How Climate Physical Risks and Transition Risks Affect Bank Lending *

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Abstract

This study examines how banks incorporate firms' exposure to physical and transition risks, along with their interactions, when making lending decisions. Utilizing detailed firm-bank matched data from Denmark—which covers a wide range of firms, with a special focus on SMEs, and banks of various sizes—we find that banks generally reduce the growth of credit for firms exposed to higher physical and transition risks. We also find a nuanced response to the interaction of physical and transition risks from banks, which seem to favor firms with slightly lower combined risks. Additionally, small firms and those with high leverage and capital intensity are particularly impacted, experiencing a notable decline in credit growth. Lastly, the results primarily stem from the impact on the supply side of credit rather than the demand side.

Keywords: Climate change, physical risks, transition risks, bank lending.
JEL Codes: G21, G30, H23, Q54, Q56

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1 Introduction

Over the past decades, central banks and financial regulators have increasingly recognized climate-related risks—both physical and transition risks—as significant sources of financial instability (Carney, 2015; ECB, 2021a,b; Fed, 2021). Consequently, they have mandated banks to integrate these risks into their risk management frameworks and disclose related information. Furthermore, some central banks have initiated the development of climate stress tests to evaluate banks' vulnerability to adverse climate-related events and scenarios. These regulatory interventions have heightened the awareness and perceptions of climate risks among banks and investors (Krueger et al., 2020).

Existing empirical literature on banking provides some evidence that large global banks have begun to respond to physical risks (Meisenzahl, 2023; Faiella and Natoli, 2019a) and transition risks (Kacperczyk and Peydró, 2022; Reghezza et al., 2022), typically through their syndicated loans to large publicly listed firms. However, there is limited knowledge about whether and how banks, particularly small and regional banks, adjust their lending to small and medium-sized enterprises (SMEs) and privately held firms. It is possible that small banks could fill the gap if large banks reallocate credit away from polluting and risky firms.

Moreover, existing studies often examine banks' responses to physical and transition risks separately, despite the fact that these risks are interconnected and may compound each other. Therefore, it is essential to develop a comprehensive understanding of banks' lending practices under the influence of both physical and transition risks, considering their interactions. This calls for the use of comprehensive bank-firm linked data encompassing all firm sizes and bank sizes (De Haas, 2023; Hoffner and Steffen, 2022).

In this paper, we examine whether and to what extent banks integrate both physical and transition risks, as well as their interactions, into their lending practices, using a comprehensive sample, that not only include listed and large firms but also SMEs as well as banks of all sizes. Focusing on bank lending, particularly to private firms and SMEs, is crucial for transforming the global economy to net zero, as this transition requires substantial investment to support sustainability efforts. Approximately 70 percent of this investment is estimated to come from private sources.[1] Given that private firms typically rely heavily on bank credit, banks can significantly influence these firms' sustainability practices by adjusting their access to finance.

[1] According to the International Energy Agency (IEA), a successful transition to net zero by 2050 will require additional global investments amounting to 0.6 to 1 percent of annual global GDP over the next two decades, totaling a cumulative 12$trillionto$20 trillion. Thirty percent of this investment is expected to come from public sources, while 70 percent is anticipated to come from private sources (IEA, 2021).

We focus on the two types of climate risks that banks are indirectly exposed to through their lending activities: (i) physical risks, resulting from damages due to increasing extreme climate events, and (ii) transition risks, associated with the implementation of unexpected climate policies aimed at reducing emissions from high-emitting firms. Both physical and transition risks can be transmitted to banks' own risk profiles through their loan portfolios. For instance, physical hazards translate into credit risks for banks when borrowers cannot repay loans (the income effect) or when banks cannot fully recover the value of loans in the event of default due to diminished collateral value (the wealth effect) (BIS, 2021; ECB, 2021b). Existing studies often examine physical and transition risks separately despite their interrelated nature and the potential for compounded risks. For example, increasing the frequency or intensity of extreme weather events (rising physical risks) could prompt the implementation of stringent policies to limit carbon emissions (higher transition risks). Additionally, climate-related scenario analyses for banks are gradually evolving to include both physical and transition risks, underscoring the importance of evaluating banks' responses to these intertwined risks together.[2]

We examine this question within the context of Denmark, utilizing credit registers to access account-specific information for all bank loan relationships among Danish firms, a majority of which are privately held SMEs, across various bank-size distributions.[3] Denmark serves as an intriguing case study due to its notable disparities in both physical and transition risks. With a coastline spanning 4,545 miles and the highest elevation points reaching 170 meters, Denmark faces escalating risks from storms and coastal flooding as sea levels rise and precipitation patterns evolve. At the same time Numerous investments, including firm factories and residential properties, are situated in flood-prone areas.[4] Consequently, the heightened physical risks stemming from flooding and extreme precipitation events are likely to capture the attention of banks. Regarding transition risks, both the Danish government and the European Union have implemented proactive measures aimed at reducing emissions and enhancing energy efficiency over recent decades. Consequently, those firms with high emission intensities face heightened susceptibility to climate policy uncertainties, which are more likely to influence banks' lending behaviors.

[2]For example, the Network for Greening the Financial System (NGFS) has designed four scenarios consisting of varying levels of physical and transition risks that are widely adopted by central banks. The four scenarios are: 1) low physical and low transition risks (orderly scenario); 2) low physical and high transition risks (disorderly scenario); 3) high physical and low transition risks (hothouse world scenario); and 4) high physical and high transition risks (too little, too late scenario).

[3]According to the OECD, SMEs represented 98.7% of all enterprises and accounted for 39.1% of all full-time employees in Denmark in 2019.

[4]For instance, Danmarks Nationalbank estimates that between 0.9% to 1.2% of Danish homes are currently exposed to flood risks, a figure projected to nearly double by 2071 (Mirone and Poeschl, 2021).

We map firms' exposure to physical and transition risks at a high level of granularity. Specifically, to construct firms' physical risks exposure, we leverage the firms' exact locations at parish level over time and link them with forward-looking projected flood risk maps aggregated at the parish level and historical extreme weather (we focus on extreme precipitation as it is more likely to lead to floods) aggregated at the parish level across time.[5] Our assumption is that the occurrence of past extreme precipitation events and future flood risks is more likely to raise the attention of banks in Denmark and prompt updates in their beliefs about climate physical risks across locations over time. Firms' exposure to transition risks is then calculated as the interaction between firm-level emission intensity and the environmental tax, enabling us to measure banks' response to the vulnerability of brown firms to tighter environmental regulations over time.

The main identification strategy to tease out the impact of physical risks on bank lending is based on the assumption that the occurrence of abnormal extreme precipitation variations and floods is largely driven by nature and largely exogenous (Dell et al., 2014). As it is more difficult for banks and firms to anticipate climate events, physical risks are less likely to be correlated with unobserved idiosyncratic shocks to the firms or banks that could affect banks' lending decisions. However, one concern is that firms could adapt to physical risks by relocating their factories away from high physical risk zones (e.g., some areas close to the coast) or avoiding building new offices in those areas, which could be correlated with banks' credit allocation. To eliminate this concern, we include the refinement where we exclude those firms that relocate in order to compare the credit outcomes for firms that stay in the same locations. To address the concerns that certain areas (e.g., capital city) are more productive than other areas as firms tend to concentrate geographically around those areas, which could be related to credit allocation, we include location (parish) fixed effects in our specifications to control for any unobserved location-specific factors that affect banks' credit decisions.

Contrary to physical risks, our measure of transition risks is potentially more endogenous, given that its variation is firm-by-year. For instance, firms with high emission intensity to start with might seek to reduce the emissions intensity by investing in green projects after receiving the credits, which may bias the estimation. To reduce this reverse causality issue in the regression analysis, we include a refinement with a base-year approach, i.e., measuring emission intensity in the first year in which a firm in the sample is observed. As the physical risks are aggregated at the parish-time level, while transition risks are measured at the firm-

[5]A parish refers to a small administrative region encompassing multiple villages or localities in Denmark, with origins dating back to the Middle Ages. The establishment of these parishes was formalized in 1841, and since then, their boundaries have been minimal alterations. Currently, Denmark comprises a total of 2,141 parishes.

time level, we use different sets of controls and a comprehensive set of fixed effects to tease out the effects of physical and transition risks. As a result, the source of identification varies depending on the set of fixed effects and controls we included.

In baseline empirical analysis where we estimate the static effects of physical and transition risks on credit allocation, we find evidence that, on average, banks decrease the growth of credits allocated to firms exposed to higher physical and transition risks after controlling for other firm and bank characteristics, while modestly, consistent with the results found in the global syndicated loan market (Kacperczyk and Peydró, 2022; Reghezza et al., 2022). In addition, we find a nuanced response to the interaction of physical and transition risks from banks, which seem to favor firms with slightly lower combined risks. We also find significant heterogeneity across firms, summarized as follows: 1) smaller firms show heightened sensitivity to physical risks and the combined effect of physical and transition risks. 2) banks are more restrictive in lending to highly leveraged firms exposed to physical risks, likely due to these firms' limited financial buffer to absorb shocks from climate-related disasters. 3) banks are less inclined to increase lending growth or initiate new loans for high capital-intensive firms facing significant physical risks. Furthermore, when exploring the underlying mechanisms, we emphasize that our results are primarily driven by changes in credit supply from the banks, which can stem from financial considerations, as banks perceive firms facing high climate risks as experiencing greater financial stress and credit risks. Lastly, we use a simple model of bank portfolio choice to rationalize our empirical finding.

Our study contributes to the empirical sustainable banking literature by providing evidence for banks' response to climate risks based on a unique sample consisting of all firm-size and bank-size distribution, which allows us to assess how smaller banks adjust lending to smaller firms in response to climate risks. We also shed light on how banks incorporate both types of climate risks, physical and transition risks (and their interactions), providing a more complete evaluation of climate risks. Our results are consistent with the finding using global syndicating loans (Kacperczyk and Peydró, 2022; Mueller and Sfrappini, 2022), and respond to the concerns raised by policymakers regarding the potential financial stability issues imposed by climate risks (ECB, 2021b; Fed, 2021).

Although our findings provide evidence that banks have incorporated both physical and transition climate risks into their lending practices to SMEs, our study does not directly evaluate the actual impact of these practices on emission reductions (Hartzmark and Sussman, 2019) or green innovations (Accetturo et al., 2022). Additionally, despite our efforts to disentangle the supply and demand factors influencing credit supply, we recognize the inherent challenges in clearly separating these effects. Therefore, we advocate for further research to explore the underlying mechanisms driving banks' motivations for green lending. Such investigations are crucial for understanding how financial institutions can more effectively support the green transition and contribute to broader sustainability goals.

The remainder of this paper is structured as follows. Data and summary statistics are presented in Section 4, followed by the empirical strategy in Section 5. Empirical results are presented in Section 6. Finally, we rationalize our empirical results in a simple model in Section 7 and conclude our paper in Section 8.

2 Related Literature

This paper contributes to four strands of research. Existing studies tend to estimate the implications of physical risks and transition risks separately. The first strand of study we add to is on the implications of transition risks in financial markets, specifically in the credit market. A large amount of literature in this line of work has focused on whether and how transition risks, commonly using different measures of carbon emissions or environmental policies as proxies, are priced in the financial market (Altavilla et al., 2023). Previous literature has found support that investors collectively value sustainability (Starks, 2023; Hartzmark and Sussman, 2019; Baker et al., 2022b; Krueger et al., 2020; Heeb et al., 2023; Ilhan et al., 2023; Flammer, 2015). For instance, in the equity market, there is evidence for the presence of either a carbon or a pollution premium, i.e., investors asking for higher returns to compensate for carbon (Bolton and Kacperczyk, 2021, 2023; Pástor et al., 2022; Bolton et al., 2022) or pollution (Hsu et al., 2023) risk exposure. Similar evidence is found in the options market (Ilhan et al., 2021) and the real estate market (Bernstein et al., 2022; Giglio et al., 2021; Eichholtz et al., 2013, 2010; Baldauf et al., 2020). In the bond market, Seltzer et al. (2022); Baker et al. (2022a); Köuml;lbel and Lambillon (2022); Zerbib (2019) document a premium for green bonds while Larcker and Watts (2020); Flammer (2021) find no difference in yields.

In contrast to the vast growing literature in other markets, there are relatively fewer studies in the bank credit market. Most of the research in this line of work focuses on the asset pricing perspective of transition risks and is based on syndicated loans, which only account for a small share of the total credit market. So far, researchers have found mixed evidence. There is positive evidence that banks price stringent environmental regulations (Fard et al., 2020), environmental concerns such as hazardous chemicals, substantial emissions (Chava, 2014), or higher carbon emissions (Ehlers et al., 2022; Altavilla et al., 2023), and price firms' holdings of fossil fuel reserves after 2015 (Delis et al., 2018). Moreover, green banks rewarded cheaper loans to green firms after 2015 (Degryse et al., 2023), and there is assortative firm-bank matching based on their ESG profiles (Houston and Shan, 2022). In contrast, other researchers do not find evidence that banks in the syndicated loan market price this risk of stranded assets held by fossil fuel firms (Beyene et al., 2021) and flood risk (Schubert, 2021). Antoniou et al. (2020) document that in contrast with the program intentions of the EU Emission Trading System (EU ETS), there is a significant decline in loan spreads among those participating firms. Huang et al. (2021) find state-owned banks failed to price in environmental policy exposure while joint-equity commercial banks manage better. Some scholars also shed light on the channels. Banks' behaviors are driven by local beliefs and regulatory enforcement (Erten and Ongena, 2023), or financial risks associated with regulation and banks' preferences for sustainable lending (Mueller and Sfrappini, 2022).

This paper is closer to the studies that investigate the implications of transition risks on banks' credit supply (quantity adjustment). We believe that compared with pricing, the quantity of loans, or where the credit goes, has a more direct impact on firms' investment decisions and their stances towards sustainability (Takahashi and Shino, 2023). However, there is surprisingly much less research in this area. A few notable exceptions are Kacperczyk and Peydró (2022) and Reghezza et al. (2022), which find banks allocate fewer credits to large corporations with higher carbon emissions in the syndicated loan market and Mueller and Sfrappini (2022) find that the effects depend on the borrower's region. In contrast, Giannetti et al. (2023) find evidence of greenwashing within the European banking sector and show banks continue to lend to brown borrowers. Unlike most of the studies that focus on syndicated loans for publicly listed firms, we contribute to the literature by analyzing climate risks in bank credit supply based on a more representative sample of firms and banks' entire loan portfolios over a longer period.[6]

Secondly, our study contributes to prior research on the implications of natural disasters and physical climate change risks on the bank credit market. Similarly, a large literature focuses on the pricing of physical risks, proxied by indicators such as weather-related natural disasters, in different markets and has offered mixed evidence. Prior studies find that sea-level rise (SLR) exposure risks are priced in the bond market (Goldsmith-Pinkham et al., 2015), and in the real estate market (Bernstein et al., 2019; Baldauf et al., 2020; Nguyen et al., 2022). In the bank credit market, Javadi and Masum (2021) find firms with higher exposure to drought risk pay higher spreads on their bank loans while Schubert (2021) and Garbarino and Guin (2021) do not find that banks fully price the flood risks and track the impact of floods ex-post closely. There are also mixed results regarding how physical risks affect credit supply. Meisenzahl (2023) and Aslan et al. (2022) suggest that banks reduce

[6]The few exceptions are Takahashi and Shino (2023), who use bank-firm matched data of Japanese listed firms to link GHG emissions and credit supply, and Giannetti et al. (2023); Sastry et al. (2024), who use euro-area credit registry to study the credibility of the sustainability disclosure and voluntary lender net zero commitments.

lending to areas more impacted by climate change after 2015. Similarly, Faiella and Natoli (2019b) find that the amount of loans granted to firms depends negatively on their flood risk exposure. However, there is also evidence that when local demand increases after natural disasters, multi-market banks reallocate capital (Cortés and Strahan, 2017) and increase recovery lending to firms inside affected counties (Koetter et al., 2020; Ivanov et al., 2022). Previous studies also suggest a cross-country lending channel: domestic banks increase cross-border lending to firms in countries with lighter environmental policies when facing stringent regulations in their home country (Benincasa et al., 2022; Laeven and Popov, 2023). Our study contributes to the literature by using a more granular measure of physical risks and combines both types of climate risks to have a more complete evaluation of the risks posed by climate change.

Thirdly, our study responds to the call for a better understanding of the climate risk implications for the banking industry and the behavior of banks. Previous studies found that banks exposed to higher climate risks make faster adjustments to their optimal capital structure (Bakkar, 2023), and raise deposit rates of bank branches both in affected and in adjacent unaffected counties, (Barth et al., 2024), make worse performance (Li and Pan, 2022) and adversely impacts overall liquidity creation (Lee et al., 2022). In addition, there are concerns that climate risks negatively affect the financial stability of banks (Noth and Schüwer, 2023; Jung et al., 2023) and the entire financial system (Chabot and Bertrand, 2023; Battiston et al., 2021). We contribute to the literature by examining whether banks factor in these risks in their lending decisions and address the concerns raised by central banks that banks may not internalize those risks, which adversely impact financial stability (ECB, 2021a,b; Fed, 2021). Our results show evidence that banks are responding to the increasing climate risks by adjusting the supply of loans, confirming the evidence found by researchers such as Kacperczyk and Peydró (2022) and Mueller and Sfrappini (2022). This study also opens future research avenues regarding banks' role in green transition (Degryse et al., 2021; Lee et al., 2024).

