2.36	4.91
Precipitation (Avg) Anomaly (2017)	3,104	0.11	0.46	−1.18	−0.20	0.36	3.07
30-yr Temperature (Min) Anomaly (2017)	3,104	1.58	0.63	−1.09	1.26	1.99	3.38
30-yr Temperature (Max) Anomaly (2017)	3,104	1.36	0.68	−1.74	0.98	1.81	3.30
30-yr Temperature (Avg) Anomaly (2017)	3,104	1.47	0.57	−1.31	1.21	1.84	3.20
Precipitation (Avg) Anomaly (2018)	3,104	0.61	0.67	−1.75	0.09	1.08	3.01
30-yr Temperature (Min) Anomaly (2018)	3,104	0.78	0.98	−2.50	0.07	1.56	3.92
30-yr Temperature (Max) Anomaly (2018)	3,104	−0.19	0.94	−4.07	−0.60	0.36	2.92
30-yr Temperature (Avg) Anomaly (2018)	3,104	0.30	0.84	−3.10	−0.11	0.90	2.76
Precipitation (Avg) Anomaly (2019)	3,104	0.37	0.57	−2.68	0.02	0.76	2.69
30-yr Temperature (Min) Anomaly (2019)	3,104	0.37	1.26	−3.25	−0.56	1.39	4.21
30-yr Temperature (Max) Anomaly (2019)	3,104	−0.35	1.71	−5.75	−1.44	1.04	4.22
30-yr Temperature (Avg) Anomaly (2019)	3,104	0.01	1.45	−3.99	−1.00	1.24	4.21

C.4. Regression tables including controls

Tables 26, 27, 28, 29, 30, and 31 present the regression results for all the main variables as well as the controls.

TABLE 26. Detailed regression Results: (Impact of events on the change in estimated percentage who believe climate change might cause moderate to strong harm to the future generations (2020-2018))

