Climate Change and Bank Lending: Evidence from Physical and Transition Risks *

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Abstract

This study examines how firms' exposure to climate-related physical and transition risks affects bank credit allocation. Using novel, granular measures for both risk types, merged with matched firm-bank data from Danish registers, I find that banks reduce credit growth to firms with higher physical and transition risks. A one standard deviation increase in each type of risk results in a 1%-2% reduction in loan growth, representing about an 8%-16% deviation from the mean. These effects are most pronounced for constrained firms (e.g., small or highly leveraged) and are concentrated within banks with high exposure to risk and repeat lending relationships. Additionally, the evidence suggests that more credit is allocated to risky but "greening" firms and firms with low combined physical and transition risks. Finally, the credit supply side is likely to play a more important role in the observed effect, partly due to banks' credit risk concerns.

Keywords: Climate change, physical risks, transition risks, bank lending.

JEL Codes: G21, G30, H23, Q54, Q56

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1 Introduction

The impact of climate-related risks on the banking sector has been an increasing concern for financial regulators. This is due to the potential for climate risks to affect financial stability and the broader economy (Carney, 2015; ECB, 2021a,b; Fed, 2021). Furthermore, understanding how the banking sector responds to climate risks is crucial for achieving sustainability goals as banks play in key role in directing funds toward green projects, and incentivizing firms to engage in sustainability practices.

There are two types of climate-related risks that banks are indirectly exposed to via their lending: (i) physical risks, resulting from damages to firms due to increasing frequency and intensity of extreme climate events, and (ii) transition risks, associated with the implementation of climate policies aimed at reducing emissions of high-emitting firms. In this paper, I examine how firms' exposure to physical and transition risks affects banks' credit allocation. To do so, I utilize novel, granular measures of both types of risks, merged with firm-bank matched Danish register data that are representative of all types of firms, ranging from listed large firms to non-listed small and medium-sized companies (SMEs).

It remains an empirical question whether firms' exposure to climate risks affects credit outcomes. Existing studies provide evidence that global banks have begun to respond to climate risks, largely based on syndicated loans to listed firms (Kacperczyk and Peydró, 2022; Degryse et al., 2023; Mueller and Sfrappini, 2022). In this paper, I extend the analysis to non-listed firms, which typically includes SMEs that rely on bank credit and have less capacity to adapt to climate risks.[1] Moreover, I investigate whether banks allocate credit to risky firms actively reducing emissions, or "greening" firms. Given that banks are exposed to both physical and transition risks, I examine not only the individual effects of each type of risk but also how these risks interact with each other.

This paper investigates the question in the context of Denmark for two reasons. First, using a unique credit register that provides information on the universe of bank loan relationships, I match firms with banks and link their employer-employee data to evaluate credit evolution over nearly 20 years. Second, Denmark has substantial variations in both physical and transition risks. Regarding physical risks, with a coastline spanning 7300 km and

[1] 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. It is not clear ex-ante whether the same results in the syndicated loan market apply to non-listed firms. On the one hand, these firms may be penalized more as they tend to be riskier and have less capacity to adapt to climate risks compared to large, listed firms. Additionally, they rely more heavily on bank credit due to the difficulty of accessing other external financing options, such as corporate bonds. On the other hand, banks may not yet be concerned about the climate risks' impact on nonlisted firms, as large firms are more likely to be exposed to transition risks, given that climate policies tend to hit them first.

the highest elevation points reaching only 170 meters, Denmark faces increasing risks from storms and coastal flooding due to rising sea levels and extreme precipitation. and extreme precipitation.[2] Regarding transition risks, both the Danish government and the European Union have implemented proactive measures aimed at reducing emissions and improving energy efficiency. For instance, the International Energy Agency has documented that over 200 policies have been implemented during the same period to achieve these goals.