Lastly, this paper broadly relates to the extensive literature on the implications of climate risks on firm performance and behaviors. Physical risks induced by climate change, such as sea level rise (SLR), drought, and floods are examined by Huang et al. (2018, 2022); Kling et al. (2021); Pankratz et al. (2019); Hong et al. (2019); Huynh et al. (2020); Ginglinger and Moreau (2023); Elnahas et al. (2018) and the effects of transition risks using proxies such as firms' GHG emissions, carbon emissions, and ESG scores are explored by Nguyen (2018); Reboredo and Ugolini (2022); Bolton and Kacperczyk (2021); Krueger (2015); Ardia et al. (2022). Overall, previous study finds that climate risks adversely impact firm performance and increase operational, financial, and default risks. Our results add to the literature

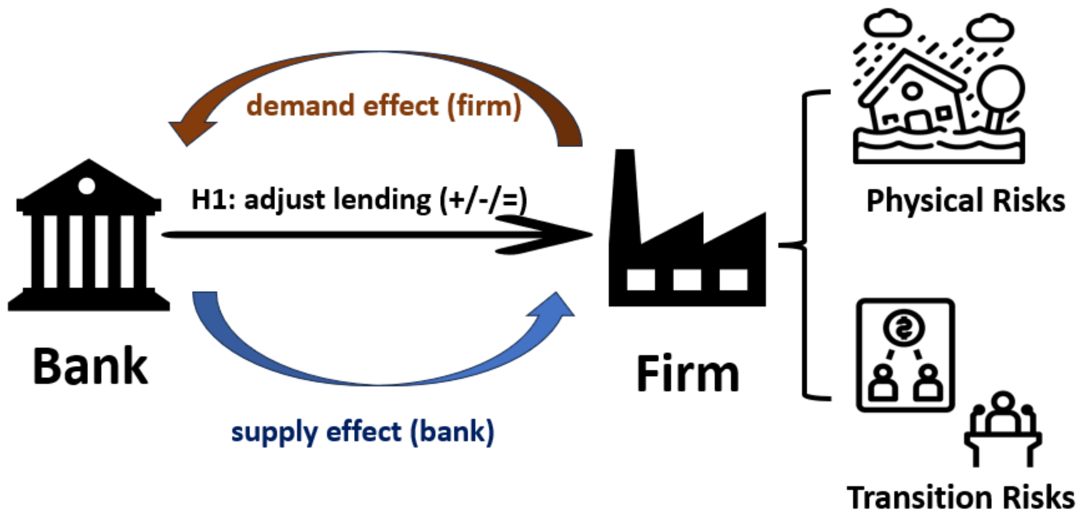

Figure 1: Illustration

and suggest one channel that climate risks may negatively affect firms: the bank financing channel. Firms with higher exposure to climate risks may face more challenges in accessing bank finance, using a more complete evaluation of both types of climate risks.

3 Theoretical Mechanisms

In this section, we conceptually show how physical and transition risks may impact banks' provision of credit to their client firms. Given that we can only observe equilibrium outcomes—specifically, the quantity of credits banks extend to firms, and the total amount of credits received by firms—both the supply side (banks) and the demand side (firms) may influence total credit provisions. Since factors on both sides could exert conflicting influences, the net effects are uncertain ex-ante. The anticipated sign could be positive, negative, or inconclusive, as shown in Figure 1. The following section will examine the potential impacts of climate risks on credit outcomes and the various factors or theoretical mechanisms on the supply and demand sides that could drive these results.

Climate risks may negatively relate to credit outcomes. On the one hand, from the supply side, banks have both financial and non-financial incentives to reduce lending to firms with high exposure to climate risks, aligning with the "values" versus "value" considerations defined by Starks (2023).[7] Financially, it is optimal for banks to adopt "green" policies

[7] Starks (2023) group different motivations of sustainable investment into: 1) values: examples include

from a risk and return perspective as it is associated with the probability of default and the loss given the default. In a theoretical Modigliani–Miller world without any frictions (Modigliani and Miller, 1958), banks should not be concerned about their clients' exposure to climate risks if they can financially price in these risks and be fully insured. However, due to market frictions, banks must consider climate risks related to firms' default risks (Huang et al., 2018; Kabir et al., 2021). Existing credit risk models may fail to account for tail-risk events, such as sudden and unexpected environmental policy changes (transition risks) or acute natural disasters (physical risks) (Schubert, 2021; Huang et al., 2021; Beyene et al., 2021; Garbarino and Guin, 2021). Consequently, banks might directly reduce or cease lending to firms with high exposure to these physical and transition risks due to the financial consideration of credit risks. Besides financial incentives, banks may have other non-pecuniary considerations. For example, implementing green lending policies can signal a positive response to increasing climate concerns from the public and activist shareholders. Additionally, a bank's leadership team or loan officers may prefer supporting businesses that reflect their values (Bu et al., 2023).

On the other side, from the demand side, both physical and transition risks may have adverse effects on the fundamental operations of businesses, leading to decreased productivity and, consequently, depressing firm investment and a reduction in credit demand (Huang et al., 2018; Kacperczyk and Peydró, 2022; Bolton et al., 2019).

Furthermore, banks might be concerned about these compounded physical and transition risks. Although physical risks and transition risks differ in nature, the first one is primarily associated with the geographical locations of firms, while the latter is more closely correlated with emissions, regulatory changes, and policy uncertainties. So, certain firms may be more materially affected by physical risks, while others may be more materially impacted by transition risks. However, the two risks can interact and amplify each other, leading to compounded effects that exacerbate the overall risk profile of firms. For example, a company facing physical risks such as flooding may also encounter challenges in complying with increasing regulations to reduce carbon emissions. Consequently, banks might be concerned about these compounded risks and choose to divest from firms that are exposed to both high physical and transition risks.

Those discussions of existing theories point to the following hypothesis.

H1A: Banks extend fewer credits to firms with high exposure to physical risks and transition risks, especially those firms with compounding of both risks.

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non-pecuniary preferences or reasons of the firm's leadership, a desire not to support businesses associated with objectionable products or conduct, or a desire to support businesses that reflect their religious values; and 2) value: a firm's financial risk and return opportunities.

At the same time, contrary forces might drive banks to increase lending to firms with high exposure to climate risks. On the demand side, empirical evidence suggests that firms tend to seek more credit following natural disasters, likely due to the need for financing post-disaster recovery efforts (Cortés and Strahan, 2017; Koetter et al., 2020; Ivanov et al., 2022). Additionally, firms might pursue extra credit to fund adaptation and mitigation investments. From the credit supply perspective, studies have shown that green investment has lower risk and higher profitability, resulting in higher realized returns for investors (Hartzmark and Sussman, 2019; Albuquerque et al., 2019), so it could be profitable for banks to assist high-risk firms in financing green investments to reduce their emissions intensity or flood risks. Moreover, since firms with high climate risk exposure are associated with high credit risks, banks might be motivated to engage with and support these firms in mitigating risks by maintaining a consistent flow of credit.

This discussion of existing theories leads us to formulate the following hypothesis.

H1B: Banks extend more credits to firms with high exposure to physical risks and transition risks, particularly those engaging in climate adaptation and mitigation activities.

On the other hand, several contrasting reasons may lead banks to maintain their practices. Banks are large and sophisticated institutions that face significant adjustment costs when adopting environmental strategies in lending. For example, they need to adjust their existing organizational structures, build new systems, train current employees, or hire new experts. Additionally, compared to selling a stock in the capital markets—where most information is publicly available—there is higher information asymmetry in the loan market. It is more costly to obtain and screen environmental-related information for their clients. As a result, profit-driven banks may adhere to their traditional practices and will only adopt green behaviors if the returns outweigh the costs. Furthermore, banks with legacy positions in older, "brown" firms may be reluctant to provide credit to newer, greener firms as the entry of green firms devaluates legacy positions with incumbent clients (Degryse et al., 2020). As a result, despite banks increasingly marketing themselves as "green," studies have questioned the credibility of their sustainability claims (Giannetti et al., 2023; Sastry et al., 2024) and concerns about greenwashing in the banking industry (EBA, 2023).

These theoretical mechanisms point to the following hypothesis.

H1C: Banks do not adjust credits to firms with high exposure to physical risks and transition risks and keep business as usual.

Testing these opposing hypotheses allows us to assess the strategies that banks use to incorporate climate risks in lending. Evidence supporting the H1A hypothesis would point to divesting strategies (Kacperczyk and Peydró, 2022; Degryse et al., 2023) while H1B is consistent with engagement strategies that banks facilitate the browner firms to be greener

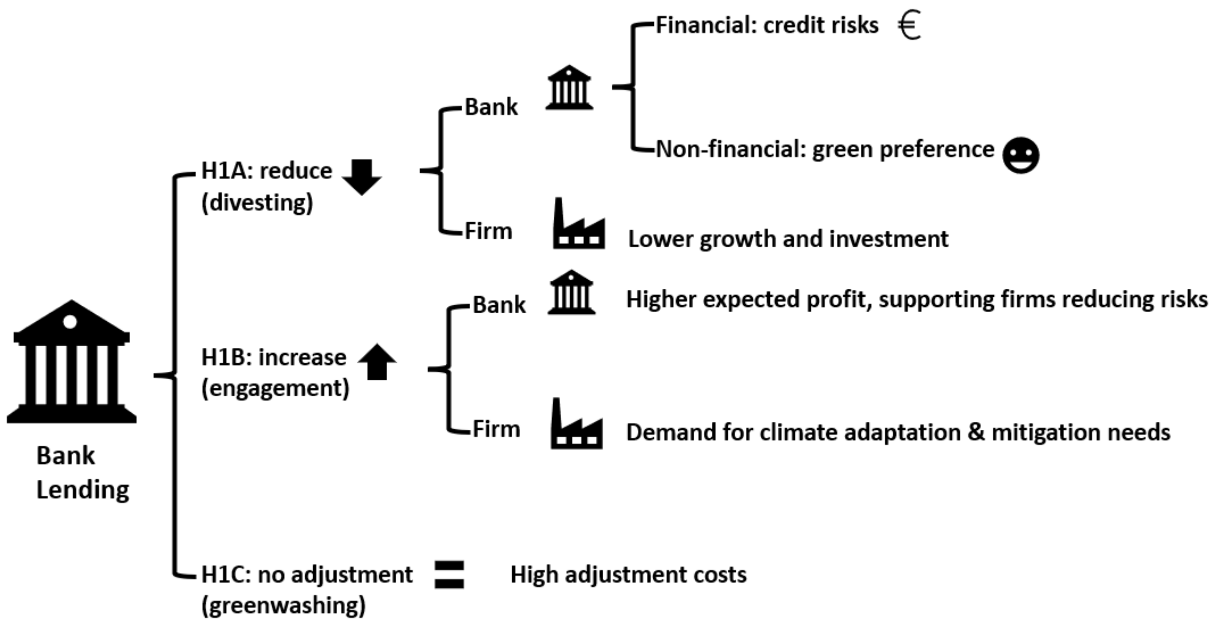

Figure 2: Hypothesis and Theoretical Mechanism

(Broccardo et al., 2022). Evidence supporting H1C will indicate that they don't adjust their behavior in response to climate risks.[8] Testing these opposing hypotheses also enables us to assess the relative importance of alternative theoretical mechanisms on both the firm and bank side.

Figure 2 summarizes the potential direction of the credit adjustment due to increasing climate risks we could test and the theoretical mechanism on the demand and supply side. Note that despite our attempt to enumerate as many factors as possible that affect both the demand and supply side, the points discussed are non-exhaustive and non-mutually inconclusive. In the empirical section, we will attempt to test a few theoretical mechanisms on both the firm and bank side and examine which side drives the estimated outcomes.

4 Data

Our analysis is based on several administrative registers containing banks', firms', and workers' information collected by Statistics Denmark and merged with external data to map non-financial firms' exposures to physical and transition risks. The final dataset matches the

[8]There is also evidence of greenwashing activities that show those banks which marketing themselves as "green" banks do not do as they state (Sastry et al., 2024; Giannetti et al., 2023). However, we cannot directly test the greenwashing hypothesis in this study because we cannot identify the name of the individual bank in the sample due to data confidentiality.

universe of bank loans that linked Danish banks and firms. This section provides a detailed description of different data sources and descriptive statistics.

4.1 Danish Administration Data

4.1.1 Employer-employee data

The starting point is to construct matched employer-employee data based on several registers administered by Statistics Denmark. Firm-level information is collected from general firm statistics (FIRM) and firm-level accounting statistics (FIRE). FIRM covers the universe of private-sector firms over the years from 1995-2019 and contains detailed information on firm characteristics, such as firm size, age, capital, revenue, location, and industry affiliation. FIRE contains detailed accounting information at the firm level, particularly information on firms' energy purchases for heating and production, which will allow us to measure the transition risks, as we will explain below.[9] To further link with employers' information, we exploit the Integrated Database for Labor Market Research (IDA), which covers the detailed demographic and employment information for all individuals employed in the recorded population of Danish firms at the firm and plant level. Using the Firm-Integrated Database for Labor Market Research (FIDA), every worker in IDA can be linked to every firm in FIRM and FIRE data using a unique identifier, which enables us to create an employer-employee matched data covering a representative sample of private-sector firms as well as their workers. The combined data allow us to construct several firm and worker characteristics at the firm and bank level, such as size, location, industry, revenue, and average workers' work experience, that will be used as important controls in our regressions.

4.1.2 Credit data

To link firms with banks, we exploit a unique database based on tax records that report the account-level data for the universe of bank loan relationships available at Statistics Denmark. Every year, all Danish entities that have extended credit during the previous 12 months are requested to report to the Danish Tax Authority (SKAT), including the account's number, type, and balance, together with its ownership status and the sum of interest payments on December 31st of each year. Since these reports are used to calculate tax obligations, the data is of high quality. We use the part of this dataset that covers firms (URTEVIRK), where the majority of the banks are domestic banks. Using unique banks' and firms' identifiers, we can link each loan account to the corresponding banks and borrowing firms, which further enables

[9]We deflate all monetary values using the GDP deflator provided by Statistics Denmark (pris112) with 2015 as the base year.

us to merge credit information with employer-employee matched data.[10] With the resulting dataset, we are able to observe the bank loans with the characteristics of the corresponding banks and firms. Following Hviid et al. (2022); Renkin and Züllig (2021), we collapse the raw data at the firm-bank-account-year level to the firm-bank-year level by taking the sum of the loan account balance and interest payments.

4.1.3 Sample constructions

To arrive at our final sample, we restrict the data in different ways. At the bank level, we drop micro banks with less than 50 employees as a large number of those micro banks only account for a small share of total lending while a few big banks dominate a significant share of the lending market. We drop those micro banks with less than 50 employees and focus on the medium and large banks to have a cleaner sample.[11] At the firm level, we drop firms with fewer than 10 employees from FIRM and FIRE registers as accounting information for micro firms may not be completely reliable. We also exclude firms operating in the financial industry, as these companies tend to be different from typical firms due to their significantly higher leverage levels. To account for possible measurement errors, we also dropped a few observations with negative values for account balance and interest payment. Figure C.1 shows the number of firms and banks in the final sample over the sample period. The banking sector has been consolidating in the aftermath of the 2007-2008 global financial crisis (GFC), with the number of banks steadily declining since 2008.

The descriptive statistics at the firm level for the sample are presented in Table A1.

4.2 Exposure to climate risks

The literature widely classifies exposure to climate-related risks into two categories: (1) physical risks, arising from extreme weather events; and (2) transition risks, resulting from policy and regulatory changes aimed at high-emitting firms to mitigate climate change (ECB,

[10] Specifically, on the bank side, using unique bank ID variables (op_se_nr), we can link the credit data to the employer-employee data to obtain firm and worker information at the bank level, including the total number of employees in the bank, affiliated industry, and locations, etc. We validate the credit data by tabulating some key descriptive statistics. We detect that the majority of the observations are ordinary debt in a bank and are associated with two-digit NACE sector code 64 (Financial service activities, except insurance and pension funding) after matching credit data with employer-employee data. We drop those observations if the bank ID is outside of the financial industry in the final sample, as financial firms leverage differently. On the borrowing firm side, we match employer-employee data with credit data using the unique firm identifiers (cvrnrs) to obtain the characteristics of the borrowing firms.

[11] There are over 200 micro banks but only account for less than 3% total lending in total. However, the 7 largest banks together account for over half of total lending.

2021b; TCFD, 2017; NGFS, 2021).[12] Banks are primarily exposed to physical and transition risks indirectly, through the firms to which they lend, rather than through direct exposure at their office locations (Faiella and Natoli, 2019b). This section details our methodology for measuring these two key variables: firms' exposure to physical risks and transition risks. A notable limitation is the unavailability of the specific data that banks use to assess climate risks. Nonetheless, we rely on publicly available information and firm-level data that are accessible to banks. Furthermore, we show that our measurements of climate risks are associated with lower firm profitability and a higher probability of firms exiting the sample, which correlates with a higher default rate—a significant concern for banks.

4.2.1 Physical risks data

To measure firms' exposure to physical risks, we construct a risk indicator that varies over time at the local parish level - a granular geographic unit in Denmark, by combining flood risk data and extreme weather data. In the following section, we will document the two data sources and the methodology to map firms' exposure to physical risks.

Extreme weather data Using weather data to measure exposure to climate change is widely adopted in the existing literature due to its exogenous variations within a specific area over time (Hsiang, 2016; Lemoine, 2018; Dell et al., 2014). While many studies focus on average weather characteristics, such as temperature and precipitation, we argue that extreme weather occurrences provide a more direct measure of the physical risks induced by climate change and, therefore, better reflect banks' perceptions or beliefs regarding climate risks. To capture this, we constructed a dataset that measures the frequency and intensity of weather anomalies using raw observation data from over 200 weather stations operated by the Danish Meteorological Institute (DMI).[13]

Given that extreme precipitation is closely correlated with flooding, our primary analysis focuses on extreme precipitation episodes. Rather than using a fixed threshold to define absolute extreme precipitation, we assume a moving distribution that varies across stations each month. This approach addresses the concern that some locations or seasons experience higher rainfall and volatility, and firms may already anticipate and adapt to these. Instead, we construct relative extreme precipitation based on the difference between a given daily

[12] Transition risks can also include technological risks and shifts in consumer demand that lead to stranded assets. However, following the literature, we primarily focus on policy risks, as the other two are more challenging to quantify.