	Dependent variable: **$\text{Futuregen}_{2020-2018}$**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Futuregen}_{2018-2016}$	-0.085^{***}	-0.100^{***}	-0.109^{***}	-0.122^{***}	-0.117^{***}	-0.131^{***}
	(0.026)	(0.030)	(0.031)	(0.033)	(0.032)	(0.034)
Futuregen_{2014}	0.033	0.052^{**}	0.039^{*}	0.066^{***}	0.033	0.060^{**}
	(0.020)	(0.022)	(0.022)	(0.024)	(0.022)	(0.025)
Events_{1819}	0.559^{***}		1.079^{***}		0.976^{***}	
	(0.174)		(0.260)		(0.245)	
Events_{0517}		0.129^{***}		0.238^{***}		0.222^{***}
		(0.034)		(0.047)		(0.045)
Share of votes (Republicans)			0.009^{**}	0.011^{**}	0.007	0.009^{*}
			(0.004)	(0.005)	(0.005)	(0.005)
$\text{Events}_{1819} \times \text{Futuregen}_{2018-2016}$	0.012^{***}		0.013^{***}		0.014^{***}	
	(0.003)		(0.003)		(0.003)	
$\text{Events}_{1819} \times \text{Futuregen}_{2014}$	-0.004		-0.009^{**}		-0.008^{**}	
	(0.003)		(0.004)		(0.004)	
$\text{Events}_{0517} \times \text{Futuregen}_{2018-2016}$		0.003^{***}		0.003^{***}		0.003^{***}
		(0.001)		(0.001)		(0.001)
$\text{Events}_{0517} \times \text{Futuregen}_{2014}$		-0.001^{**}		-0.003^{***}		-0.002^{***}
		(0.001)		(0.001)		(0.001)
$\text{Events}_{1819} \times$ RepublicanVoteShare			-0.002^{***}		-0.001^{***}	
			(0.0005)		(0.0005)	
$\text{Events}_{0517} \times$ RepublicanVoteShare				-0.0003^{***}		-0.0003^{***}
				(0.0001)		(0.0001)
30-yr Temperature (Avg) Anomaly (2018)			0.052	0.052		
			(0.061)	(0.059)		
30-yr Temperature (Avg) Anomaly (2019)			-0.090	-0.085		
			(0.058)	(0.056)		
30-yr Precipitation (Avg) Anomaly (2018)			-0.010	-0.013		
			(0.050)	(0.051)		
30-yr Precipitation (Avg) Anomaly (2019)			-0.049	-0.054		
			(0.060)	(0.062)		
$(30-yrTemperature(Avg)Anomaly(2018))^2$					0.007	0.008
					(0.033)	(0.032)
$(30-yrTemperature(Avg)Anomaly(2019))^2$					0.028	0.028
					(0.019)	(0.019)
$(30-yrPrecipitation(Avg)Anomaly(2018))^2$					-0.017	-0.019
					(0.023)	(0.024)
$(30-yrPrecipitation(Avg)Anomaly(2019))^2$					-0.084^{***}	-0.087^{***}
					(0.029)	(0.028)
Elevation			0.0003^{**}	0.0003^{**}	0.0003^{***}	0.0003^{***}
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Total Pop.)			0.078^{**}	0.079^{**}	0.078^{***}	0.080^{***}
			(0.031)	(0.032)	(0.030)	(0.031)
Pop. enrolled in college			-0.00000	-0.00000	-0.00000	-0.00000
			(0.00000)	(0.00000)	(0.00000)	(0.00000)
Pop. enrolled in graduate/professional school			0.00003^{*}	0.00003^{*}	0.00003^{*}	0.00003^{*}
			(0.00001)	(0.00001)	(0.00001)	(0.00001)
Log(Median HH. Income)			0.055	0.057	0.064	0.068
			(0.133)	(0.134)	(0.126)	(0.128)
Constant	-4.525^{***}	-5.274^{***}	-7.982^{***}	-9.133^{***}	-7.447^{***}	-8.702^{***}
	(1.030)	(1.112)	(2.108)	(1.952)	(1.990)	(1.896)
Observations	3,104	3,104	3,104	3,104	3,104	3,104
R^2	0.292	0.292	0.303	0.304	0.305	0.305
Adjusted R^2	0.280	0.280	0.289	0.289	0.290	0.291

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

TABLE 27. Detailed regression Results: (Impact of events on the change in estimated percentage who believe climate change might cause moderate to strong harm to the US in the short-run (2020-2018))