The main dependent variables in the empirical analysis are credit allocation (lending) outcomes, measured by loan growth (intensive margin), and the likelihood of initiating new loans (extensive margin). The key independent variables capture firms' exposure to two types of climate risks. Specifically, to proxy for physical risks, I construct a novel risk indicator that varies over time at a fine geographical unit, covering over 2,000 Danish parishes.[3] This indicator combines flood risk projections with historical data on extreme precipitation, while also accounting for geographic spillover effects. The underlying assumption is that extreme weather events, like heavy precipitation and floods, directly reflect climate change impacts and are therefore more likely to raise banks' awareness and shift their perception of climate risks (Gu and Hale, 2023). To measure transition risks, I interact firm-level energy intensity (scope 2 emission intensity) with industry-level environmental taxes, a proxy for climate-related policy stringency. This measure allows for capturing the vulnerability of high emission-intensive firms to stricter environmental regulations over time.[4]

To identify the impact of climate risks on credit allocation, I exploit variations in physical risks across time and parishes and variations in transition risks across firms, time, and industries using fixed effect regression models. All climate risks measures and control variables are lagged to avoid reverse causality. To compare the individual effects of the two risks, I include both risk measures in the same model. My main identification strategy to examine the impact of physical risks relies on the assumption that extreme precipitation variations and floods are largely driven by nature and can be considered exogenous (Dell et al., 2014). Transition risks, however, are less exogenous, as they are firm- or industry-specific. There-

[2]For instance, the Danish Meteorological Institute (DMI) reports that over 40 storms have battered the country in the past three decades, with at least 10 of these storms leading to natural disasters that caused severe damage to homes, infrastructure, farmland, and human lives. A recent report from the Technical University of Denmark (DTU) has estimated that the cost of flooding could reach DKK 406 billion over the next 100 years, see http://bit.ly/3Cu6gMq.

[3]This is an improvement compared to the broader 50 km x 50 km grid cell resolution used in existing databases, which corresponds to fewer than 50 geocodes in Denmark, e.g., GAME-LIGHTS, while The Emergency Events Database (EM-DAT) often misses the specific geo-locations for the events in the case of Denmark.

[4]In a refinement, I also consider alternative emission measures including industry year level scope 1 emissions, and alternative measures for policy stringency such as energy-related taxes or changes in climate-related policies.

fore, I gradually saturate the model with a complete set of fixed effects to absorb unobserved heterogeneity and alleviate concerns about omitted variables or spurious effects, in the spirit of Khwaja and Mian (2008), Jiménez et al. (2012), and Jiménez et al. (2014). In the most saturated model, I incorporate parish fixed effects to account for unobserved location-specific factors, 2-digit industry-year fixed effects for industry-specific shocks, bank-year fixed effects for unobserved bank supply shocks, and firm-bank fixed effects to control for endogenous matching.[5] Therefore, the identification relies on exploiting credit evolution for the same firm-bank pair within the same location and industry, in response to the change of climate risks over time. As I add more granular fixed effects, the estimated effects decrease, with the most saturated model providing a lower bound for these estimates.[6]

The main empirical analysis suggests that firms' exposure to higher physical or transition risks is associated with lower loan growth. Specifically, a one standard deviation increase in a firm's exposure to physical risks, results in a 1.1%-1.4% reduction in loan growth, representing about 8%-10% deviation from the sample mean.[7] Meanwhile, the impact of transition risks is slightly larger, a one standard deviation increase in transition risks is associated with an about 1.6%-2.2% decrease in loan growth, representing 11%-16% deviation from the mean.[8] Those results echo the findings in the syndicated loan markets. On the extensive margin, I find only higher physical risks are associated with a lower likelihood of receiving new credit. In an extension to the baseline analysis, I use alternative credit outcomes and find that banks also adjust their relationships with firms but no evidence of adjusting the pricing of existing loans yet. The results hold when I focus on the tail of physical and transition risks using extreme dummies. The baseline analysis is also robust to specific choices of variables, econometric specifications, and subsamples.

I further examine the role of the "greening" firms and the interaction of two risks. The results support that more credit is allocated to these risky or initially "brown" firms that engage in climate adaptation or mitigation, positive evidence in banks' engagement in green transition. When it comes to the interaction of two risks, I find evidence that banks tend to favor firms with lower interaction (or compounded) risks, indicated by positive coefficients for extremely low-risk dummies. In other words, the observed negative effects can be mitigated

[5] Note I cannot add parish-year fixed effects and firm-year fixed effects as they would absorb the variations of the main variables of my interests.