[13] Some raw weather data are observed hourly, while others are recorded every 10 minutes. We first aggregated the raw data daily and constructed the daily weather anomalies, similar to Felbermayr et al. (2022).

precipitation value and the historical long-run mean value observed at the same station and month, standardized by its volatility. Specifically, we calculate a daily extreme precipitation indicator, $\nu^{precip}_{c,m,d,t}$, as follows:

$$\nu^{precip}_{c,m,d,t} = \frac{x^{precip}_{c,m,d,t} - \overline{x}^{precip}_{c,m}}{\sigma^{precip}_{c,m}}$$

where c denotes the climate station, m the month, d the day, and t the year. The indicator is calculated by subtracting the monthly average precipitation, $\overline{x}^{precip}_{c,m}$, from the daily precipitation, $x^{precip}_{c,m,d,t}$, and dividing the difference by the corresponding monthly standard deviation, $\sigma^{precip}_{c,m}$. This indicator captures both positive and negative precipitation anomalies. However, since only positive precipitation anomalies may lead to floods, we define extreme precipitation events as $\nu^{precip}_{c,m,d,t} > 2$.[14]

We then count the occurrence of such extreme events for each parish p in year t, denoting it as $freq_{p,t}$.[15] The intensity of events, $intensity_{p,t}$, for parish p in year t, is calculated as the average of $\nu^{precip}_{c,m,d,t}$ for extreme precipitation events (i.e., $\nu^{precip}_{c,m,d,t} > 2$) occurring that year. We find that the extreme precipitation events across parishes and years have a mean frequency of 16.44 (std. dev. = 5.68) and a mean intensity of 3.45 (std. dev. = 0.52). As expected, both the mean frequency and mean intensity of these events have increased over the sample period.

Projected flood risks data We focus on flood risks as they constitute one of the primary physical threats for countries with extensive coastlines and low altitudes, such as Denmark. Flood risk data is sourced from the Technical University of Denmark (DTU) and the Danish Meteorological Institute (DMI), which project flood occurrences and magnitudes across Denmark at a resolution of 200×200 meter grid cells. These projections are based on geographic features, climate data, water level statistics, and sea level estimates (**?**). For our baseline scenario, we aggregate this detailed data to the parish level by calculating the proportion of each parish exposed to 100-year flood events over a 20-year horizon, as illustrated in Figure C.2.[16]

Importantly, the flood risk data incorporates both historical and forward-looking perspectives. The simulations utilize historical data and future climate scenarios, providing a comprehensive view that can better inform banks' risk perceptions.

[14] Notably, when we set the indicator threshold below -2, we did not identify any drought events in our data over the sample period.

[15] In some parishes without a weather measurement station, each parish is assigned to the closest weather station. Using the detailed locations of the stations, we map each climate station to the neighboring parishes using the geo-weighting indicator described in the **??**.

[16] A 100-year flood event or return period indicates that a storm of this magnitude is expected to occur, on average, once every 100 years. Further details are provided in **?**.

The flood risks map reflects, in short, whether a given parish is likely to be flooded given its geography. However, since the flood risk data is static and only has cross-sectional variation, we then interact it with historical extreme precipitation event data to add a dimension of time variation in our data (i.e., I in the equation below). The idea is that if a parish gets extreme rain and at the same time is classified as very likely to be flooded given its geography, then we assume that the parish is likely flooded.

Physical risks indicator The main variable of interest to proxy physical risks is $\textit{Physical risks}_{p,t}$, constructed using a distance-weighted sum of extreme precipitation and flood exposures in surrounding locations.[17] This method has become standard to measure the proximity of a given location to other locations and has its roots in agglomeration economies.[18]

Specifically, $\textit{Physical risks}_{p,t}$ for each parish p and year t is calculated as:

$$\textit{Physical risks}_{p,t} = \sum_{r \neq p} I_{r,t} e^{-\delta x_{p,r}}$$

The variable $\textit{Physical risksp}, t$ aggregates heavy precipitation and flood exposure for all parishes r, incorporating distances to parish p as weights. This indicator not only assesses climate physical risks for a specific parish p at time t but also considers neighboring parishes r. The variable xp, r represents the Euclidean distance in kilometers between parishes p and r. The parameter δ serves as a decay parameter, reflecting the extent to which the effects of a climate event propagate to neighboring parishes, ranging from 0 to 1. We initially set δ to 0.06, a value deemed reasonable from an economic standpoint, serving as our baseline measure. In subsequent analysis, we demonstrate the robustness of our results to varying decay parameter values. The weight for each parish r is computed as $e^{-\delta x_{p,r}}$, where $e^{-\delta x_{p,r}}$ is a function of the decay parameter δ and the distance x in kilometers between parish p and r. Appendix C illustrates the variations in weight functions $e^{-\delta x_{p,r}}$ for different values of δ. The variable $I_{p,t}$ represents physical risks as the product of extreme precipitation and flood risks. As we can observe the firms' headquarters location at the parish level, we then overlap the firms' location map with the physical risks map and obtain the firms' exposure to physical risks.

There are three major advantages of using this measure. First, it incorporates the geographical spillover effects of extreme climate events. Those events often have consequences beyond the boundaries of one specific parish and can affect neighboring areas, depending on the magnitude of the events. Moreover, banks with client firms in neighboring areas

[17] We focus on anomalous precipitation in the main analysis as heavy rainfall weather is more likely to increase flood risks. In the refinement, we also use alternative definitions to proxy physical risks.

[18] See De Borger et al. (2019) as one example using a similar method with Danish data.

may also update their beliefs about climate risks and change their behaviors, even when not directly affected. This method can, therefore, reflect banks' perceptions of climate change. Second, it measures risk exposure at a much smaller geographical area, i.e., for over 2000 Danish parishes, which is an improvement in the measure of precision compared with existing studies. For example, the grid-cells data provided by Felbermayr et al. (2022) cover only 50 units in Denmark while The Emergency Events Database (EM-DAT) often misses the specific geo-locations for the events in the case of Denmark. Third, it aggregates the risks at a level that can be safely considered exogenous to banks' and firms' decisions, as the parish-level aggregation dates back to the Middle Ages.

?? visually depicts substantial variations in physical risks across different geographical locations in the year 2019, with the west coast and southern part of Zealand experiencing higher physical risks compared to other areas.

4.2.2 Transition risks data

Certain firms and industries with high emission intensities face elevated transition risks due to the targeting of climate mitigation policies and regulations (Gu and Hale, 2023). To quantify firm-level transition risk exposure, we initially identify polluting firms with high emission intensities. This is achieved by gathering firm-level energy purchases from the FIRE register, which is the expenses for energy purchases (for heating and production) and expenses for electricity, oil, gas, and district heating.[19] This data enables us to quantify scope 2 emissions at the firm level over an extensive sample period. However, we also acknowledge there are two concerns arise using this measure: 1) we cannot differentiate renewable energy sources. Nonetheless, data from the IEA indicate that coal, oil, and gas collectively constitute over half of the total energy supply in 2022, as depicted in Figure C.5. 2) we cannot access direct greenhouse gas (GHG) emissions (scope 1 emissions) at the firm level. Consequently, we include on scope 1 emissions at the industry level in our refinement.[20]

Next, we normalize these emissions by the firm-level value added to account for differences in firm size.[21] Specifically, the emission intensity for firm i in industry j at time t is calculated

[19] The variable is named "KENE" in the FIRE register. Notice that it excludes fuel expenses for registered motor vehicles used for external transport and deductible energy taxes. The amount is documented in 1,000 DKK. Further details on the KENE variable can be accessed at `https://www.dst.dk/extranet/staticsites/TIMES3/html/ca145bb4-4483-4607-9e60-57af2fb4c8b2.htm`.

[20] Scope 1 emissions refer to emissions directly owned or controlled by the company, such as fuel combustion in factories. Scope 2 emissions include emissions indirectly caused by companies through energy purchases, such as electricity generation. Scope 3 emissions include indirect emissions produced throughout the reporting company's value chain, encompassing both upstream and downstream emissions.

[21] This is captured by the variable GF_VTV in the FIRM register. Further information can be accessed at `https://www.dst.dk/da/TilSalg/Forskningsservice/Dokumentation/hoejkvalitetsvariable/firmastatistik/gf-vtv`.

as follows:

$$Emission\ intensity_{ijt} = \frac{Energy\ consumption_{ijt}}{Value\ added_{ijt}}$$

Here, all monetary values are adjusted using the GDP deflator, with 2015 as the base year. Consequently, emission intensity measures a firm's total energy consumption scaled by its value added for each year. We aggregate the mean emission intensity at the industry level and depict the distribution of emission intensity across industries in 2019, as illustrated in Figure C.4. Notably, the manufacturing and transport sectors exhibit significantly higher emission intensities, while the information, communication, and technical service sectors display relatively lower emission intensities.

To measure a climate-related policy stringency, we then use annual public environment-related tax at a 2-digit sector level from StatBank Denmark as a proxy.[22] This measure reflects industry-specific real costs or risks linked to the environment.[23] We acknowledge the challenge that transition risks are also associated with future climate policies, making them hard to measure, especially due to their dependence on specific climate scenarios. Nevertheless, our measure capture those industries that pay higher environmental policy-related costs over time and assume those are likely confront greater policy risks in the future. To address the issue of some industries being larger and contribute to higher environmental tax, we adjust the total environmental tax for each industry by its value added. This helps to balance out differences in industry size and tax revenue generation.

Specifically, $Enviromental\ tax_{jt}$ is calculated as:

$$Enviromental\ tax_{jt} = \frac{Total\ environmental\ tax_{jt}}{Value\ added_{jt}}$$

for firm i, industry j, year t. The distribution of environmental tax data across industries in 2019 is depicted in Figure C.6. Notably, the transport, electricity, and construction sectors exhibit comparatively higher environmental tax costs compared to other industries. In the robustness check, we also explore alternative measures for policy stringency, including changes in past climate policies within Denmark and the EU, as well as an index measure of climate policy uncertainties. However, since the environmental tax data offers more detailed variations at both the industry and year levels, we utilize it as our baseline analysis.

[22]The detailed database can be found at https://www.statbank.dk/statbank5a/SelectVarVal/Define.asp?MainTable=MRS1&PLanguage=1&PXSId=0&wsid=cftree

[23]We acknowledge that environmental policies do not perfectly reflect climate change mitigation policies. However, environmental taxes are an essential policy tool to curb emissions. By using environmental taxes as a measure of policy stringency, we can evaluate the environmental policy-related costs imposed on each industry over time.

As a result, the main proxy for firms' exposure to transition risks for each firm i in the industry j at time t is $\textit{Transition risks}_{ijt}$, which an interaction term between firm-level emission intensity $\textit{Emission intensity}_{ijt}$ and industry-level energy tax $\textit{Enviromental tax}_{jt}$, in order to capture firms' vulnerability to the increasing stringency of climate-related policies targeted at firms that are more emission-intensive. Specifically, $\textit{Transition risks}_{ijt}$ is calculated as:

$$\textit{Transition risks}_{ijt} = \textit{Emission intensity}_{ijt} \times \textit{Enviromental tax}_{jt}$$

for firm i, industry j, year t.

5 Empirical Strategy and Identification

5.1 Empirical specification and identification

In this section, we provide the main empirical specification and identification strategy to investigate the effects of physical and transition risks on bank credit supply. On the one hand, the main identification strategy to tease out the impact of physical risks on bank lending is based on the assumption that the occurrence of abnormal extreme precipitation variations and projected flood risks within narrowly defined geographic units over time is largely driven by nature and largely exogenous (Dell et al., 2014). On the other hand, transition risks, measured as the interaction of firms' emission intensity and exposure to future climate policy risks proxies by incurred environmental taxes, are firm-specific and less exogenous to the lending outcomes. We include a comprehensive set of firm and bank-level confounding factors that control for credit supply and demand and granular fixed effects to account for potential unobserved trends and factors, such as industry-year, bank-year, and bank-firm unobserved trends and characters. By controlling for these variables, we can more carefully examine the effects of transition risks on credit outcomes.

We analyze both the intensive and extensive margins of the credit outcomes, primarily using OLS regression models (linear probability models for the extensive margins). Since credit outcomes are measured annually, we lag all climate risk variables by one year. This accounts for the possibility that extreme events and environmental tax changes may occur late in the year, and credit decisions typically experience substantial lags. We also consider firm and bank-level controls, such as size, profit, etc., all lagged by one year for the same reason to avoid reverse causality. Standard errors are clustered at the firm level to account for potential serial correlation within the same firm, and the results are robust to other clustering levels, including at both the firm and bank levels (multi-way clustering), where we allow correlations within both firm and bank. Control variables, summarized in Table A1, generally have expected effects and vary in statistical significance, which is unsurprising given that different specifications include different sets of fixed effects. We report the main variables of interest for brevity in the main analysis.

The dependent variable measures both the intensive and extensive margins. 1) intensive margins: the loan growth rate of firm i received from bank b in a given year t, conditional on firm bank relations being present in both prior and current year, for the intensive margins. This refers to the changes in the volume or amount of loan balance. To incorporate the 0 in the loan outstanding balance, we calculate the growth rate as

$$\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$$

2) extensive margins: new loans indicator, which is a 0/1 dummy variable indicating whether a given firm i received new loans from a given bank b in a given year, conditional on firm bank relations being present in both prior and current year. It is calculated as 1 when the loan growth rate is positive, implying whether a firm gets any new credit at all, as opposed to how much credit it gets.

As discussed, physical risks are aggregated at the parish-time level, while transition risks are measured at the firm-time level, we include different sets of controls and a comprehensive set of fixed effects to tease out the effects of physical and transition risks. As a result, the source of identification varies depending on the set of fixed effects and controls we included. For illustration purposes, we carefully write out each specification and discuss how we gauge the effects of climate risks in each empirical specification in the following section. We start with parsimonious specification, where only the physical and transition risks variables and firm, bank, and time-fixed effects are included.

The regression for the main effects of physical risks and transition risks are as follows:

$$Lending_{ibt} = \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + \alpha_i + \alpha_b + \alpha_t + \epsilon_{ibt} \tag{1}$$

where dependent variable $Lending_{ibt}$, is either the loan growth between year t-1 and t for a firm i from bank b, as a measure of the intensive margin of credit supply, or extensive margin equivalent, calculated as a dummy equal to 1 if the loan growth rate is positive. This measure can be interpreted as the likelihood of the firm i getting access to new loans from firm b in a given year t.

The primary independent variables are denoted as $Physical\ risks_{pt-1}$ and $Transition\ risks_{it-1}$. The first variable is a proxy for physical risks that varies by parish and time, which captures the exposure of extreme precipitation and flood risks, while the second one measures firms' vulnerability to climate regulatory risks, as described in Section 4.2, varying by firm and time. As both physical risks and transition risks are measured on different scales, we standardize climate risk variables in the regressions for a meaningful comparison of their relative magnitudes and impacts, despite the differences in their scales and units.

In the simple specification above in Equation (1), we only include the most essential fixed effects α_i, α_b, and α_t to absorb all common trends and fluctuations, time-invariant characteristics at firm and bank level. α_i is a vector of firm fixed effects that captures any unobservable firm-specific factors that are relatively stable over time, such as firm business model, culture, managerial quality, or risk appetite. Similarly, α_b is a vector of bank fixed effects that captures any unobservable bank-specific time-invariant characteristics such as bank risk appetite and culture. α_t is time-fixed effects that absorb all the time-varying trends or shocks to business cycles, for example, macroeconomic variables such as GDP, unemployment rate, inflation, or policy rate. Finally, ϵ_{ibt} is the idiosyncratic error term. Identification thus rests on exploiting two sources. Firstly, the credit differences within a given firm (borrower) with the change of exposure to climate risks over time borrowing from a given bank (lender), as shown in Figure C.8. The second source of identification relies on the differences between the high-climate-risk borrowers relative to the low-climate-risk borrowers borrowing from a given bank in a given year, as shown in Figure C.9. Thus, the main coefficients of interest β_1 and β_2, measure whether a bank is more or less likely to extend a loan (for extensive margin) or increase the loan amount (for intensive margin) to a firm with a change of exposure to climate risks over time, as well as for the credit differences of two comparable firms with different climate risks profile in a given year. The expected sign of β_1 and β_1 is not clear ex-ante, as there are both positive and negative forces that drive the bank and firm side, as explained in Section 3. A negative coefficient of β_1 and β_2 would indicate that an increase in a given firm's exposure to physical risks or transition risks over time or an increase in a firm's risk exposure relative to other firms is associated with lower credit outcomes. This is consistent with the divesting hypothesis H1A, which indicates that banks may perceive both physical and transition risks as additional costs/risks that may affect them through their client firms and divest from those firms. However, a positive or null coefficient will be consistent with the engagement or no adjustment hypothesis (H1B or H1C).