	Dependent variable: $\mathbf{HarmUS_{2020-2018}}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{HarmUS_{2018-2016}}$	-0.125^{***}	-0.143^{***}	-0.158^{***}	-0.179^{***}	-0.164^{***}	-0.186^{***}
	(0.030)	(0.038)	(0.028)	(0.032)	(0.028)	(0.033)
$\mathbf{HarmUS_{2014}}$	0.065^{**}	0.084^{***}	0.059^{**}	0.081^{***}	0.054^{**}	0.076^{***}
	(0.025)	(0.028)	(0.024)	(0.029)	(0.025)	(0.029)
$\mathbf{Events_{1819}}$	0.281		0.677^{***}		0.577^{**}	
	(0.207)		(0.262)		(0.232)	
$\mathbf{Events_{0517}}$		0.078^{*}		0.153^{***}		0.137^{***}
		(0.041)		(0.052)		(0.046)
Share of votes (Republicans)			0.007	0.008	0.005	0.006
			(0.005)	(0.005)	(0.005)	(0.005)
$\mathbf{Events_{1819}} \times \mathbf{HarmUS_{2018-2016}}$	0.014^{***}		0.015^{***}		0.015^{***}	
	(0.003)		(0.003)		(0.003)	
$\mathbf{Events_{1819}} \times \mathbf{HarmUS_{2014}}$	-0.005		-0.008^{*}		-0.007	
	(0.005)		(0.005)		(0.004)	
$\mathbf{Events_{0517}} \times \mathbf{HarmUS_{2018-2016}}$		0.003^{***}		0.003^{***}		0.004^{***}
		(0.001)		(0.001)		(0.001)
$\mathbf{Events_{0517}} \times \mathbf{HarmUS_{2014}}$		-0.002^{*}		-0.002^{**}		-0.002^{**}
		(0.001)		(0.001)		(0.001)
$\mathbf{Events_{1819}} \times$ **RepublicanVoteShare**			-0.001^{*}		-0.001	
			(0.001)		(0.001)	
$\mathbf{Events_{0517}} \times$ **RepublicanVoteShare**				-0.0002^{*}		-0.0002
				(0.0001)		(0.0001)
30-yr Temperature (Avg) Anomaly (2018)			0.033	0.027		
			(0.066)	(0.064)		
30-yr Temperature (Avg) Anomaly (2019)			-0.097	-0.092		
			(0.071)	(0.069)		
30-yr Precipitation (Avg) Anomaly (2018)			0.002	0.00001		
			(0.055)	(0.056)		
30-yr Precipitation (Avg) Anomaly (2019)			-0.054	-0.060		
			(0.075)	(0.076)		
$(30 - yrTemperature(Avg)Anomaly(2018))^2$					-0.017	-0.018
					(0.034)	(0.034)
$(30 - yrTemperature(Avg)Anomaly(2019))^2$					0.032^{*}	0.033^{*}
					(0.019)	(0.018)
$(30 - yrPrecipitation(Avg)Anomaly(2018))^2$					-0.013	-0.013
					(0.030)	(0.030)
$(30 - yrPrecipitation(Avg)Anomaly(2019))^2$					-0.079^{**}	-0.080^{**}
					(0.036)	(0.036)
Elevation			0.0003^{***}	0.0003^{***}	0.0003^{***}	0.0003^{***}
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Total Pop.)			0.182^{***}	0.182^{***}	0.181^{***}	0.180^{***}
			(0.042)	(0.043)	(0.040)	(0.042)
Pop. enrolled in college			-0.00001^{***}	-0.00001^{***}	-0.00001^{***}	-0.00001^{***}
			(0.00000)	(0.00000)	(0.00000)	(0.00000)
Pop. enrolled in graduate/professional school			0.00003^{**}	0.00003^{**}	0.00003^{**}	0.00003^{**}
			(0.00001)	(0.00001)	(0.00001)	(0.00001)
Log(Median HH. Income)			0.391^{***}	0.402^{***}	0.399^{***}	0.412^{***}
			(0.130)	(0.135)	(0.121)	(0.126)
Constant	-2.103^{*}	-2.858^{**}	-9.789^{***}	-10.668^{***}	-9.260^{***}	-10.229^{***}
	(1.134)	(1.257)	(2.065)	(2.099)	(1.963)	(2.035)
N	3,104	3,104	3,104	3,104	3,104	3,104
R^2	0.180	0.181	0.220	0.221	0.221	0.222
Adj. R^2	0.166	0.167	0.203	0.205	0.205	0.206

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

TABLE 28. Detailed regression Results: (Impact of crop and property damages on the change in estimated percentage who believe climate change might cause moderate to strong harm to the future generations (2020-2018))