[6] One threat to the identification of physical risks comes from firms relocating away from high-risk areas, I therefore exclude these firms in a refined model. To mitigate reverse causality in transition risks, I use a base-year approach in a refinement, measuring energy intensity in the first year a firm appears in the sample.

[7] Physical risks: mean 0.99, sd 1.162; loan growth: mean -14.225%, sd 117.261. This effect only translates to about 0.1 change in standard deviation, which is relatively modest given the large variability or dispersion in loan growth.

[8] Transition risks: mean 26.678, sd 150.140; loan growth: mean -14.225%, sd 117.261. Similarly, this effect translates to about 0.1 change in standard deviation.

when firms face low levels of both physical and transition risks.

In the heterogeneity analysis, I examine which factors at the firm or bank-level may amplify the observed effects. On the firm side, I find that more constrained firms (e.g., small and high-leveraged firms) are more negatively affected. This is consistent with the idea that those constrained firms are riskier with higher asymmetric information (Hadlock and Pierce, 2010; Jiménez et al., 2014; Laeven and Popov, 2023), and banks may divest from those firms to avoid compounding risks (Dunz et al., 2023). On the bank side, I find that observed reductions in credit are more pronounced for banks with repeat lending relationships and high exposure to risks, calculated based on the loan-weighted average of climate risks among their client firms. This finding supports the notion that banks have an information advantage when dealing with existing clients (Petersen and Rajan, 1994; Diamond, 1991; Sharpe, 1990; Rajan, 1992), and that highly exposed banks may be more proactive in managing these risks. Lastly, banks specialized in brown industries, measured in the spirit of the specialization measures in Paravisini et al. (2023), are more likely to increase lending, consistent with the findings from Laeven and Popov (2023) and Degryse et al. (2020).

Given that the observed credit outcomes can be driven by both the demand (firm) and supply (bank) sides, a natural question arises: which side plays a bigger role? Distinguishing between credit supply and demand is not an easy task, and I acknowledge the challenges involved, as discussed in the empirical banking literature (Khwaja and Mian, 2008; Jiménez et al., 2020; Degryse et al., 2019). Nevertheless, leveraging rich firm-level data, I attempt to conduct a set of empirical tests on the relationship between climate risks and firm-level indicators to shed light on the relative importance of the two sides. First, on the credit demand side, I test whether climate risks are linked to lower firm growth, resulting in reduced credit demand, which is proxied by various firm-level growth indicators. However, the empirical evidence does not support this channel.[9] Second, on the credit supply side, I apply the method proposed by Degryse et al. (2019), which controls for local credit demand variations within the same industry, location, size, and time using ILST fixed effects. The robust negative relationship between climate transition risks and loan growth confirms the supply-side explanation. Finally, I explore banks' motivations by testing the financial incentives (credit risk) channel, showing empirically that higher climate risks are associated with increased credit risk, as measured by various firm-level financial stress and survival proxies.

This study contributes to the empirical sustainable banking literature in the following

[9]Specifically, I do not observe the correlation between climate risks and investment growth, employment growth as proxies for credit demand from firm expansion, fixed asset growth as an indicator of funding needs for capital expenditure, and sales growth as a measure of credit demand for working capital.

ways. First, unlike existing studies that are mostly based on syndicated loans to large publicly listed firms (Javadi and Masum, 2021; Kacperczyk and Peydró, 2022; Reghezza et al., 2022), which only account for a small share of the total credit market, this study complements the literature using a more representative sample of firms and banks. Second, compared with most studies that focus only on physical risks (Meisenzahl, 2023; Aslan et al., 2022) or transition risks (Ginglinger and Moreau, 2023; Mueller and Sfrappini, 2022; Sastry et al., 2024), I provide a more complete evaluation of climate risks by examining both risk types and their interactions using novel, granular risk measures. Third, this study responds to the concerns raised by policymakers regarding the potential financial stability concerns posed by climate risks (ECB, 2021b; Fed, 2021). I also provide evidence of banks' engagement by looking at firms "greening" efforts, an aspect that has largely been overlooked. Finally, the results add to the literature on the climate risks implications for firms, suggesting climate risks may negatively affect firms via the bank financing channel.