We then add firm-level and bank-level control variables to absorb those time-varying characters that capture firm credit demand and bank credit supply that might be correlated with climate risk variables as well as lending outcomes, as shown in Equation (2). Vector X_{it} denotes a set of firm-level variables that could have an impact on bank lending, such as firm size, leverage ratio, and ROA. The vector Z_{it} includes bank-level character variables such as bank size.

$$Lending_{ibt} = \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \alpha_i + \alpha_b + \alpha_t + \epsilon_{ibt} \tag{2}$$

In order to incorporate the unobserved geographic-specific features that are stable over time, such as productivity and firm size differences across locations, which may affect credit allocation and bias the estimation, we add location (parish) fixed effects. Parish fixed effect also helps to address the endogeneity caused by firms that might anticipate that some areas are likely to be exposed to higher physical risks, e.g., areas close to the sea, and avoid building factories in those areas or relocating from the high to low-risk zones. The identification thus comes from the evolution of lending from a given bank b to a given firm i in the same location p over time.

$$\begin{aligned} Lending_{ibt} = {} & \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \alpha_i + \alpha_b + \alpha_t + \\ & \alpha_p + \epsilon_{ibt} \end{aligned} \tag{3}$$

Similarly, we further saturate the model by adding industry-fixed effects α_i to account for time-invariant industry-specific industry characters that may be correlated with both climate risk factors and credit outcomes. This also addresses the endogeneity concerns raised by firms that move out from the brown into relatively clean industries. Therefore, the expected magnitude of the coefficients is likely to be lower compared with Equation (2) as we control for firms that move in and out of industry and locations and only compare the credit allocation within location and industry. The identification relies on the evolution of lending from a given bank b to a given firm i in the same location p and same industry j over time. The identification here thus relies on the assumption that the change of the physical risks in a given location and transition risks in a given firm over time are more likely to be exogenous as it is more challenging to predict relative to the current level of physical or transition risks exposure. The empirical specifications are expressed below:

$$\begin{aligned} Lending_{ibt} = {} & \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \alpha_i + \alpha_b + \alpha_t + \\ & \alpha_p + \alpha_j + \epsilon_{ibt} \end{aligned} \tag{4}$$

We further advance the model by adding a host of high-dimensional fixed effects. To absorb any time-varying factors common to all firms in a particular industry, such as the industry business cycle, we include a matrix of 2-digit industry and time dummies. We also include bank-time fixed effects that control for credit supply and thus remove the bias that could result from these unobserved, bank-specific factors that vary over time, such as banks' financial health, internal policies regarding loan approval processes, changing regulatory environment, etc. Note that we could not add bank-level control variables Z'_{bt-1} in this case as they are absorbed by bank time fixed effects. Individual bank, industry, and time fixed effects are also absorbed by higher dimensional fixed effects. However, we cannot add parish-time fixed effects and firm-time fixed effects as they will absorb the variations of the main variables of our interests.

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + \alpha_i + \\ & \alpha_p + \alpha_{jt} + \alpha_{bt} + \epsilon_{ibt} \end{aligned} \tag{5}$$

Thanks to the granularity of the data, we can observe bank-firm lending relationships that allow us to incorporate firm-bank fixed effects to control for the endogenous matching between firm and bank that may affect credit allocation, e.g., relationship lending. This teases out the differences across different banks lending to the same firm in a given year and, therefore, biases the outcomes and ensures the identification relies on the same firm bank group. The identification thus comes from the differences in lending outcomes for the same firm and bank pair, while the borrower firm has a change in the exposure to climate risks over time, as shown in Figure C.8. In addition, adding bank-time and bank-firm fixed effects allows us to control the credit demand in the spirit of Khwaja and Mian (2008) and Jiménez et al. (2012). However, we cannot add firm-time fixed effects as this will absorb the variations in transition risks that are measured at the firm time level, but we include as much firm-level control as reasonable as possible to proxy for credit demand. We acknowledge that including many fixed effects could attenuate the estimated impacts of physical and transition risks. Hence, the estimated effects are the lower bounds of the impact.

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + \\ & \alpha_p + \alpha_{jt} + \alpha_{bt} + \alpha_{bf} + \epsilon_{ibt} \end{aligned} \tag{6}$$

5.2 Threats to identification

Despite our efforts to add a host of fixed effects and a comprehensive set of control variables to address the endogeneity concerns, other potential threats to identification can still arise.

One concern is that certain areas exhibit higher precipitation and volatility than others. Consequently, the same volume of precipitation in one place may appear normal and an anomaly in another, even if observed simultaneously. Therefore, firms may adapt their behavior to mitigate the adverse effects of extreme precipitation in advance through strategic location choices, infrastructure upgrades, building floodwalls, etc. However, our measure of extreme precipitation is calculated as the relative precipitation shocks based on the difference between a given daily precipitation value and the historical mean value observed in the same station and month, standardized by its volatility.[24] By construction, the variations in relative precipitation shocks come from within location variation. As a result, predicting and consequently adapting to future extreme precipitation deviations from the local historical mean is challenging. Therefore, one may expect that relative extreme precipitation will be more likely to shock both firms and banks and raise their attention to climate risks and less likely to be correlated with unobserved idiosyncratic factors that affect banks' lending decisions. With respect to the exposure to future flood risks, with the variation largely coming from across locations, we expect that firms are likely to adapt and mitigate the risks by relocating their factories away from high flood risk zones (e.g., some areas close to the coast) or avoiding building new offices in those areas, which could be correlated with banks' credit allocation. To eliminate this concern, we include the refinement where we exclude those firms that relocate in order to compare the credit outcomes for firms that stay in the same locations. In addition, we add location (parish) fixed effects in our specifications to control for any unobserved location-specific factors that affect banks' credit decisions. This also addresses the concerns that certain areas (e.g., capital city) are more productive than others as firms tend to concentrate geographically around those areas, which could be related to credit allocation.

Another concern is that our measure of transition risks varies from year to year and firm to firm, which are likely to be endogenous. One example is that firms with high emission intensity might seek to reduce emissions by investing in green projects after receiving bank loans, which may bias the estimation. To reduce this reverse causality issue in the regression analysis, we include a refinement where we measure transition risks with a base-year approach, i.e., measuring emission intensity in the first year in which a firm in the sample is

[24] By construction, we allow for different precipitation distributions for a given station each month.

observed. Specifically, transition risks are measured as: *Transition risks*$_{ijt}$ is calculated as:

$$\textit{Transition risks}_{ijt} = \textit{Emission intensity}_{ij0} \times \textit{Enviromental tax}_{jt}$$

for firm i, industry j, year t.

6 Empirical Results

6.1 Main results

6.1.1 Intensive margin of lending

The main estimation results for the effects of physical and transition risks on the intensive margins of the lending, i.e., the loan growth rate in percentage points, are reported in Table 1. Only the estimated coefficients for physical and transition risks are reported for brevity. We begin by estimating a parsimonious model in Equation (1), then gradually building towards more saturated specifications as shown from Equation (2) to Equation (6).

In column 1 of Table 1, we estimate a simple model where we only include a set of dummy variables, namely firm, bank, and year dummies, which allows us to control for the most important unobserved time-invariant common factors and trends at firm and bank level, such as firm-specific heterogeneity, and bank-specific heterogeneity that affects credit demand and supply, as well as time trends such as business. The estimates reported in column 1 highlight two main findings. First, on average, higher physical risks are associated with lower credit growth. Banks significantly allocate fewer credits to those firms located in high-physical-risk zones than they do in low-physical-risk zones in the same year. In addition, banks reallocate credits away from those firms located in areas with increasing physical risks over time. The coefficient of -1.368 indicates that a one standard deviation increase in the physical risk of a firm's location—given that the mean and standard deviation of physical risk are 0.99 and 1.162 respectively (see Table A1), which implies that if the mean average goes from 0.99 to 2.152 (0.99+1.162=2.152) - results in about 1.4 percentage points reduction in credit growth in terms of absolute change. This reduction per standard deviation change of physical risks represents a 10% change relative to the sample mean loan growth (-1.4%/-14%)= 10%), which represents a sizable reallocation of lending relative to the sample mean. However, in terms of standard deviation change of loan growth, this reduction represents only about 0.1 (=(-1.4-(-14))/117=0.1) standard deviation away from the sample mean of loan growth, indicating a mild effect relative to the overall variability.

Second, higher firm-specific transition risks are also related to lower credit growth. An increase in the same firm's exposure to transition risks over time or an increase in a firm's transition risk exposure relative to other firms in the same year is associated with lower credit growth. The magnitude of the measured coefficient suggests that if a firm's transition risks exposure increases by one standard deviation over time or compared with another comparable firm, which implies a considerable jump from an average of 28.72 to 191.038 (28.72+ 162.32 = 191.038), the credit growth of the firm received from banks reduce by about 2.2 percentage points. This is about 0.1 (=(-2.2-(-14))/117 = 0.1) standard deviation from the sample mean of loan growth, which indicates while there is a measurable impact of transition risks, the effect is yet relatively modest.

We then advance the model with important control variables for firms and banks to absorb those time-varying confounding factors that affect both credit outcomes and climate risks in column 2. We further saturate the model with parish fixed effects to account for the unobserved geographic-specific features in column 3 and industry fixed effects to absorb time-invariant unobserved industry-specific trends in column 4. In column 5, we include high-dimensional fixed effects to absorb any time-varying factors common to all firms in a particular industry (industry-time fixed effects) and any time-varying shocks to bank credit supply (bank-time fixed effects). Lastly, we add granular firm-bank fixed effects to address the endogenous matching between firm and bank and the effect of existing relationships between firms and banks in column 6. As we saturate the model with more restrictions, the estimated coefficients β_1 and β_2 overall decline, but the coefficients remain negative and significant. Overall, our evidence indicates that increased physical and transition risks are linked to reduced credit growth. However, the observed effect is relatively modest relative to the sample mean of loan growth, given the substantial variability.

Table 1: Climate Risks and Loan Growth (Intensive Margin)

	Loan Growth					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Physical Risks	-1.368***	-1.483***	-1.274***	-1.276***	-1.283***	-1.143**
	(0.489)	(0.490)	(0.491)	(0.491)	(0.489)	(0.540)
Transition Risks	-2.208***	-2.203***	-2.100***	-2.146***	-1.783***	-1.632***
	(0.598)	(0.574)	(0.547)	(0.562)	(0.441)	(0.427)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Time Fixed Effects	Yes	Yes	Yes	Yes		
Bank Fixed Effects	Yes	Yes	Yes	Yes		
Parish Fixed Effects			Yes	Yes	Yes	Yes
2-digit Industry Fixed Effects				Yes		
2-digit Industry-Time Fixed Effects					Yes	Yes
Bank-Time Fixed Effects					Yes	Yes
Bank-Firm Fixed Effected						Yes
Firm Variables		Yes	Yes	Yes	Yes	Yes
Bank Variables		Yes	Yes	Yes	Yes	Yes
Mean Y	-14.078	-14.069	-14.137	-14.141	-14.130	-11.318
R-sq	0.086	0.087	0.097	0.097	0.123	0.190
N	189,200	189,142	187,764	187,760	187,700	179,374

Notes: The table presents the estimation results for the effects of physical and transition risks on loan growth from OLS regressions. The dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, conditional on firm bank relations being present in both prior and current year, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$. The main independent variables are physical risks indicators and transition risk indicators. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

6.1.2 Extensive margin of lending

We present the estimation results for the extensive margin, defined as the probability of receiving new loans, in Table 2. New loans are represented by a dummy variable set to 1 if the loan growth rate is positive, indicating the likelihood of firm i receiving new credit from bank b in a given year t. Similar to the loan growth rate analysis, we begin with a simple model shown in column 1 (Equation (1)), then include additional controls in column 2 (Equation (2)), and incorporate granular fixed effects from column 3 to column 6, as specified from Equation (3) to Equation (6).

The estimates reported in Table 2 indicate that only higher physical risks are related to a lower likelihood of receiving new credits, but the results are not significant anymore after adding granular firm-bank fixed effects. This shift indicates that the observed relationship is likely to be confounded by other factors specific to the firm-bank relationship, such as historical lending behavior, the quality, and history of the firm's relationship with a particular bank, which is more influential in the decision to extend credit than the physical risks alone. Additionally, although the coefficients for transition risks are negative, they are not significantly associated with the probability of the firm receiving new credits in any of the specifications. This suggests that banks may not necessarily cut off initial credit and stop lending loans regardless of increased transition risk. That could be due to relationship lending, i.e., they might prioritize maintaining existing relationships with firms by offering new loans, regardless of their climate risk exposure. Instead, they could regulate the growth of the credit, as shown in Table 1, or ask for more collateral, set stricter lending terms, or adjust the interest rate to manage overall climate risk exposure.

All in all, we find evidence indicating that physical and transition risks impact lending primarily on the intensive margin rather than the extensive margin. Specifically, firms facing increased physical or transition risks over time experience reduced credit growth, suggesting that banks are cutting the growth of credit extended to these firms due to perceived or actual increases in risk. However, this effect is relatively modest. On the extensive margin, the evidence is limited. Overall, this implies that banks are more likely to adjust the amount of credit they extend rather than their decision to provide credit altogether. Our findings modestly support the divesting hypothesis H1A, which suggests that banks divest from firms with high exposure to physical or transition risks.

Table 2: Climate Risks and New Loans (Extensive Margin)

	New Loans					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Physical Risks	-0.004**	-0.005**	-0.004**	-0.004**	-0.003*	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Transition Risks	-0.001	-0.001	-0.001	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Time Fixed Effects	Yes	Yes	Yes	Yes		
Bank Fixed Effects	Yes	Yes	Yes	Yes		
Parish Fixed Effects			Yes	Yes	Yes	Yes
2-digit Industry Fixed Effects				Yes		
2-digit Industry-Time Fixed Effects					Yes	Yes
Bank-Time Fixed Effects					Yes	Yes
Bank-Firm Fixed Effected						Yes
Firm Variables		Yes	Yes	Yes	Yes	Yes
Bank Variables		Yes	Yes	Yes		
Mean Y	0.390	0.390	0.390	0.390	0.390	0.390
R-sq	0.139	0.141	0.148	0.148	0.171	0.265
N	209,659	209,659	209,659	209,659	209,659	209,659

Notes: The table presents the estimation results for the effects of physical and transition risks on new loan initiation from OLS regressions (linear probability model). The dependent variable is a new loans indicator, which is a 0/1 dummy variable indicating whether a given firm i received new loans from a given bank b in a given year. It is calculated as 1 when the loan growth rate is positive, implying whether a firm gets any new credit at all, as opposed to how much credit it gets. The main independent variables are physical risk indicators and transition risk indicators. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

6.1.3 Other outcomes: firm-bank relationships and interest rates

We further explore other outcomes of bank lending, including how banks may adjust firm-bank relationships and interest rates as a response to firms' exposure to physical risks and transition risks, as shown in Table 3. We comprehensively incorporate fixed effects into the model, including firm, parish, industry-time, and bank-time fixed effects, as presented in Equation (5). First, we investigate the effects of entering into new relationships in column 1, where ”enter” is a dummy variable set to 1 if a firm and bank establish a relationship for the first time. Similarly, in column 2, "exit" is a dummy variable set to 1 if a previously existing firm-bank relationship discontinues. The evidence shows that banks are cautious about entering into new relationships with firms exposed to high transition risks. Additionally, if the physical risk associated with existing clients becomes too significant, banks may choose to exit those relationships. At first glance, this might appear to be contrary to the previous findings, where we find banks continue lending to existing clients despite the heightened risk, likely to maintain existing relationships due to the value of the established relationship and the information advantage they possess. However, this analysis focuses on forming new relationships and suggests that banks are more cautious when it comes to initiating new relationships or continuing with firms where the risks have become too high.

We then proceed by evaluating the price of the loans in column 3. To calculate the interest rate, we acknowledge that one limitation is that loan maturity and the contractual interest rate are not systematically reported as they are not tax-relevant variables in the credit data. As a result, following Jensen and Johannesen (2017), we calculate the effective interest rate for a firm i borrowing from bank b in year t as $Interest\ rate_{ibt} = \frac{Interest\ payment_{ibt}}{0.5(Loans_{ibt}+Loans_{ib,t-1})} \times 100$. It is essentially calculated as the sum of interest payments made in year t divided by the average outstanding loan balance at the end of the current and previous years, where the implicit assumption is that loan balances evolve linearly over the year. Nevertheless, it captures the average rate a firm pays on its outstanding loans over a given period and offers a measure of the accrued cost of loans. Column 3 shows that the cost of loans does not significantly exhibit a direct correlation with physical and transition risks despite the estimated sign being positive. This finding suggests while banks may be cautious in forming new relationships, this does not seem to be incorporated in adjusting the pricing of existing loans.

Table 3: Climate Risks and Bank Lending: Relationship Lending and Interest Rate

	Enter (1)	**Exit** (2)	**Interest Rate** (3)
Physical Risks	0.000	0.003**	0.003
	(0.001)	(0.001)	(0.018)
Transition Risks	-0.001***	0.000	0.008
	0.000	(0.001)	(0.012)
Firm Fixed Effects	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes
Mean Y	0.215	0.217	4.754
R-sq	0.510	0.493	0.437
N	305,194	305,194	188,147

Notes: The table presents the estimation results for the effects of physical and transition risks on relationship changes and interest rate from OLS regressions. We comprehensively incorporate fixed effects into the model, including firm, parish, industry-time, and bank-time fixed effects, as presented in Equation (5). In column 1, the dependent variable is a dummy variable "enter" set to 1 if a firm and bank establish a relationship for the first time. In column 2, "exit" is a dummy variable set to 1 if a previously existing firm-bank relationship discontinues. The dependent variable in column 3 is the effective interest rate, calculated as $Interest\ rate_{ibt} = \frac{Interest\ payment_{ibt}}{0.5(Loans_{ibt}+Loans_{ib,t-1})} \times 100$, which measures the average rate a firm pays on its outstanding loans over a given period. The main independent variables are physical risk indicators and transition risk indicators. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

6.1.4 Alternative tests

In the appendix, we present several alternative tests. In Table A2, we use different measures of loan growth: column 1 utilizes the log of the loan amount ($\log(loan_{ibt})$), and column 2 employs the log difference of the loan amount in percentage points, calculated as $\log(loan_{ibt})-\log(loan_{ibt-1})\times 100$. Due to the presence of zero values in the loan account balances, taking the logarithm results in these observations being treated as missing data, reducing the number of observations in the estimation. In column 3, we focus on positive loan growth, setting negative loan growth to zero. This adjustment addresses the concern that our baseline measure of loan growth captures both the amount of the new loan origination and the repayment speed of existing loans, leading to both positive and negative growth, depending on the balance between these two components. While this comprehensive measure provides insights into how climate risks may impact both the amount of extending new loans and adjusting old loan repayments, we also consider the scenario where only positive loan growth is analyzed, effectively ignoring the existing loan repayment. The results indicate that most of the point estimates for β_1 and β_2 remain negative, although some estimates show a loss of significance.