	Dependent variable: **Futuregen$_{2020-2018}$**		
	Futuregen$_{2020-2018}$		
	(1)	(2)	(3)
Futuregen$_{2018-2016}$	−0.024	−0.040	−0.043
	(0.030)	(0.032)	(0.032)
Futuregen$_{2014}$	0.020*	−0.003	−0.006
	(0.012)	(0.017)	(0.017)
Share of votes (Republicans)		−0.001	−0.001
		(0.002)	(0.002)
Crop Damages (in $) - Quartile 4	0.147	0.208	0.234
	(0.811)	(0.829)	(0.852)
Property Damages (in $) - Quartile 2	0.646	0.551	0.461
	(0.609)	(0.634)	(0.618)
Property Damages (in $) - Quartile 3	0.851	0.699	0.560
	(0.670)	(0.676)	(0.681)
Property Damages (in $) - Quartile 4	1.467**	0.986	0.906
	(0.709)	(0.679)	(0.680)
Futuregen$_{2018-2016}$×Crop Damages (in $) - Quartile 4	−0.003	−0.003	−0.001
	(0.039)	(0.039)	(0.040)
Futuregen$_{2014}$×Crop Damages (in $) - Quartile 4	−0.003	−0.004	−0.004
	(0.014)	(0.014)	(0.014)
Futuregen$_{2018-2016}$×Property Damages (in $) - Quartile 2	−0.006	−0.004	−0.008
	(0.040)	(0.042)	(0.042)
Futuregen$_{2018-2016}$×Property Damages (in $) - Quartile 3	0.025	0.027	0.030
	(0.047)	(0.049)	(0.048)
Futuregen$_{2018-2016}$×Property Damages (in $) - Quartile 4	0.005	−0.007	−0.007
	(0.053)	(0.049)	(0.048)
Futuregen$_{2014}$×Property Damages (in $) - Quartile 2	−0.010	−0.009	−0.007
	(0.010)	(0.011)	(0.010)
Futuregen$_{2014}$×Property Damages (in $) - Quartile 3	−0.016	−0.013	−0.010
	(0.011)	(0.011)	(0.012)
Futuregen$_{2014}$×Property Damages (in $) - Quartile 4	−0.026**	−0.017	−0.016
	(0.012)	(0.011)	(0.011)
Constant	−1.467**	−2.001	−2.247*
	(0.637)	(1.365)	(1.326)
Observations	2,926	2,926	2,926
R^2	0.304	0.312	0.313
Adjusted R^2	0.289	0.294	0.296

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01
Regressions 2-3 control for state fixed-effects, county-level income,
population, educational attainment, and linear and quadratic 30-year temperature and precipitation anomalies

TABLE 29. Detailed regression Results: (Impact of crop and property damages on the change in estimated percentage who believe climate change might cause moderate to strong harm to the US in the short-run (2020-2018))

	Dependent variable: $\textbf{HarmUS}_{\textbf{2020-2018}}$		
	$\textbf{HarmUS}_{\textbf{2020-2018}}$		
	(1)	(2)	(3)
$\textbf{HarmUS}_{\textbf{2018-2016}}$	-0.121^{***}	-0.140^{***}	-0.144^{***}
	(0.047)	(0.043)	(0.042)
$\textbf{HarmUS}_{\textbf{2014}}$	0.045^{***}	0.021	0.019
	(0.016)	(0.017)	(0.017)
Share of votes (Republicans)		0.001	0.0001
		(0.002)	(0.002)
Crop Damages (in $) - Quartile 4	-1.153^{*}	−0.826	−0.829
	(0.620)	(0.609)	(0.618)
Property Damages (in $) - Quartile 2	0.487	0.458	0.444
	(0.565)	(0.574)	(0.556)
Property Damages (in $) - Quartile 3	0.862	0.632	0.539
	(0.818)	(0.907)	(0.887)
Property Damages (in $) - Quartile 4	1.093	0.502	0.493
	(0.748)	(0.760)	(0.753)
$\textbf{HarmUS}_{\textbf{2018-2016}}$×Crop Damages (in $) - Quartile 4	0.024	−0.002	−0.001
	(0.056)	(0.050)	(0.051)
$\textbf{HarmUS}_{\textbf{2014}}$×Crop Damages (in $) - Quartile 4	0.025^{*}	0.017	0.017
	(0.013)	(0.013)	(0.013)
$\textbf{HarmUS}_{\textbf{2018-2016}}$×Property Damages (in $) - Quartile 2	0.058	0.039	0.039
	(0.046)	(0.045)	(0.045)
$\textbf{HarmUS}_{\textbf{2018-2016}}$×Property Damages (in $) - Quartile 3	0.121^{*}	0.122^{*}	0.126^{*}
	(0.070)	(0.070)	(0.068)
$\textbf{HarmUS}_{\textbf{2018-2016}}$×Property Damages (in $) - Quartile 4	0.099^{**}	0.091^{**}	0.094^{**}
	(0.045)	(0.043)	(0.042)
$\textbf{HarmUS}_{\textbf{2014}}$×Property Damages (in $) - Quartile 2	−0.010	−0.009	−0.009
	(0.012)	(0.012)	(0.011)
$\textbf{HarmUS}_{\textbf{2014}}$×Property Damages (in $) - Quartile 3	−0.021	−0.015	−0.013
	(0.017)	(0.019)	(0.019)
$\textbf{HarmUS}_{\textbf{2014}}$×Property Damages (in $) - Quartile 4	-0.026^{*}	−0.011	−0.011
	(0.016)	(0.016)	(0.016)
Observations	2,926	2,926	2,926
R^2	0.194	0.228	0.229
Adjusted R^2	0.176	0.209	0.209