The remainder of this paper is organized as follows: I begin with a review of the literature in Section 2.1 and outline the conceptual framework and hypotheses in Section 2.2. Section 3 presents the data and summary statistics, followed by the empirical strategy discussed in Section 4. The empirical results are detailed in Section 5. Finally, a discussion and conclusions of the paper are reported in Section 6.

2 Related Literature and Conceptual Framework

2.1 Related Literature

This paper relates to four strands of research: 1) transition risks and the credit market, 2) physical risks and the credit market, 3) the implications of climate risks for the banking industry, and 4) the implications of climate risks for firm performance and behavior. In this section, I provide an overview of each literature strand and explain in detail how this study contributes to each.

The first research strand examines the implications of transition risks in financial markets, specifically within the credit market. Unlike the extensive literature on other markets, such as the equity market (Bolton and Kacperczyk, 2021, 2023; Pedersen et al., 2021; Pástor et al., 2022; Hsu et al., 2023), options market (Ilhan et al., 2021), real estate market (Giglio et al., 2021), and bond market (Seltzer et al., 2022; Flammer, 2021), there are relatively fewer studies in the bank credit market.[10] Most studies in this area focus on asset pricing aspects of transition risk, primarily based on syndicated loans, which represent only a small

[10] For more details, see Appendix B.1.

share of the total credit market, with mixed evidence is found in this line of work, e.g., Fard et al. (2020a); Delis et al. (2024); Degryse et al. (2023); Antoniou et al. (2020).[11] The literature investigating the implications of transition risks on banks' credit supply (quantity adjustment) is rather sparse. A few notable exceptions are Kacperczyk and Peydró (2022) and Reghezza et al. (2022), who find banks allocate less credit 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 Mésonnier (2022) suggest that French banks continue to lend to SMEs in carbon-intensive industries. Some scholars also shed light on the channels. Banks' behaviors can be 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). Unlike most of those studies that focus on syndicated loans to publicly listed firms, this paper contributes to the literature by analyzing climate risks in bank credit supply based on a more representative sample of matched firms and banks for almost 20 years.[12] This rich data allows me to capture a broader spectrum of the credit market, including small banks and SMEs, and to control for more granular fixed effects, accounting for unobserved firm-bank heterogeneity.

Second, this paper contributes to research on the implications of climate-related physical risks for the bank credit market. Similarly, a large body of literature focuses on how physical risks, proxied by indicators such as climate-related natural disasters, are priced in the credit market (Javadi and Masum, 2021; Garbarino and Guin, 2021) or other financial markets (Goldsmith-Pinkham et al., 2015; Nguyen et al., 2022).[13] Among a few studies that relate to credit provision, mixed results are offered. For example, Meisenzahl (2023); Faiella and Natoli (2019), and Aslan et al. (2022) suggest that banks reduce lending to areas more impacted by climate change after 2015. In contrast, evidence shows that when local demand increases after natural disasters, multi-market banks reallocate capital (Cortés and Strahan, 2017) and increase recovery lending to firms within affected counties (Koetter et al., 2020; Ivanov et al., 2022).[14] This study contributes to this literature by using a more granular measure of physical risks that includes geographic spillover effects, and by integrating both

[11] More details in Appendix B.2.

[12] Notable exceptions include Takahashi and Shino (2023) and Mésonnier (2022), who focus on Japan and France, respectively, and Giannetti et al. (2023); Sastry et al. (2024) use euro-area credit registry data to assess the credibility of sustainability disclosures and voluntary lender net-zero commitments.

[13] See more details in Appendix B.

[14] Previous studies also suggest the existence of 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).

types of climate risks for a comprehensive evaluation.