6.2 Response to the tail of physical and transition risks

As the impacts of climate risks are primarily related to the extreme ends of the risk distribution—often referred to as the "tail risks"—rather than the average modest risks, we, therefore, proceed by focusing on these tails rather than the whole distribution. Since banks may prioritize managing tail risks, they are likely to be more responsive to firms that exhibit extremely high-risk profiles and reallocate credits away from those firms into low-risk firms. Specifically, we focus on both the left-hand tail (extreme low values) and the right-hand tail (extreme high values) of the risk distribution for physical and transition risks. We define a high physical risk dummy variable (High PR) and a high transition risk dummy variable (High TR). These dummy variables are set to 1 if the respective risk indicator for physical or transition risks falls into the top 75th quantile of the distribution in a given year. The low physical risk dummy variable (Low PR) and low transition risk dummy variable (Low TR) are then defined as 1 if the risk falls into the bottom 25th quantile of the distribution in a given year. We then investigate how banks respond to the tail risks and decompose the credit allocation among different groups using the following specifications:

$$\begin{aligned} Lending_{ibt} = & \boldsymbol{\beta_1} High\ PR_{it-1} + \boldsymbol{\beta_2} High\ TR_{it-1} + \boldsymbol{\beta_3} Low\ PR_{it-1} + \boldsymbol{\beta_4} Low\ TR_{it-1} \\ & + X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + FEs + \epsilon_{ibt} \end{aligned}$$

for firm i, bank b, year t, and parish p.

The estimated results for the model above are presented in Table 4. In columns 1-2, the dependent variable is the loan growth in percentage points as intensive margin, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$. The dependent variable in columns 3-4 measures the extensive margin, which is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. The signs of the point estimates for the high physical risk (PR) dummy and high transition risk (TR) dummy are negative, whereas those for low PR and high TR are positive. This pattern suggests a reallocation of credit away from firms with extremely high-risk profiles towards those with lower-risk profiles, compared to firms with medium-risk exposure, both at intensive and extensive margins. However, it should be noted that the magnitude of these effects is relatively modest.

Table 4: Climate Risks and Lending: Response to the Tail Risks

	Loan Growth		**New Loans**	
	(1)	**(2)**	**(3)**	**(4)**
High PR	-1.401*	-1.583*	-0.005	-0.005
	(0.846)	(0.855)	(0.003)	(0.003)
High TR	-3.094***	-2.713***	-0.007*	-0.008**
	(0.994)	(1.018)	(0.004)	(0.004)
Low PR	2.210***	1.860**	0.009***	0.008**
	(0.773)	(0.785)	(0.003)	(0.003)
Low TR	0.057	0.106	-0.001	0.001
	(1.162)	(1.218)	(0.004)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes		Yes	
Bank Fixed Effects	Yes		Yes	
Parish Fixed Effects		Yes		Yes
2-digit Industry Fixed Effects				
2-digit Industry-Time Fixed Effects		Yes		Yes
Bank-Time Fixed Effects		Yes		Yes
Firm Variables	Yes	Yes	Yes	Yes
Bank Variables	Yes		Yes	
Mean Y	-14.069	-14.130	0.383	0.383
R-sq	0.087	0.123	0.140	0.171
N	189,142	187,700	220,890	219,167

Notes: The table presents the estimation results for banks' lending response to the tail physical and transition risks from OLS regressions, with extreme risks defined based on a moving distribution. In columns 1-2, the dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$. The dependent variable in columns 3-4 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. High PR and Low TR are set to 1 if the respective risk indicator for physical or transition risks falls into the top 75th quantile of the distribution *in a given year*. Low PR and Low TR are then defined as one if the risk falls into the bottom 25th quantile of the distribution *in a given year*. The main independent variables are the four dummies, indicating the extremely high and low physical and transition risks. All RHS variables are lagged by one year. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

The analysis above assumes that the climate risk distribution shifts over time and uses a moving threshold to define extreme values across time. We also use a fixed threshold based on the risk distribution for the entire sample to define extreme values, assuming that the distribution is stable over the sample period. The results are robust to this alternative definition, as shown in Table A4.

6.3 The role of interactions of physical and transition risks

Physical and transition risks are often intertwined or interact with one another in complex ways (ECB, 2021b). This interaction can occur because, for example, increasing physical risks, such as those associated with extreme weather events, can trigger more stringent policies and, therefore, higher transition risks. In the previous section, we found that both physical and transition risks affect lending, primarily on the intensive margin, with limited evidence on the extensive margin. Physical risks, such as those from natural disasters and extreme weather, are mostly location-dependent, while transition risks are industry or firm-specific. Consequently, firms may face varying degrees of exposure depending on their geographic location or industry sector. The combination of the high (low) physical risks and transition risks exposure can be plotted into a 2×2 matrix, as shown in Figure C.10. Some firms may concurrently face both types of risks, such as companies operating in emission-intensive industries while also being located in regions prone to flooding or other physical hazards. This interaction of high physical and transition risks presents a compounded challenge for these dual-risk firms. Banks might, therefore, exercise greater caution in extending credit to these firms, curbing loan growth, or posing tighter lending conditions as those firms carry a higher overall risk profile, and banks tend to minimize exposure to the compounding of risks (Dunz et al., 2023).

To further investigate how banks respond to the interaction of the high (low) physical risks and transition risks exposure and reallocate credits among different groups, we estimate the following specifications:

$$\begin{aligned} Lending_{ibt} = &\boldsymbol{\beta_1} Low\ PR_{it-1} \times Low\ TR_{it-1} + \boldsymbol{\beta_2} High\ PR_{it-1} \times Low\ TR_{it-1} + \boldsymbol{\beta_3} Low\ PR_{it-1} \\ &\times High\ TR_{it-1} + \boldsymbol{\beta_4} High\ PR_{it-1} \times High\ TR_{it-1} + X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + FEs + \epsilon_{ibt} \end{aligned}$$

for firm i, bank b, year t, and parish p.

The main variables of interest in our analysis are the four interaction dummies that capture the combined effects of high (low) physical and transition risks, as defined in Section 6.2. These interaction effects are represented by the coefficients β_1 through β_4. According to Table A3, the positive estimated coefficients for β_1, specifically for the interaction term $Low\ PRit-1 \times Low\ TRit-1$, across columns 1 to 4, suggest a slight positive credit reallocation towards firms with extremely low compounded risks. For firms with dual high-risk exposures, we observe a negative impact on credit growth and the initiation of new loans, although these findings are not statistically significant. This indicates a nuanced response from banks, which appear to slightly favor firms with lower combined risks while not significantly altering their credit policies towards high-risk firms.

6.4 Heterogeneity analysis

We then proceed with the heterogeneity section and ask what factors might amplify the effect of physical and transition risks on lending patterns. Identifying these would also help us understand how different characteristics influence the sensitivity of banks to climate-related risks and shed light on some microeconomic mechanisms that could plausibly be behind the observed reallocation of credits, as we outlined in Section 3.

Firm size We begin by examining the heterogeneous effects across different firm sizes. As smaller firms are more informational opaqued, risky, and more likely to be financially constrained (Hadlock and Pierce, 2010). It is natural to hypothesize that small-sized firms may be more negatively affected when banks decide on the direction of relocating credits. To test this, we categorize firms into small, medium, and large groups, with large firms defined as having more than 250 full-time equivalent workers and small firms as those with fewer than 20 employees. We present a modified version of Equation (2), which includes a triple interaction with size dummy variables, as well as the relevant double interactions. As shown in column 1 of the estimation results in Table A6, small firms appear particularly sensitive to physical risks and the combined effect of physical and transition risks. In contrast, large firms exhibit a nuanced positive response in loan growth to increased physical risks, as shown in column 5. These results are robust across various model specifications, including different controls and fixed effects.

Financial leverage Firms with high leverage are likely to face more significant financial constraints and risk profiles, which can then influence bank lending decisions (Jiménez et al., 2014; Laeven and Popov, 2023). In light of this, we examine the role of financial leverage in the observed reallocation of credits in response to heightened climate physical and transition risks. To address this, we present findings in Columns 1 and 2 of Table A7, where we incorporate this factor into our analysis by augmenting the model from Equation (2). Specifically, we include a triple interaction term that combines a dummy variable for high financial leverage with the key variables of interest alongside the double interaction terms. The significant negative coefficient for the interaction between physical risks and high leverage dummy in columns 1 and 2 indicates that highly leveraged firms experience a more pronounced reduction in loan growth and new loans when exposed to physical risks. Banks appear to be more restrictive in lending to highly leveraged firms facing physical risks, perhaps due to their lack of financial cushion and lower financial flexibility to absorb adverse shocks related to climate disasters. Furthermore, banks are more concerned when financial risks and physical and transition risks are compounded, as indicated by a significant negative coefficient for the triple interaction.

Capital intensity Capital intensity plays different roles in affecting the bank lending decision. On the one hand, those firms with high capital intensity have significant investments in physical assets, which may be directly affected by climate-related physical risks (e.g., damage from extreme weather and flooding). On the other hand, firms with high capital intensity may have more assets that can serve as collateral, potentially providing a buffer against risks. To test the role of capital intensity, we include a triple interaction term that combines a dummy variable for high capital intensity, which is 1 if the share of fixed assets as a fraction of total assets is above 50% quantiles, with the physical and transition risks variables, alongside the double interaction terms. The evidence presented in columns 3 and 4 of Table A7 indicates that banks are likely to reduce lending growth and less likely to initiate new loans to those high capital-intensive firms exposed to high physical risks. The evidence is concerned with the notion that banks are more concerned about the direct exposure of tangible assets, i.e., machines and factories, to physical risks. Given that capital intensity varies significantly across industries, we also illustrate these variations in Figure C.11. It can be inferred that industries with fewer physical assets, like the information and communication sector, R&D sector, and wholesale, are generally less susceptible to disruptions from weather or natural disasters. In contrast, industries such as manufacturing and transport, which have a higher proportion of physical assets, are more vulnerable to climate shocks.

6.5 Mechanisms

Since the observed credit outcomes represent the equilibrium between bank lending and firm borrowing, we explore whether our results are primarily driven by supply-side or demand-side effects and examine the motivations behind these behaviors. On the demand side, firms facing high climate risks might request less credit from banks. Prior studies, such as those by Huang et al. (2018); Kacperczyk and Peydró (2022); Bolton et al. (2019), have shown that firms often deleverage and initiate divestment in response to uncertainties and external shocks, resulting in reduced credit demand. On the supply side, banks may choose to offer less credit to firms with high climate risks due to the increased perceived risk of default or other non-financial considerations. In our analysis, we acknowledge the inherent challenge of distinctly separating supply-side effects from demand-side factors, as discussed in the empirical banking literature (Khwaja and Mian, 2008; Jiménez et al., 2020; Degryse et al., 2019). Nonetheless, we endeavor to empirically examine both the demand and supply sides to have an understanding of the primary driver behind the observed credit outcomes.

6.5.1 Climate risks and credit demand

We begin by examining the effects of climate risks on lending outcomes for a subset of firms that exhibit positive credit demand. The rationale behind this approach is that if the negative effects of climate risks on loan growth persist even among firms with high credit demand, it would suggest that the demand effect is not the primary driver. Typically, The estimation results testing the credit demand channel are presented in Table 5. We re-estimate the baseline regression from Equation (5) using a different sample of firms that serve as proxies for positive credit demand. In columns 1-2, we focus on firms with positive investment growth and employment growth, using these metrics as proxies for growing firms. Column 3 includes firms with positive fixed asset growth as an indicator of funding needs for capital expenditure, and column 4 uses a sample of firms with positive sales growth to measure the demand for working capital. We acknowledge that an ample credit supply can stimulate firm growth and, in turn, create credit demand. Nevertheless, these proxies, such as sales growth, originate from the firm's internal activities and reflect a firm's inherent demand for resources and can, therefore, serve as indicators of credit demand. The evidence that negative effects persist among firms with substantial credit demand supports our hypothesis that these effects may primarily be attributed to the supply side rather than a lack of demand.

Table 5: Climate Risks and Credit Demand: Firms with Positive Credit Demand

	Loan Growth			
Included Sample	Positive Investment Growth	Positive Employment Growth	Positive Fixed Assets Growth	Positive Sale Growth
	(1)	**(2)**	**(3)**	**(4)**
Physical Risks	-1.596*	-0.156	-1.032	-1.562**
	(0.877)	(0.769)	(0.847)	(0.754)
Transition Risks	-2.597***	-1.056	-1.957**	-1.071
	(0.950)	(0.961)	(0.986)	(0.920)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes
Mean Y	-7.689	-7.721	-5.641	-10.947
R-sq	0.222	0.19	0.212	0.184
N	76,128	91,536	75,520	97,882

Notes: The table presents the estimation results for Equation (5) to test for the credit demand effect, conditional on those firms with positive credit demand. The dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times$ 100%, for the intensive margin. Firms with positive credit demands tend to be those experiencing growth and requiring substantial funding for capital expenditures or working capital. In columns 1-2, we focus on firms with positive investment and employment growth as proxies for growing firms. Column 3 includes firms with positive fixed asset growth as an indicator of funding needs for capital expenditure, while column 4 uses a sample of firms with positive sales growth to measure the demand for working capital. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

To examine whether climate risks directly impact firm growth and reduce investment demand, we conduct an auxiliary regression, as detailed in Equation (7). This regression analyzes the relationship between climate risk variables and a range of firm-level indicators that reflect credit demand. Specifically, we use investment growth and employment growth as proxies for credit demand from expanding firms. Additionally, we consider fixed asset growth as an indicator of funding needs for capital expenditure and sales growth as a measure of demand for working capital.

$$Credit\ Demand_{it} = \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + \alpha_i + \alpha_p + \alpha_{jt} + \epsilon_{it} \tag{7}$$

A significant negative coefficient would suggest that higher climate risks are associated with reduced credit demand, implying that credit demand factors could be driving the observed results. However, our analysis does not find evidence supporting this credit demand channel. The coefficients presented in columns 1 through 4 indicate that climate risks are not positively correlated with any of the firm-level proxies for credit demand. This lack of correlation further suggests that other factors, possibly related to supply-side constraints or banks' risk perceptions, may be more influential in the observed credit reallocation in the context of climate risks.

Table 6: Climate Risks and Credit Demand Proxies

	Investment Growth	**Employment Growth**	**Fixed Assets Growth**	**Sale Growth**
	(1)	**(2)**	**(3)**	**(4)**
Physical Risks	-1.529	0.003	0.001	-0.161
	(1.145)	(0.002)	(0.204)	(0.163)
Transition Risks	-0.242	0.000	0.012	-0.002
	(0.236)	(0.001)	(0.025)	(0.003)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes
Mean Y	1.525	0.305	1.878	0.305
R-sq	0.204	0.201	0.25	0.339
N	204,175	218,934	217,494	218,807

Notes: The table presents the estimation results for the climate risks variables and proxies for credit demand, as shown in Equation (7). Columns 1 and 2 use investment growth and employment growth as dependent variables, respectively, to serve as proxies for credit demand from expanding firms. The dependent variable in column 3 is fixed asset growth, as a measure of needs for capital expenditure, while column 4 uses sales growth to measure the demand for working capital. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 20l9. The detailed firm-level variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

6.5.2 Climate risks and credit supply

In our baseline analysis, as shown from Equation (2) to Equation (6), we incorporate several key firm-level control variables, such as firm size and Return on Assets (ROA), to account for variations in credit demand. Additionally, we include a comprehensive set of fixed effects, such as firm, industry-year, and firm-bank fixed effects, to control for unobserved characteristics that may influence credit demand, whether specific to the firm, the industry-year context, or the firm-bank relationship. However, one concern is that it may not fully capture all relevant unobserved credit demand factors. Given the detailed nature of our data, we can introduce even more granular, high-dimensional fixed effects to better proxy for local credit demand variations within a size group for specific industries and geographic locations, in the spirit of (Degryse et al., 2019). The underlying hypothesis is that firms of similar size, operating within the same industry and geographic location, are expected to exhibit comparable credit demands within a given year. By grouping firms with these common characteristics, we can reduce the variability in credit demand that is not related to supply-side factors. However, one caveat of using too many fixed effects is that it may also absorb significant variations of interest, so we estimate a lower bound. Nevertheless, we present the results in Table A8, where we saturate the model with Industry-Location-Size Fixed Effects (ILS) in column 1, Industry-Location-Time Fixed Effects (ILT) in column 2, and Industry-Location-Size-Time Fixed Effects (ILST) in column 3. The evidence indicates a robust negative relationship between transition risks and loan growth. As firms' exposure to transition risks increases, banks tend to reduce their lending, leading to lower loan growth, while the effects of physical risks disappear.