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01
Regressions 2-3 control for state fixed-effects, county-level income,
population, educational attainment, and linear and quadratic 30-year temperature and precipitation anomalies

TABLE 30. Detailed regression Results: (Impact of events on the change in estimated percentage who support regulating CO2 as a pollutant (2020-2018))

	Dependent variable: **$\text{Regulate}_{2020-2018}$**					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{RegulateCO2}_{2018-2016}$	0.195***	0.211***	0.189***	0.189***	0.186***	0.186***
	(0.035)	(0.038)	(0.034)	(0.036)	(0.035)	(0.037)
$\text{RegulateCO2}_{2014}$	0.024	0.057**	−0.035***	−0.025	−0.038***	−0.027
	(0.024)	(0.027)	(0.014)	(0.018)	(0.014)	(0.018)
Events_{1819}	0.210		0.181		0.117	
	(0.286)		(0.141)		(0.120)	
Events_{0517}		0.106**		0.050*		0.039
		(0.045)		(0.029)		(0.026)
Share of votes (Republicans)			−0.037***	−0.038***	−0.037***	−0.038***
			(0.003)	(0.003)	(0.003)	(0.003)
$\text{RegulateCO2}_{2018-2016} \times \text{Events}_{1819}$	0.001		−0.0004		−0.0003	
	(0.004)		(0.004)		(0.004)	
$\text{RegulateCO2}_{2014} \times \text{Events}_{1819}$	−0.002		−0.001		−0.001	
	(0.004)		(0.002)		(0.002)	
$\text{RegulateCO2}_{2018-2016} \times \text{Events}_{0517}$		−0.0002		−0.0001		−0.00004
		(0.001)		(0.001)		(0.001)
$\text{RegulateCO2}_{2014} \times \text{Events}_{0517}$		−0.001**		−0.001		−0.0005
		(0.001)		(0.0004)		(0.0004)
$\text{Events}_{1819} \times$ Share of votes (Republicans)			0.00001		0.0001	
			(0.0005)		(0.001)	
$\text{Events}_{0517} \times$ Share of votes (Republicans)				0.00005		0.0001
				(0.0001)		(0.0001)
30-yr Temperature (Avg) Anomaly (2018)			0.032	0.030		
			(0.045)	(0.045)		
30-yr Temperature (Avg) Anomaly (2019)			−0.069	−0.070		
			(0.044)	(0.044)		
30-yr Precipitation (Avg) Anomaly (2018)			0.019	0.020		
			(0.036)	(0.036)		
30-yr Precipitation (Avg) Anomaly (2019)			0.020	0.018		
			(0.043)	(0.043)		
$(30-yrTemperature(Avg)Anomaly(2018))^2$					0.001	0.001
					(0.024)	(0.024)
$(30-yrTemperature(Avg)Anomaly(2019))^2$					0.016	0.017
					(0.015)	(0.015)
$(30-yrPrecipitation(Avg)Anomaly(2018))^2$					0.008	0.009
					(0.018)	(0.018)
$(30-yrPrecipitation(Avg)Anomaly(2019))^2$					−0.022	−0.023
					(0.022)	(0.022)
Elevation			0.00002	0.00002	0.00003	0.00003
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Total Pop.)			−0.057**	−0.056**	−0.057**	−0.055**
			(0.025)	(0.026)	(0.024)	(0.026)
Pop. enrolled in college			−0.00000*	−0.00000*	−0.00000*	−0.00000*
			(0.00000)	(0.00000)	(0.00000)	(0.00000)
Pop. enrolled in graduate/professional school			0.00003***	0.00003***	0.00003***	0.00003***
			(0.00001)	(0.00001)	(0.00001)	(0.00001)
Log(Median HH. Income)			−0.013	−0.023	−0.013	−0.023
			(0.085)	(0.090)	(0.083)	(0.087)
Constant	−6.418***	−8.595***	0.533	0.121	0.911	0.466
	(1.658)	(1.820)	(1.166)	(1.279)	(1.070)	(1.221)
Observations	3,104	3,104	3,104	3,104	3,104	3,104
R^2	0.165	0.167	0.385	0.385	0.384	0.385
Adjusted R^2	0.150	0.153	0.372	0.372	0.372	0.372