Third, this study responds to the call for a better understanding of the climate risks implications for the banking industry and the behavior of banks (Fed, 2021; ECB, 2021b; Battiston et al., 2021). 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). I contribute to the literature by examining banks' adjustments in lending, providing evidence that they divest from risky firms and allocate more credit to "greening" firms. This responds to the concerns raised by central banks that banks may not fully internalize climate-related risks, potentially adversely impacting financial stability (ECB, 2021a,b; Fed, 2021). This study also opens future research avenues regarding banks' real impact in green transition (Degryse et al., 2021; Lee et al., 2024).

Last, this paper broadly relates to the 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. The results add to the literature and suggest one channel that climate risks may negatively affect firms: the bank financing channel. Firms with higher exposure to climate risks (both physical and transition risks) may face more challenges in accessing bank credit.

2.2 Conceptual Framework and Hypotheses

The study aims to investigate the relationship between climate risks and credit allocation. Given I only observe equilibrium outcomes, specifically, the quantity of credit banks allocate and the total credit received by firms, both the supply side (banks) and the demand side (firms) may influence total credit allocation. As a result, the net effects are unclear ex-ante and the anticipated sign could be positive, negative, or inconclusive, as shown in Figure D.1.

In this section, I conceptually show the potential theoretical mechanisms of the supply and demand sides at play and highlight a few hypotheses to guide my empirical work.

First, one possible outcome is that I do not observe any credit adjustment, possibly due to banks' preference in maintaining their practices due to high adjustment costs, or banks' legacy positions in brown firms (Degryse et al., 2020). For instance, some papers have shown banks do not do as they say, despite increasingly marketing themselves as "green". (Giannetti et al., 2023; Sastry et al., 2024; EBA, 2023). Alternatively, the positive effect and negative effects of climate risks may cancel out and no credit adjustment is observed.

This points to the following hypothesis.

H1: No credit adjustment to firms with high climate risks exposure.

Second, another possibility is that higher exposure to climate risks is positively related to credit outcomes. This can be driven by firms engaging in climate adaptation and mitigation, or "greening" firms. Empirical evidence suggests that climate risks may induce firms to participate in green innovation activities to reduce emissions (Miao and Popp, 2014; Gramlich et al., 2020; Liu et al., 2024), and thus demand more credit. In addition, firms tend to seek more credit following natural disasters for financing post-disaster recovery efforts (Cortés and Strahan, 2017; Koetter et al., 2020; Ivanov et al., 2022). Moreover, from the supply side, as firms with high climate risks exposure are associated with high credit risk, 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 to another hypothesis.

H2: More credit is allocated to firms with high climate risks exposure but "greening" firms.

Last, higher exposure to climate risks may be negatively related to credit outcomes, as observed in the syndicated loan market (Kacperczyk and Peydró, 2022; Mueller and Sfrappini, 2022). The negative outcome can be driven both by the demand side and the demand side. To evaluate the relative importance of each side, I split the last hypothesis into two sub-hypotheses. On the demand side, physical and transition risks may adversely affect the fundamental operations of businesses, and consequently, lower firm growth and credit demand (Huang et al., 2018; Kacperczyk and Peydró, 2022; Bolton et al., 2019).

This points to the following hypothesis:

H3A: Less credit is allocated to firms with high climate risks exposure, due to lower firm growth.

Another driver for the negative effect comes from the supply side: banks may have financial incentives to divest from risky firms as climate risks are associated with the probability of default and the loss given the default (Huang et al., 2018; Kabir et al., 2021). Conceptually, 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 perfectly price in these risks and be fully insured. However, due to market frictions, banks should take into account climate risks because 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), therefore, banks might simply reduce or cease lending to risky firms.[15]

Those discussions point to the following hypothesis.

H3B: Less credit is allocated to firms with high climate risks exposure due to banks' credit risk concerns.

Testing H3A and H3B will help assess the relative importance of supply-side versus demand-side factors. Evidence supporting the H3A hypothesis would indicate the demand side story, while evidence supporting the H3B hypothesis would point to the supply side explanation and indicate banks' divesting strategies from risky firms (Kacperczyk and Peydró, 2022; Degryse et al., 2023).