Credit risks channel So far, our empirical evidence appears to suggest that the observed outcomes are driven mainly by a shift in the credit supply from banks rather than a change in credit demand from firms in response to increasing climate risks. This further raises the question: why are banks supplying less credit to firms that are exposed to higher climate risks? To explore this issue, we consider several potential reasons. On the one hand, banks might consider the financial aspect and perceive higher climate risks as increasing the likelihood of defaults, leading to more cautious lending practices. On the other hand, non-financial factors, such as growing climate concerns among the public and pressure from activist shareholders, could also influence their lending decisions.

In the following section, we attempt to empirically test the financial insensitive (credit risks) channel by directly examining whether exposure to climate risks is associated with increased credit risk for firms. Specifically, we assess whether climate risks correlate with higher probabilities of firm default or bankruptcy, as well as a higher likelihood of being financially stressed. To measure actual default rates, we use a proxy based on firms' exits from the sample. This exit variable is a binary indicator that equals one if a firm exits the sample, thereby providing an upper bound estimate of default likelihood. Figure C.12 in the appendix details the number of firms that left the sample over the study period, highlighting a notable surge during the global financial crisis of 2007-2009, which aligns with expected economic stress periods. In Table 7, column 1 presents the results from regressing the exit variable on climate risk exposure. The coefficients are not statistically significant, suggesting that the effect of climate risks on firm default rates is not robustly established.

We also use additional proxies for a firm's credit risks. Column 2 uses a dummy variable indicating negative EBIT (Earnings Before Interest and Taxes) as a proxy for credit risk. A negative EBIT suggests higher financial difficulties, which may increase credit risk. Column 3 employs a dummy variable for high financial stress, defined as 1 if a firm has a low-interest coverage ratio (ICR).[25] The positive coefficients for transition risk in both columns 2 and 3 suggest firms exposed to higher transition risks are more likely to experience negative EBIT and high financial stress, which are perceived as having higher credit risks and are relevant in a bank's conventional credit risks assessment matrix.

Overall, our evidence suggests that the observed reduction in credit is likely to be driven by banks' responses to increasing climate risks, and this could be due to the financial consideration that banks perceived those firms exposed to high climate risks experience higher financial stress indicators and higher credit risks. Unfortunately, we cannot empirically evaluate non-financial incentives in this paper, as this would require data from surveys. Further research is therefore needed to explore banks' motivations in shifting their lending behaviors.

[25] The ICR, calculated as EBIT divided by interest expenses, measures a firm's ability to meet its interest obligations. A lower ICR indicates higher credit risk and financial stress.

Table 7: Climate Risks and Credit Risks Channel

	Exit	**Low EBIT**	**Financial Distress**
	(1)	**(2)**	**(3)**
Physical Risks	0.000	0.000	0.003
	(0.001)	(0.002)	(0.003)
Transition Risks	0.000	0.003*	0.002*
	0.000	(0.001)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes
Mean Y	0.017	0.220	0.489
R-sq	0.431	0.369	0.449
N	219,185	219,185	219,185

Notes: The table presents the estimation results to test for the credit risks channel. The dependent variable in column 1 is the firms' likelihood to exit the sample as a proxy for the probabilities of firm default or bankruptcy. The dependent variable in column 2 is a dummy indicating negative EBIT. The dependent variable in column 3 is a dummy for a high financial stress level, defined as 1 if a firm has a low-interest coverage ratio (ICR), calculated as EBIT divided by interest expenses to measure how well a firm can pay the interest due on outstanding debt. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

7 A Simple Model of Bank Portfolio Choice for Green and Brown Firm

Our findings overall support the divesting hypothesis H1A, which suggests that banks divest from firms with high exposure to physical or transition risks. To rationalize this empirical finding that banks allocate fewer credits and divest from firms exposed to high physical and transition risks due to financial and non-financial motivations, we present a simple partial equilibrium model that analyzes the optimal portfolio allocation for a bank that can lend to a green firm (lower exposure to physical risks, transition risks, or interaction of both risks) or a brown firm (higher exposure firms) or invest in a risk-free asset. As climate risks can affect both the mean return and volatility of the firm's profitability (Huang et al., 2018; Pham et al., 2023; Bonato et al., 2023), we assume that banks perceive that the green firm has a higher expected return and lower volatility than the brown firm. We also incorporate a green preference parameter for the bank's non-financial motives in prioritizing green investments

(Pedersen et al., 2021).

Specifically, we consider that a bank can adjust the weight/share of total loan lending to a green firm (w_g), a brown firm (w_g), and a risk-free asset (w_f), with the expected returns denoted as μ_g, μ_b, and r_f respectively. The volatility for green and brown firms is σ_g and σ_b, with ρ representing the correlation coefficient between the returns of the green and brown firms. We assume that $\mu_g > \mu_b$ while $\sigma_g < \sigma_b$. The bank's risk aversion parameter is denoted as λ, and α represents the green preference parameter, where a higher value of α indicates a stronger preference for the green firm (we assume $\alpha \geq 0$). Using a simple mean-variance framework, the bank's objective is to maximize the portfolio's expected return while minimizing risk and incorporating the preference for green investments. The utility function of the bank is given by:

$$U = \mathbf{w}^T \mu - \frac{\lambda}{2} \mathbf{w}^T \Sigma \mathbf{w} + \alpha w_g$$

s.t.

$$w_g + w_b + w_f = 1$$

$$w_g, w_b, w_f \geq 0$$

As shown in the proof Appendix A, we can then solve the closed-form solutions for the optional weight for allocating to green firm (w_g) and brown firm (w_b):

$$w_g = \frac{\sigma_b^2(\mu_g - r_f) - \rho\sigma_g\sigma_b(\mu_b - r_f) + \alpha\sigma_b^2}{\lambda(\sigma_g^2\sigma_b^2 - \rho^2\sigma_g^2\sigma_b^2)}$$

$$w_b = \frac{\sigma_g^2(\mu_b - r_f) - \rho\sigma_g\sigma_b(\mu_g - r_f)}{\lambda(\sigma_g^2\sigma_b^2 - \rho^2\sigma_g^2\sigma_b^2)}$$

To directly compare w_g and w_b, we calculate the difference $w_g - w_b$:

$$w_g - w_b = \frac{\sigma_b^2(\mu_g - r_f) - \sigma_g^2(\mu_b - r_f) + \alpha\sigma_b^2 + \rho\sigma_g\sigma_b(\mu_g - \mu_b)}{\lambda(\sigma_g^2\sigma_b^2 - \rho^2\sigma_g^2\sigma_b^2)}$$

Given the assumption that $\mu_g > \mu_b$, the weight allocated to the green firm (w_g) is higher than the weight allocated to the brown firm (w_b) as the term $\sigma_b^2(\mu_g - r_f)$ in the numerator of w_g increases the weight of the green firm more than the corresponding term $\sigma_g^2(\mu_b - r_f)$ in the numerator of w_b. Furthermore, given that green firms are perceived to have lower volatility ($\sigma_g < \sigma_b$), this further reduces the denominator $\lambda(\sigma_g^2\sigma_b^2 - \rho^2\sigma_g^2\sigma_b^2)$, and increase w_g. Lastly, the parameter α directly increases w_g, showing the bank's preference for green investments. As a result, the bank's optimal portfolio allocation will tilt a higher share of loans to green firms than to brown firms due to the financial attractiveness of the green firms from a risk and return perspective, as well as ethical preferences for sustainable investments.

8 Conclusion

Existing research on banking has highlighted that large global banks are beginning to consider physical and transition risks, typically through syndicated loans to large publicly listed firms (Meisenzahl, 2023; Faiella and Natoli, 2019a; Kacperczyk and Peydró, 2022; Reghezza et al., 2022). However, there is limited understanding of how smaller and regional banks adjust their lending practices, particularly concerning small and medium-sized enterprises (SMEs) and privately held firms. Furthermore, current studies often isolate the impacts of physical and transition risks despite their interconnected nature and potential for compounding effects.

In this paper, we examine whether and to what extent banks integrate both physical and transition risks, along with their interactions, into their lending decisions, using comprehensive firm-bank matched data from Denmark, which includes a diverse range of firms, with a particular focus on SMEs, and banks of varying sizes. We find evidence that banks are more likely to decrease the amount of credit they provide to high-exposure firms rather than stop lending to them completely. The overall effect on credit growth is modest, with limited evidence affecting the extensive margin. We also find a nuanced response to the interaction of physical and transition risks from banks, which seem to favor firms with slightly lower combined risks. We further explore the heterogeneity of observed credit allocation among different characters, summarized as follows: 1) smaller firms show heightened sensitivity to physical risks and the combined effect of physical and transition risks. 2) banks are more restrictive in lending to highly leveraged firms exposed to physical risks, likely due to these firms' limited financial buffer to absorb shocks from climate-related disasters. 3) banks are less inclined to increase lending growth or initiate new loans for high capital-intensive firms facing significant physical risks. Furthermore, we empirically examine both the credit demand and supply sides and find that the observed reduction in credit is likely to be driven by banks' reactions to rising climate risks, which can stem from financial considerations, as banks perceive firms facing high climate risks as experiencing greater financial stress and credit risks. Lastly, we use a simple model of bank portfolio choice to rationalize our empirical finding.

Our study contributes to the empirical sustainable banking literature by providing evidence for banks' response to climate risks based on a unique sample consisting of all firm-size and bank-size distribution, which allows us to assess how smaller banks adjust lending to smaller firms in response to climate risks. We also shed light on how banks incorporate both types of climate risks, physical and transition risks (and their interactions), providing a more complete evaluation of climate risks. Our results are consistent with the finding using global syndicating loans (Kacperczyk and Peydró, 2022; Mueller and Sfrappini, 2022), and respond to the concerns raised by policymakers regarding the potential financial stability issues imposed by climate risks (ECB, 2021b; Fed, 2021).

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APPENDIX

A Additional proof

To maximize the utility function subject to the constraints, we set up the Lagrangian function:

$$\mathcal{L} = w_g\mu_g + w_b\mu_b + (1 - w_g - w_b)r_f - \frac{\lambda}{2}\left(w_g^2\sigma_g^2 + w_b^2\sigma_b^2 + 2w_g w_b\rho\sigma_g\sigma_b\right) + \alpha w_g + \gamma(w_g + w_b + w_f - 1)$$

We can then solve for the optimal weights by taking the partial derivatives and differentiate $\mathcal{L}$ with respect to w_g, w_b, and γ.

$$\frac{\partial \mathcal{L}}{\partial w_g} = \mu_g - r_f - \lambda(w_g\sigma_g^2 + w_b\rho\sigma_g\sigma_b) + \alpha + \gamma = 0$$

$$\frac{\partial \mathcal{L}}{\partial w_b} = \mu_b - r_f - \lambda(w_b\sigma_b^2 + w_g\rho\sigma_g\sigma_b) + \gamma = 0$$

$$\frac{\partial \mathcal{L}}{\partial \gamma} = w_g + w_b + w_f - 1 = 0$$

Solving for the equations:
First, we can isolate γ:

$$\gamma = \lambda(w_g\sigma_g^2 + w_b\rho\sigma_g\sigma_b) - \mu_g + r_f - \alpha$$

$$\gamma = \lambda(w_b\sigma_b^2 + w_g\rho\sigma_g\sigma_b) - \mu_b + r_f$$

Equate the two expressions for γ:

$$\lambda(w_g\sigma_g^2 + w_b\rho\sigma_g\sigma_b) - \mu_g + r_f - \alpha = \lambda(w_b\sigma_b^2 + w_g\rho\sigma_g\sigma_b) - \mu_b + r_f$$

Simplify and solve for w_g and w_b:

$$\lambda w_g\sigma_g^2 + \lambda w_b\rho\sigma_g\sigma_b - \mu_g + r_f - \alpha = \lambda w_b\sigma_b^2 + \lambda w_g\rho\sigma_g\sigma_b - \mu_b + r_f$$

Rearranging terms:

$$\lambda w_g(\sigma_g^2 - \rho\sigma_g\sigma_b) = \lambda w_b(\sigma_b^2 - \rho\sigma_g\sigma_b) + \mu_g - \mu_b + \alpha$$

Isolate w_g:

$$w_g = \frac{\lambda w_b(\sigma_b^2 - \rho\sigma_g\sigma_b) + \mu_g - \mu_b + \alpha}{\lambda(\sigma_g^2 - \rho\sigma_g\sigma_b)}$$

Substitute w_g back into the budget constraint $w_g + w_b + w_f = 1$:

$$\frac{\lambda w_b(\sigma_b^2 - \rho\sigma_g\sigma_b) + \mu_g - \mu_b + \alpha}{\lambda(\sigma_g^2 - \rho\sigma_g\sigma_b)} + w_b + w_f = 1$$

After solving the above equation for w_g and w_b, we get the closed-form solutions:

$$w_g = \frac{\sigma_b^2(\mu_g - r_f) - \rho\sigma_g\sigma_b(\mu_b - r_f) + \alpha\sigma_b^2}{\lambda(\sigma_g^2\sigma_b^2 - \rho^2\sigma_g^2\sigma_b^2)}$$

$$w_b = \frac{\sigma_g^2(\mu_b - r_f) - \rho\sigma_g\sigma_b(\mu_g - r_f)}{\lambda(\sigma_g^2\sigma_b^2 - \rho^2\sigma_g^2\sigma_b^2)}$$

Table A1: Descriptive statistics

Variables	Definition	Mean	Sd
Loan variables			
Loan outstanding	Aggregate loan account balance at firm-bank-year level (billion dkk)	0.011	0.164
Loan growth	The annual growth rate of total loan outstanding	-10.939	115.196
New loans	A indicator for whether the loan outstanding increases	0.455	0.498
Climate risks variables			
Physical risks indicator	Geo-weighting indicator of the interaction term between flood and extreme precipitation with delta = 0.06	0.979	1.151
Energy consumption	Firm-level energy consumption at each year (million dkk)	0.003	0.053
Emissoin intensity	Firm-level emission intensity at each year, calculated as energy consumption scaled by firm value added	28.429	167.909
Environmental tax	Industry-level environmental tax expenditures each year (million dkk)	1.186	1.129
Environmental tax industry scaled	Industry-level environmental tax expenditures each year scaled by gross industry value added	0.028	0.029
Transition risks indicator	Interaction term between firm-level emission intensity and scaled environmental tax	0.852	4.512
Firm variables			
Revenue	Total revenue (million dkk)	333.983	1987.892
Profit	Total profit (million dkk)	0.024	0.473
Fixed assets	Fixed assets (million dkk)	0.191	1.914
Assets	Assets (million dkk)	0.333	2.776
Equity	Equity (million dkk)	144.773	1345.194
Size	Total number of employees	97.128	518.511
Multi-establishment	1, if the firm is a multi-establishment company	0.387	0.487
Firm age	Firm age	28.932	8.128
Bank variables			
Size	Total number of employees in the bank	3,663.55	4,106.16
Multi-establishment	1, if the bank is a multi-establishment company	0.032	0.021
Foreign	Foreign employees as a proportion off all employees in the bank		
Other variables			
Share of loans	Share of the loans a firm has in a bank relative to the total loans of the firm for each year	0.646	0.434
Number of linked banks	Number of banks a firm has connected to	2.163	1.194
Number of observations			170,387
Number of firms			16,597
Number of banks			97

Notes: All descriptive statistics are calculated as averages over the period 2004-2019. Accounting variables are in real Danish Kroner (using 2015 as the base year). 1 Danish krone is approximately 0.15 US Dollars

B Additional tables

Table A2: Climate Risks and Loan Growth: Alternative Measures of Loan Growth

	Log(loans)	**Logarithmic Growth**	**Positive Loan Growth**
	(1)	**(2)**	**(3)**
Physical Risks	-0.025*	-2.163**	-0.266
	(0.014)	(0.951)	(0.268)
Transition Risks	-0.010	-3.009**	-0.876***
	(0.011)	(1.284)	(0.223)
Firm Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes
2-digit Industry Fixed Effects	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes
Bank Variables	Yes	Yes	Yes
Mean Y	12.888	13.037	38.314
R-sq	0.565	0.089	0.155
N	162,871	150,699	187,760

Notes: The table presents the estimation results for the effects of physical and transition risks on alternative growth measures from OLS regressions. The dependent variable in column 1 is the log of loan amounts $log(loan_{ibt})$. In column 2, the dependent variable is the logarithmic growth of loans in percentage points, calculated as $log(loan_{ibt}) - log(loan_{ibt-1}) \times 100$. Due to the presence of zero values in the loan account balances, taking the logarithm results in these observations being treated as missing data, reducing the number of observations in the estimation. In column 3, we focus on positive loan growth, setting negative loan growth to zero. The main independent variables are physical risks indicators and transition risks indicators. All RHS variables are lagged by one year. All regressions include fixed effects as specified. The sample starts in 2003 and ends in 20l9. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A3: Climate Risks and Lending: Interactions of Physical and Transition Risks

	Loan Growth		New Loans	
	(1)	**(2)**	**(3)**	**(4)**
Low PR x Low TR	2.749*	2.741*	0.009*	0.009*
	(1.460)	(1.475)	(0.005)	(0.006)
High PR x Low TR	-2.133	-1.717	-0.003	0.000
	(1.599)	(1.635)	(0.006)	(0.006)
Low PR x High TR	1.713	1.369	0.009*	0.006
	(1.356)	(1.356)	(0.005)	(0.006)
High PR x High TR	-1.844	-1.464	-0.007	-0.006
	(1.413)	(1.412)	(0.006)	(0.006)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes		Yes	
Bank Fixed Effects	Yes		Yes	
Parish Fixed Effects		Yes		Yes
2-digit Industry Fixed Effects				
2-digit Industry-Time Fixed Effects		Yes		Yes
Bank-Time Fixed Effects		Yes		Yes
Firm Variables	Yes	Yes	Yes	Yes
Bank Variables	Yes		Yes	
Mean Y	-14.069	-14.130	0.383	0.383
R-sq	0.087	0.123	0.140	0.171
N	189,142	187,700	220,890	219,167