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

TABLE 31. Detailed regression Results: (Impact of events on the change in estimated percentage who support requiring utilities to produce 20% electricity from renewable sources (2020-2018))

	Dependent variable: $\textbf{SupportRPS}_{2020-2018}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\textbf{supportRPS}_{2018-2016}$	0.024	0.052^{**}	0.009	0.031	0.004	0.025
	(0.028)	(0.026)	(0.029)	(0.029)	(0.030)	(0.030)
$\textbf{supportRPS}_{2014}$	-0.051^{***}	-0.034^{**}	-0.078^{***}	-0.072^{***}	-0.081^{***}	-0.075^{***}
	(0.014)	(0.015)	(0.015)	(0.017)	(0.016)	(0.017)
$\textbf{Events}_{1819}$	0.406^{***}		0.483^{***}		0.412^{***}	
	(0.109)		(0.137)		(0.124)	
$\textbf{Events}_{0517}$		0.094^{***}		0.092^{***}		0.080^{***}
		(0.019)		(0.027)		(0.025)
Share of votes (Republicans)			-0.026^{***}	-0.025^{***}	-0.027^{***}	-0.026^{***}
			(0.004)	(0.003)	(0.004)	(0.003)
$\textbf{supportRPS}_{2018-2016} \times \textbf{Events}_{1819}$	0.004^{*}		-0.001		-0.0003	
	(0.003)		(0.003)		(0.003)	
$\textbf{supportRPS}_{2014} \times \textbf{Events}_{1819}$	-0.001		-0.002		-0.001	
	(0.002)		(0.002)		(0.002)	
$\textbf{supportRPS}_{2018-2016} \times \textbf{Events}_{0517}$		-0.0001		-0.001		-0.001
		(0.001)		(0.001)		(0.001)
$\textbf{supportRPS}_{2014} \times \textbf{Events}_{0517}$		-0.001^{**}		-0.0005		-0.0004
		(0.0004)		(0.0004)		(0.0004)
$\textbf{Events}_{1819}\times$**Share of votes (Republicans)**			-0.001^{***}		-0.001^{**}	
			(0.0004)		(0.0004)	
$\textbf{Events}_{0517}\times$**Share of votes (Republicans)**				-0.0002^{***}		-0.0002^{***}
				(0.0001)		(0.0001)
30-yr Temperature (Avg) Anomaly (2018)			0.062	0.066		
			(0.059)	(0.060)		
30-yr Temperature (Avg) Anomaly (2019)			-0.079	-0.077		
			(0.053)	(0.053)		
30-yr Precipitation (Avg) Anomaly (2018)			-0.001	-0.005		
			(0.048)	(0.048)		
30-yr Precipitation (Avg) Anomaly (2019)			-0.010	-0.010		
			(0.044)	(0.044)		
$(30-yrTemperature(Avg)Anomaly(2018))^2$					0.012	0.013
					(0.035)	(0.035)
$(30-yrTemperature(Avg)Anomaly(2019))^2$					0.022	0.021
					(0.016)	(0.016)
$(30-yrPrecipitation(Avg)Anomaly(2018))^2$					-0.029	-0.030
					(0.018)	(0.018)
$(30-yrPrecipitation(Avg)Anomaly(2019))^2$					-0.022	-0.022
					(0.020)	(0.019)
Elevation			-0.00002	-0.00003	0.00000	-0.00000
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
Log(Total Pop.)			-0.124^{***}	-0.125^{***}	-0.122^{***}	-0.122^{***}
			(0.021)	(0.021)	(0.020)	(0.020)
Pop. enrolled in college			-0.00000	-0.00000	0.00000	-0.00000
			(0.00000)	(0.00000)	(0.00000)	(0.00000)
Pop. enrolled in graduate/professional school			0.00001	0.00001	0.00001	0.00001
			(0.00001)	(0.00001)	(0.00001)	(0.00001)
Log(Median HH. Income)			-0.265^{**}	-0.269^{**}	-0.258^{**}	-0.261^{**}
			(0.111)	(0.115)	(0.108)	(0.111)
Constant	1.212^{*}	0.626	8.514^{***}	8.453^{***}	8.788^{***}	8.681^{***}
	(0.722)	(0.794)	(1.290)	(1.359)	(1.210)	(1.301)
Observations	3,104	3,104	3,104	3,104	3,104	3,104
R^2	0.373	0.373	0.479	0.479	0.480	0.480
Adjusted R^2	0.362	0.362	0.468	0.468	0.469	0.469