3 Data

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

[15] Banks may have both financial and non-financial incentives, aligning with the "values" versus "value" considerations defined by Starks (2023). Besides credit risk concerns, other non-pecuniary considerations may also play a role. For instance, a bank's leadership team may prefer supporting green businesses that reflect their values (Bu et al., 2023). Due to the difficulty in quantifying those factors, I do not empirically test non-financial channels in this paper.

3.1 Danish Administration Data

3.1.1 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 from 1995 to 2019 and includes detailed information on firm characteristics, such as size, age, capital, revenue, location, and industry affiliation. FIRE provides detailed accounting information at the firm level, particularly on firms' energy purchases for heating and production, which will allow me to measure transition risks.[16] To add workforce composition characteristics at the firm level, I use the Integrated Database for Labor Market Research (IDA), which contains detailed demographic and employment information for all individuals employed in the recorded population of Danish firms, at both the firm and plant levels. Using the Firm-Integrated Database for Labor Market Research (FIDA), each worker in IDA can be linked to every firm in the FIRM and FIRE datasets using a unique identifier, enabling me to create employer-employee matched data covering a representative sample of firms and their workers. The combined data allow me to construct several important control variables for the empirical analysis, such as firm size, return on assets (ROA), leverage ratio, and firm age, bank size. I report my findings with and without these controls, as some firm and bank characteristics could be endogenous.

3.1.2 Credit data

To link firms with banks, I 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. I 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, I link each loan account to the corresponding banks and borrowing firms, which further enables me to merge credit information with employer-employee matched data.[17] With the resulting

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

[17] Specifically, on the bank side, using unique bank ID variables (op_se_nr), I 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. To validate the credit data, I tabulated some

dataset, I am able to observe the bank loans with the characteristics of the corresponding banks and firms. Following Hviid et al. (2022); Renkin and Züllig (2021), I 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, to match the frequency of other important variables.

3.1.3 Sample constructions

To arrive at my final sample, I restrict the data in different ways. At the bank level, I drop micro banks with less than 50 employees.[18] At the firm level, I drop firms with fewer than 10 employees from FIRM and FIRE registers as accounting information for micro firms may not be completely reliable. I also exclude firms operating in the financial industry, as these companies tend to leverage differently. Finally, to account for possible measurement errors, I drop a few observations with negative values for account balance and interest payment. Figure D.2 shows the number of firms and banks in the final sample over the sample period. One interesting observation is that the banking sector has been consolidating in the aftermath of the 2007-2008 global financial crisis (GFC), as indicated by the number of banks steadily declining since 2008. The key descriptive statistics for the final sample are presented in Table 1.

3.2 Exposure to climate risks

Banks are mainly indirectly exposed to physical and transition risks through the firms to which they lend.[19] This section details how I measure these two key independent variables: firms' exposure to physical risks and transition risks.[20]

3.2.1 Physical risks data

First, to measure firms' exposure to physical risks, I construct a risk indicator that varies over time at the local parish level by combining historical extreme precipitation and forward-

key descriptive statistics. Notably, I 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 the match.On the borrowing firm side, I match employer-employee data with credit data using the unique firm identifiers (cvrnr) to obtain the characteristics of the borrowing firms.

[18]This is because there are a large number of micro banks that only account for a small share of total lending and the data for those micro banks may not be accurate.

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

[20]One concern is the unavailability of the internal data that banks use to assess climate risks. Nevertheless, I rely on publicly available information and firm-level data that are accessible to banks.

looking flood risk, while also accounting for geographic spillover effects.[21] In the following section, I will document the two important data sources and the model to map firms' exposure to physical risks.

Extreme precipitation data Using historical 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 (Dell et al., 2014; Hsiang, 2016; Lemoine, 2018). Given extreme weather occurrences such as extreme rainfall reflect the physical risks more directly, they are more likely to update banks' perceptions or beliefs regarding climate risks. To capture these extreme events, I 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). Given that extreme precipitation is closely correlated with flooding, my baseline analysis focuses on extreme precipitation episodes.[22]