Notes: The table presents the estimation results for banks' lending response to high (low) physical risks and transition risks exposure from OLS regressions, with extreme risks defined based on a moving distribution over time. In columns 1-2, the dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt}-loan_{ibt-1})}{(0.5\times loan_{ibt}+0.5\times loan_{ibt-1})} \times 100\%$. The dependent variable in columns 3-4 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. High PR and Low TR are set to 1 if the respective risk indicator for physical or transition risks falls into the top 75th quantile of the distribution *in a given year*. Low PR and Low TR are then defined as one if the risk falls into the bottom 25th quantile of the distribution *in a given year*. The main independent variables are the four dummies, indicating the extremely high and low physical and transition risks. All RHS variables are lagged by one year. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 20l9. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A4: Climate Risks and Lending: Response to the Tail Risks, Fixed Distribution

	Loan Growth		**New Loans**	
	(1)	**(2)**	**(3)**	**(4)**
High PR	-2.207**	-1.977**	-0.005	-0.004
	(0.969)	(0.973)	(0.004)	(0.004)
High TR	-2.907***	-2.660**	-0.005	-0.007
	(1.018)	(1.095)	(0.004)	(0.004)
Low PR	0.023	0.097	0.002	0.002
	(0.992)	(1.017)	(0.004)	(0.004)
Low TR	0.952	0.79	-0.003	-0.002
	(1.001)	(1.042)	(0.004)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes		Yes	
Bank Fixed Effects	Yes		Yes	
Parish Fixed Effects		Yes		Yes
2-digit Industry Fixed Effects				
2-digit Industry-Time Fixed Effects		Yes		Yes
Bank-Time Fixed Effects		Yes		Yes
Firm Variables	Yes	Yes	Yes	Yes
Bank Variables	Yes		Yes	
Mean Y	-14.069	-14.130	0.383	0.383
R-sq	0.087	0.123	0.140	0.171
N	189,142	187,700	220,890	219,167

Notes: The table presents the estimation results for banks' lending response to the tail physical and transition risks from OLS regressions, with the tail risks defined based on a fixed distribution. In columns 1-2, the dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$. The dependent variable in columns 3-4 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. High PR and Low TR are set to 1 if the respective risk indicator for physical or transition risks falls into the top 75th quantile of the distribution *for the entire sample*. Low PR and Low TR are then defined as one if the risk falls into the bottom 25th quantile of the distribution *for the entire sample*. The main independent variables are the four dummies, indicating the extremely high and low physical and transition risks. All RHS variables are lagged by one year. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 20l9. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A5: Climate Risks and Lending: Response to the Tail Risks

	Loan Growth		**New Loans**	
	(1)	**(2)**	**(3)**	**(4)**
High PR	-1.401*	-1.583*	-0.005	-0.005
	(0.846)	(0.855)	(0.003)	(0.003)
High TR	-3.094***	-2.713***	-0.007*	-0.008**
	(0.994)	(1.018)	(0.004)	(0.004)
Low PR	2.210***	1.860**	0.009***	0.008**
	(0.773)	(0.785)	(0.003)	(0.003)
Low TR	0.057	0.106	-0.001	0.001
	(1.162)	(1.218)	(0.004)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes		Yes	
Bank Fixed Effects	Yes		Yes	
Parish Fixed Effects		Yes		Yes
2-digit Industry Fixed Effects				
2-digit Industry-Time Fixed Effects		Yes		Yes
Bank-Time Fixed Effects		Yes		Yes
Firm Variables	Yes	Yes	Yes	Yes
Bank Variables	Yes		Yes	
Mean Y	-14.069	-14.130	0.383	0.383
R-sq	0.087	0.123	0.140	0.171
N	189,142	187,700	220,890	219,167

Notes: The table presents the estimation results for banks' lending response to the tail physical and transition risks from OLS regressions, with extreme risks defined based on a moving distribution. In columns 1-2, the dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$. The dependent variable in columns 3-4 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. High PR and Low TR are set to 1 if the respective risk indicator for physical or transition risks falls into the top 75th quantile of the distribution *in a given year*. Low PR and Low TR are then defined as one if the risk falls into the bottom 25th quantile of the distribution *in a given year*. The main independent variables are the four dummies, indicating the extremely high and low physical and transition risks. All RHS variables are lagged by one year. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 20l9. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A6: Climate Risks and Lending: Firm Size Heterogeneity

	Loan Growth (1)	New Loans (2)	Loan Growth (3)	New Loans (4)	Loan Growth (5)	New Loans (6)
Physical Risks	-1.333**	-0.004**	-1.422***	-0.005**	-1.586***	-0.005***
	(0.518)	(0.002)	(0.535)	(0.002)	(0.500)	(0.002)
Transition Risks	-2.236***	-0.001	-2.238***	-0.001	-2.237***	(0.001)
	(0.529)	(0.001)	(0.537)	(0.001)	(0.550)	(0.001)
Physical Risks x Transition Risks	-0.544	-0.001	-2.950**	-0.002	-1.803	0.000
	(1.324)	(0.001)	(1.437)	(0.001)	(1.229)	(0.003)
Small x Physical Risks	-1.127*	-0.004				
	(0.649)	(0.002)				
Small x Transition Risks	0.353	0.001				
	(0.571)	(0.002)				
Small x Physical Risks x Transition Risks	-3.944**	-0.003				
	(1.859)	(0.006)				
Medium x Physical Risks			-0.312	0.001		
			(0.572)	(0.002)		
Medium x Transition Risks			-0.446	-0.005*		
			(1.068)	(0.003)		
Medium x Physical Risks x Transition Risks			2.217	0.003		
			(2.213)	(0.005)		
Large x Physical Risks					4.361*	0.007
					(2.236)	(0.008)
Large x Transition Risks					-1.491	0.004
					(4.545)	(0.006)
Large x Physical Risks x Transition Risks					2.325	-0.010
					(3.724)	(0.016)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes	Yes	Yes
Bank Variables	Yes	Yes	Yes	Yes	Yes	Yes
Mean Y	-13.969	0.384	-13.969	0.384	-13.969	0.384
R-sq	0.088	0.141	0.088	0.141	0.088	0.141
N	183,479	214,263	183,479	214,263	183,479	214,263

Notes: The table presents the estimation results for the sensitivity of firm size heterogeneity on banks' lending response to climate risks. In column 1,3,5, the dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$, for the intensive margin. The dependent variable in column 2,4,6 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year for the extensive margin. Large firms are defined as having more than 250 full-time equivalent workers; small firms are defined as those with fewer than 20 employees; medium firms are classified as firms in between. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 20l9. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A7: Climate Risks and Lending: Financial Leverage and Capital Intensity

	Loan Growth (1)	New Loans (2)	Loan Growth (3)	New Loans (4)
Physical Risks	-1.186**	-0.004*	-1.165**	-0.004*
	(0.526)	(0.002)	(0.528)	(0.002)
Transition Risks	-2.147***	-0.001	-2.222***	-0.001
	(0.557)	(0.001)	(0.549)	(0.001)
Physical Risks x Transition Risks	1.875	-0.001	-1.238	-0.002
	(1.181)	(0.001)	(1.876)	(0.001)
High Leverage x Physical Risks	-1.422***	-0.005**		
	(0.540)	(0.002)		
High Leverage x Transition Risks	0.971	-0.004		
	(0.908)	(0.003)		
High Leverage x Physical Risks x Transition Risks	-5.574***	-0.002		
	(1.808)	(0.004)		
High Capital Intensity x Physical Risks			-1.615***	-0.006***
			(0.608)	(0.002)
High Capital Intensity x Transition Risks			1.841*	0.002
			(1.082)	(0.004)
High Capital Intensity x Physical Risks x Transition Risks			-0.242	0.003
			(2.249)	(0.004)
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes
Bank Variables	Yes	Yes	Yes	Yes
Mean Y	-13.969	0.384	-13.97	0.384
R-sq	0.088	0.141	0.088	0.141
N	183,479	214,263	183,457	214,229

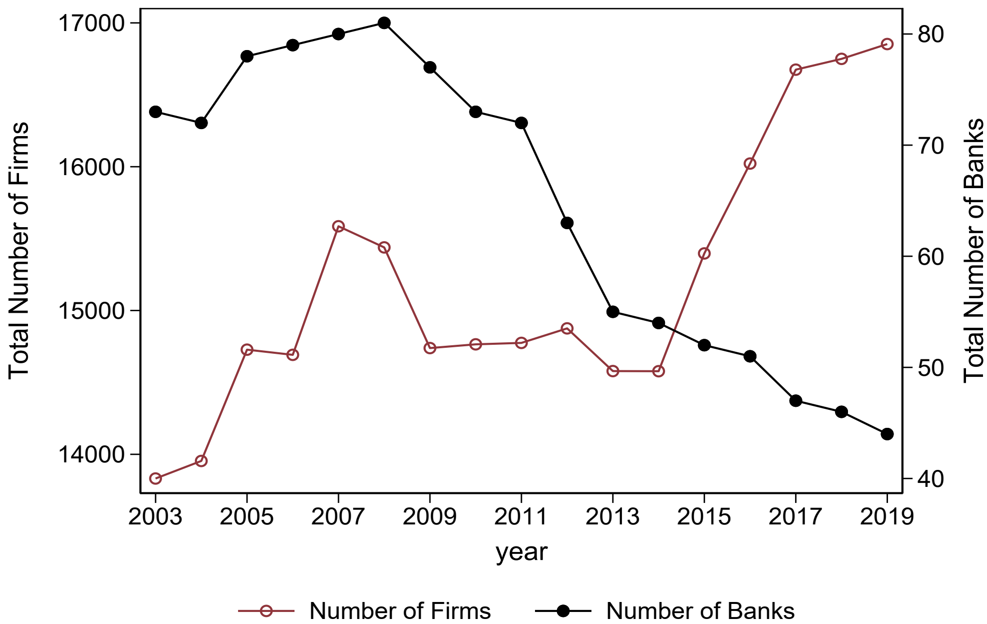
Notes: The table presents the estimation results for the sensitivity of financial leverage and capital intensity heterogeneity on banks' lending response to climate risks. In column 1 and 3, the dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$, for the intensive margin. The dependent variable in column 2 and 4 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year for the extensive margin. High financial leveraged firms are defined if the leverage ratio is above 50% quantiles, while high capital intensity is defined if the share of fixed assets as a fraction of total assets is above 50% quantiles. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A8: Climate Risks and Loan Growth: Adding ILST Fixed Effects

	Loan Growth		
	(1)	**(2)**	**(3)**
Physical Risks	-0.557	-0.807	-0.975
	(0.533)	(0.769)	(0.964)
Transition Risks	-1.352***	-1.534***	-1.681**
	(0.393)	(0.456)	(0.839)
Parish Fixed Effects	Yes	Yes	
2-digit Industry-Time Fixed Effects	Yes		
Bank-Time Fixed Effects	Yes	Yes	Yes
Bank-Firm Fixed Effected	Yes	Yes	Yes
Industry-Location-Size Fixed Effects (ILS)	Yes		
Industry-Location-Time Fixed Effects (ILT)		Yes	
Industry-Location-Size-Time Fixed Effects (ILST)			Yes
Firm Variables	Yes	Yes	Yes
Mean Y	-10.315	-10.421	-10.556
R-sq	0.217	0.304	0.396
N	206,903	198,441	182,448

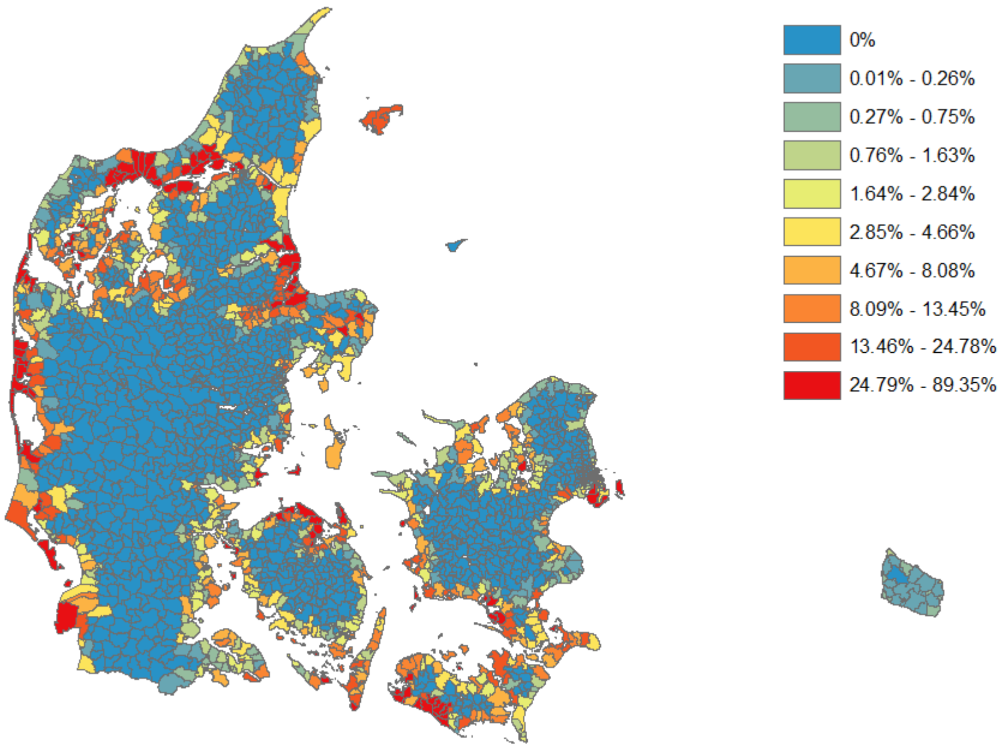
Notes: The table presents the estimation results for the climate risks and loan growth with granular high-dimensional fixed effects. The dependent variable is the loan growth in percentage points of firm i received from bank b in a given year t, calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$, for the intensive margin. We saturate the model with Industry-Location-Size Fixed Effects (ILS) in column 1, Industry-Location-Time Fixed Effects (ILT) in column 2, and Industry-Location-Size-Time Fixed Effects (ILST) in column 3. All regressions include fixed effects and control variables as specified. The sample starts in 2003 and ends in 2019. The detailed firm-level and bank-level control variable definitions are described in Table A1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Figure C.1: Number of Firms and Banks



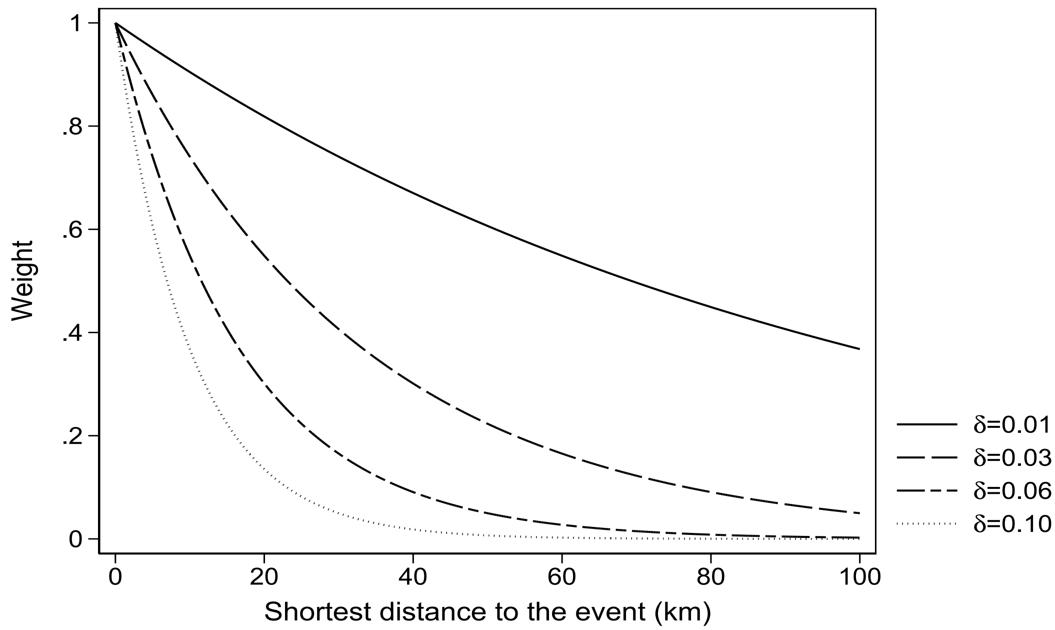
C Additional figures

Figure C.2: Share of Flood Risks by Parish



Notes: Based on flood risks in 20 years under IPCC RCP 4.5 scenario with a 100-year return period aggregated at the parish level. The grey outlines are the boundaries for each small administrative district. Source: author's calculations, data provided by DTU management

Figure C.3: The Weight Functions $\boldsymbol{e^{-\delta x_{p,r}}}$ for Different Values of δ



Notes: When $\delta = 0.06$, neighboring parishes have a weight close to 1, while a parish at a distance of 10 km has a weight of 0.55 and another parish at a distance of 100 km weights 0.002.