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

TABLE 32. Detailed regression Results: (Impact of crop and property damages on the change in estimated percentage who support regulating CO2 as a pollutant (2020-2018))

	Dependent variable: **Regulate$_{2020-2018}$**		
	(1)	(2)	(3)
RegulateCO2$_{2018-2016}$	0.194***	0.140***	0.139***
	(0.033)	(0.032)	(0.032)
RegulateCO2$_{2014}$	0.039**	−0.038***	−0.039***
	(0.018)	(0.012)	(0.012)
Share of votes (Republicans)		−0.036***	−0.036***
		(0.002)	(0.002)
Crop Damages (in $) - Quartile 4	1.049	0.242	0.251
	(1.208)	(1.097)	(1.083)
Property Damages (in $) - Quartile 2	2.771***	1.106	1.132
	(0.988)	(0.881)	(0.887)
Property Damages (in $) - Quartile 3	1.245	−0.859	−0.867
	(1.236)	(1.087)	(1.077)
Property Damages (in $) - Quartile 4	5.000***	1.883*	1.902*
	(1.057)	(1.137)	(1.138)
RegulateCO2$_{2018-2016}$× Crop Damages (in $) - Quartile 4	0.005	0.033	0.034
	(0.034)	(0.034)	(0.033)
RegulateCO2$_{2014}$× Crop Damages (in $) - Quartile 4	−0.015	−0.005	−0.005
	(0.016)	(0.015)	(0.015)
RegulateCO2$_{2018-2016}$× Property Damages (in $) - Quartile 2	0.003	0.028	0.026
	(0.040)	(0.037)	(0.037)
RegulateCO2$_{2018-2016}$× Property Damages (in $) - Quartile 3	0.047	0.075*	0.074*
	(0.036)	(0.041)	(0.041)
RegulateCO2$_{2018-2016}$× Property Damages (in $) - Quartile 4	−0.068	−0.009	−0.010
	(0.042)	(0.037)	(0.036)
RegulateCO2$_{2014}$×Property Damages (in $) - Quartile 2	−0.038***	−0.016	−0.016
	(0.013)	(0.012)	(0.012)
RegulateCO2$_{2014}$×Property Damages (in $) - Quartile 3	−0.020	0.009	0.010
	(0.017)	(0.014)	(0.014)
RegulateCO2$_{2014}$×Property Damages (in $) - Quartile 4	−0.068***	−0.026*	−0.026*
	(0.014)	(0.015)	(0.015)
Constant	−7.202***	0.789	0.665
	(1.274)	(1.050)	(1.075)
Observations	2,926	2,926	2,926
R^2	0.179	0.394	0.394
Adjusted R^2	0.161	0.378	0.378

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01
Regressions 2-3 control for state fixed-effects, county-level income, population, educational attainment, and linear and quadratic 30-year temperature and precipitation anomalies

TABLE 33. Detailed regression Results: (Impact of crop and property damages on the change in estimated percentage who support requiring utilities to produce 20% electricity from renewable sources (2020-2018))

	Dependent variable: $\mathbf{supportRPS_{2020-2018}}$		
	(1)	(2)	(3)
$\mathbf{supportRPS_{2018-2016}}$	0.087^{***}	0.020	0.018
	(0.026)	(0.026)	(0.026)
$\mathbf{supportRPS_{2014}}$	-0.037^{***}	-0.082^{***}	-0.083^{***}
	(0.013)	(0.013)	(0.013)
Share of votes (Republicans)		-0.032^{***}	-0.032^{***}
		(0.002)	(0.002)
Crop Damages (in $) - Quartile 4	1.083^{**}	0.785^{*}	0.762^{*}
	(0.539)	(0.417)	(0.413)
Property Damages (in $) - Quartile 2	1.734^{**}	0.981	0.963
	(0.682)	(0.677)	(0.681)
Property Damages (in $) - Quartile 3	0.451	−0.484	−0.537
	(0.779)	(0.697)	(0.689)
Property Damages (in $) - Quartile 4	1.624^{**}	0.219	0.232
	(0.713)	(0.822)	(0.818)
$\mathbf{supportRPS_{2018-2016}}\times$ Crop Damages (in $) - Quartile 4	−0.032	−0.019	−0.018
	(0.031)	(0.032)	(0.032)
$\mathbf{supportRPS_{2014}}\times$ Crop Damages (in $) - Quartile 4	-0.021^{**}	-0.015^{**}	-0.014^{*}
	(0.009)	(0.007)	(0.007)
$\mathbf{supportRPS_{2018-2016}}\times$Property Damages (in $) - Quartile 2	−0.051	−0.027	−0.028
	(0.033)	(0.036)	(0.037)
$\mathbf{supportRPS_{2018-2016}}\times$Property Damages (in $) - Quartile 3	−0.016	0.001	0.002
	(0.036)	(0.030)	(0.030)
$\mathbf{supportRPS_{2018-2016}}\times$Property Damages (in $) - Quartile 4	-0.078^{*}	−0.041	−0.042
	(0.042)	(0.035)	(0.035)
$\mathbf{supportRPS_{2014}}\times$Property Damages (in $) - Quartile 2	-0.033^{***}	−0.018	−0.018
	(0.012)	(0.012)	(0.012)
$\mathbf{supportRPS_{2014}}\times$Property Damages (in $) - Quartile 3	−0.009	0.009	0.010
	(0.014)	(0.012)	(0.012)
$\mathbf{supportRPS_{2014}}\times$Property Damages (in $) - Quartile 4	-0.032^{**}	−0.006	−0.006
	(0.013)	(0.015)	(0.015)
Constant	2.814^{***}	11.056^{***}	10.808^{***}
	(0.665)	(1.056)	(1.039)
Observations	2,926	2,926	2,926
R^2	0.380	0.481	0.482
Adjusted R^2	0.367	0.468	0.469

Note: Robust standard errors (clustered by state) are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01
Regressions 2-3 control for state fixed-effects, county-level income, population, educational attainment, and linear and quadratic 30-year temperature and precipitation anomalies

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