Figure C.4: Emission Intensity Across Industry, 2019

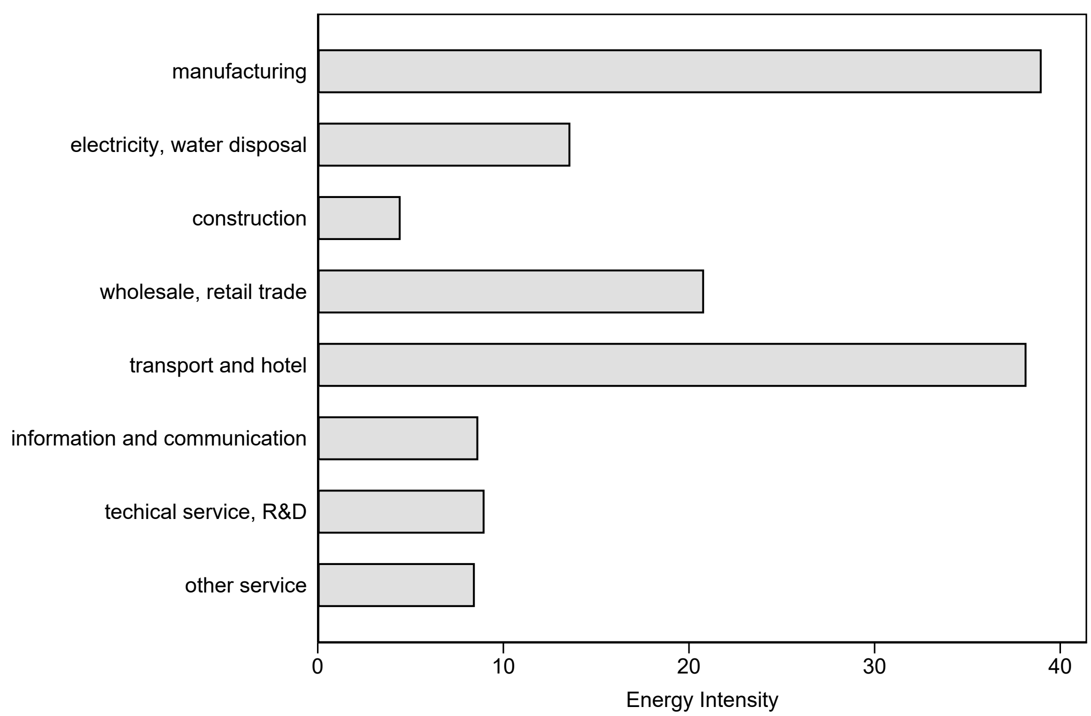
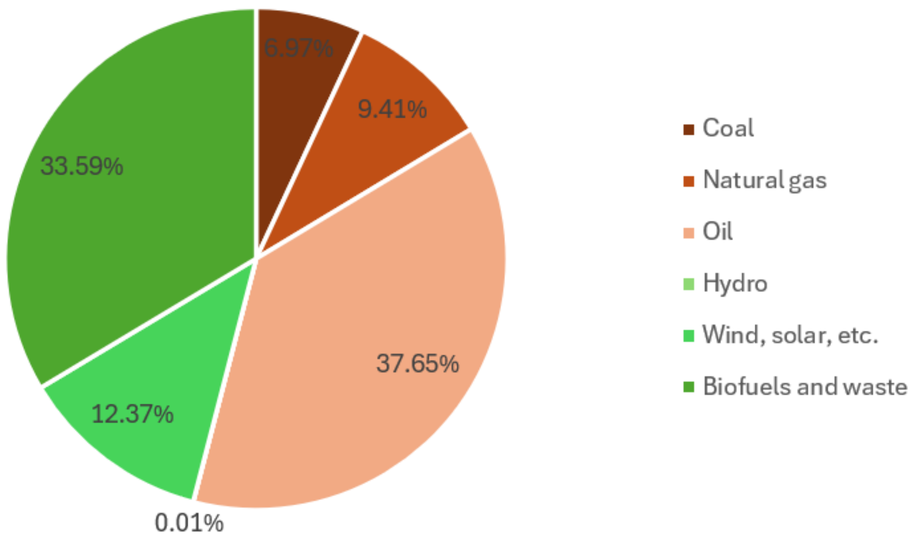


Figure C.5: Energy Mix in Denmark, 2022



Source: IEA and author's own calculation

Figure C.6: Environmental Tax Across Industry (Scaled), 2019

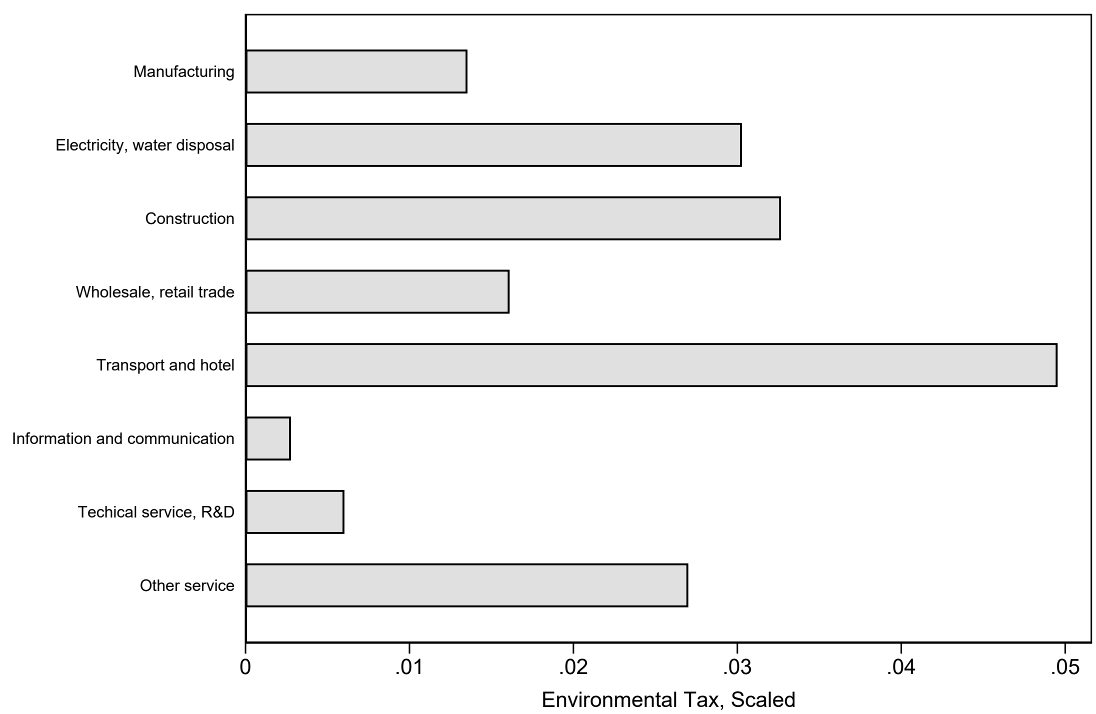
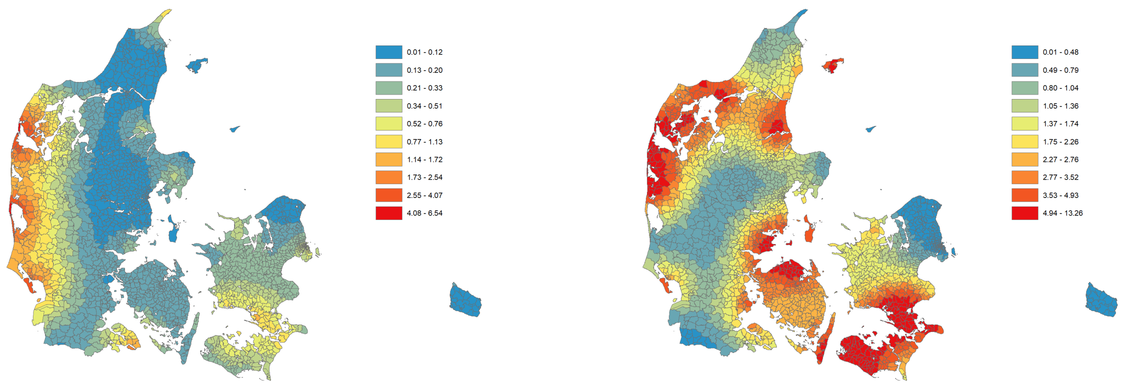


Figure C.7: Physical Risk Indicator by Parish over Time

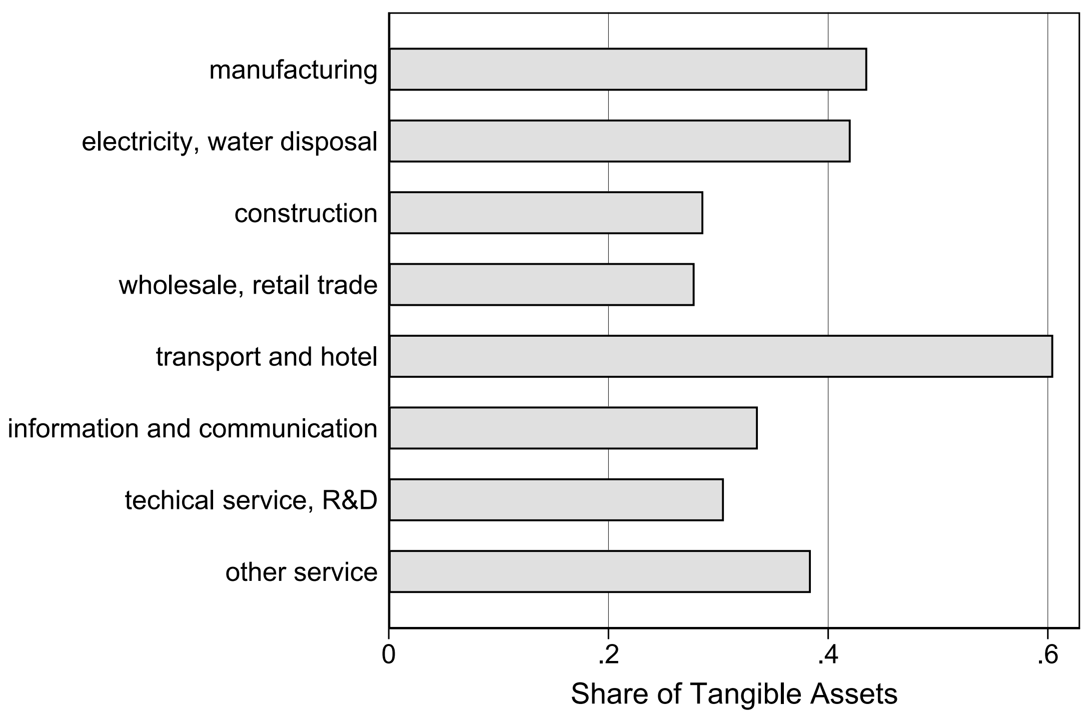
(a) Physical risk indicator, 2009

(b) Change from 2009 to 2019



Notes: Physical risk indicator is an interaction between projected flood risks and historical extreme precipitation event intensity at the parish level, using distance weighted sum with decay parameter δ equals 0.06. Flood risk measures the share of the parish that is exposed to 100-year-year flood events on the 20-year horizon under the IPCC RCP 4.5 scenario; extreme precipitation is based on weather data from DMI.

Figure C.11: Share of Tangible Assets Across Industries



Notes: Share of Tangible Assets Across Industries in Our Sample

Figure C.8: Sources of Identification: Variation Across Time

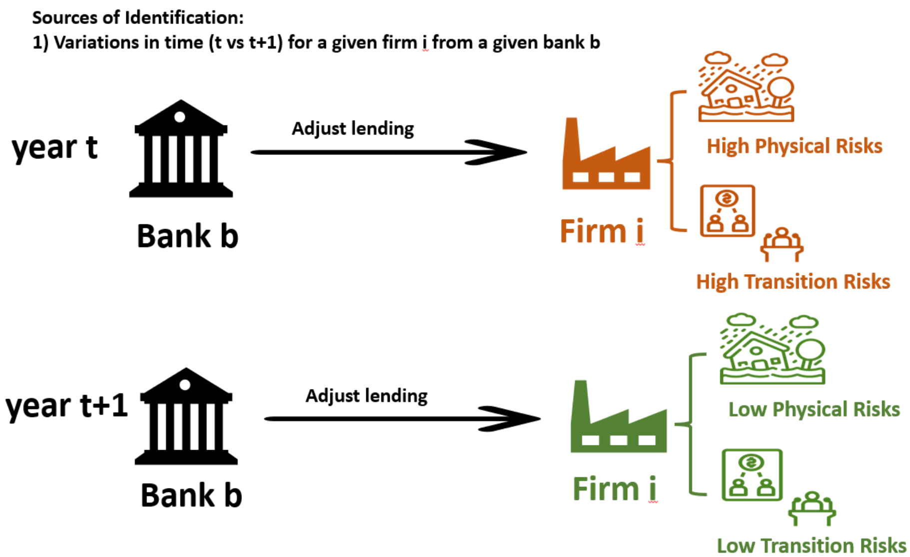


Figure C.9: Sources of Identification: Variation Across Firm

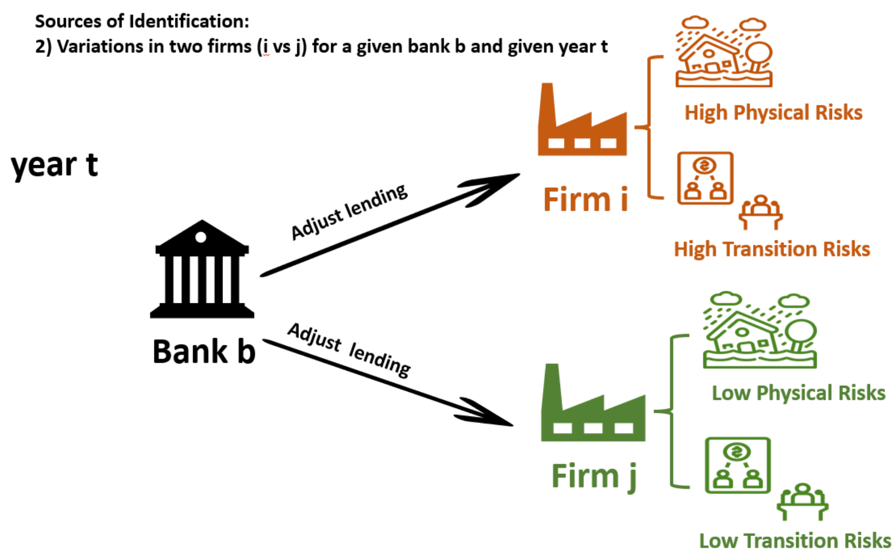


Figure C.10: Interaction of Physical and Transition Exposure

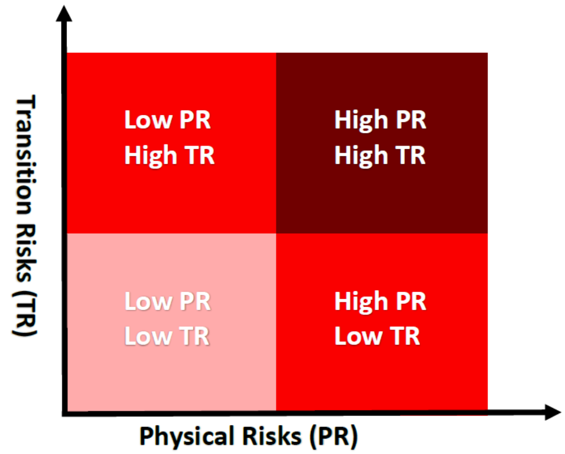
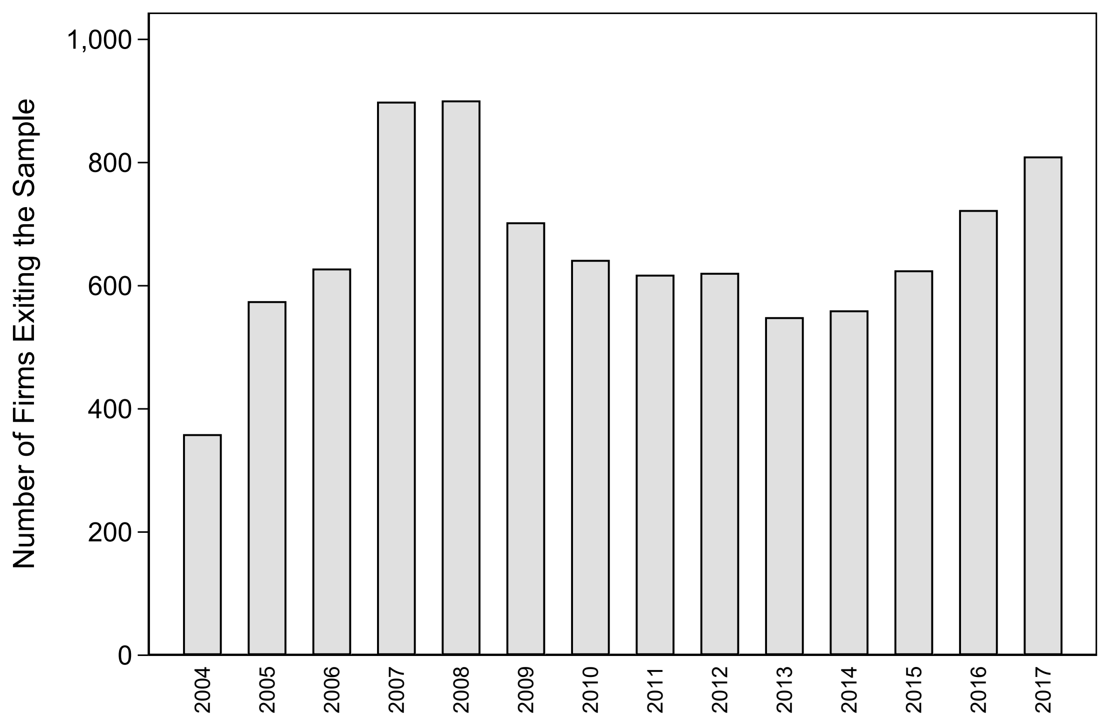


Figure C.12: Number of Firms that Exit the Sample



Notes: The start year (2014) and end of the sample year (2019) are excluded.