Specifically, I calculate a daily extreme precipitation indicator, ν_{cmdt}^{precip}, as follows:

$$\nu_{cmdt}^{precip} = \frac{x_{cmdt}^{precip} - \overline{x}_{cm}^{precip}}{\sigma_{cm}^{precip}}$$

where c denotes the climate station, m the month, d the day, and t the year. The indicator is calculated within each climate station c, by subtracting the monthly average precipitation, $\overline{x}_{cm}^{precip}$, from the daily precipitation, x_{cmdt}^{precip}, and dividing the difference by the corresponding monthly standard deviation, σ_{cm}^{precip}. Given this indicator captures both positive and negative precipitation anomalies and only positive precipitation anomalies may lead to floods, I define extreme precipitation events as $\nu_{cmdt}^{precip} > 2$.[23]

I then count the occurrence of such extreme events for each parish p in year t, denoting it as $freq_{pt}$.[24] The extreme precipitation events across parishes and years have a mean frequency of 16.44 (std. dev. = 5.68) and have been increasing over the sample period.

This relative extreme precipitation approach offers a more exogenous measure, compared with the absolute extreme. This is because the variations in relative precipitation shocks

[21] A parish is a small administrative area in Denmark that includes several villages or localities. Established formally in 1841, these parishes have had few changes since then. Currently, Denmark has about 2,141 parishes.

[22] Some raw weather data are observed hourly, while others are recorded every 10 minutes. I aggregated the raw data to the daily average and constructed the daily weather anomalies, following the method in Felbermayr et al. (2022).

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

[24] In some parishes without a weather measurement station, each parish is assigned to the closest weather station. Using the detailed locations of over 300 stations, I map each climate station to the neighboring parishes using the geo-weighting indicator described in the Section 3.2.1.

arise from within a location and month, which addresses the concern that by nature, some locations or seasons may experience higher rainfall and volatility. For instance, the same volume of precipitation in one place may appear normal and an anomaly in another, even if observed simultaneously, and firms can already anticipate and adapt to these strategically.

Projected flood risk data Flood risk is a primary source of physical risks for countries with extensive coastlines and low altitudes, such as Denmark. It can cause substantial economic damage, as numerous investments, including firm factories and residential properties, are situated in flood-prone areas.[25] Flood risk data is collected from the Technical University of Denmark (DTU) and the Danish Meteorological Institute (DMI), which project a forecast of flood occurrences and magnitudes across Denmark at a resolution of 200×200 meter grid cells. Notably, the flood risk projection data incorporates both historical and forward-looking perspectives as the simulations utilize historical data and future climate scenarios.[26] For the baseline scenario, I 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 under IPCC RCP 4.5 scenario and denoted as fl_p, see the flood map in Figure D.3.[27] Not surprisingly, the risk is concentrated in areas close to the coast and lakes.

The flood risk map reflects, in short, whether a given parish is likely to be flooded given its geography. However, since the flood risk data fl_p is static and only has cross-sectional variation, I then interact it with the frequency of historical extreme precipitation $freq_{pt}$ to add a dimension of time variation (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 I assume that the parish is likely flooded.

Physical risks indicator To account for geographic spillover effects, after interacting the static flood data with historical extreme precipitation (i.e., I in the equation below), I construct a physical risks indicator for a parish p in year t using a distance-weighted sum of I from the parish's surrounding areas. This method has become standard to measure the proximity of a given location to other locations and has its roots in agglomeration economies.[28]

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

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

[26] Specifically, these projections are based on geographic features, climate data, water level statistics, and sea level estimates, see Morten Larsen (2021).

[27] 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 can be seen in Thomson et al. (2011).

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

$$Physical\ risks\ indicator_{pt} = \sum_{r}^{R} I_{rt} e^{-\delta x_{pr}}$$
$$where\ I_{rt} = fl_r \times freq_{rt}$$

for parish p, year t, and surrounding parish r.

In short, the variable $Physical\ risks\ indicator_{pt}$ aggregates extreme precipitation and flood exposure for all surrounding parishes r, using geographic distance and the magnitude of the events as the weight. Specifically, the variable I_{rt} represents physical risks as the product of extreme precipitation and flood risk for a neighboring parish r in year t. The weight for parish r is computed as $e^{-\delta x_{pr}}$, where $e^{-\delta x_{pr}}$ is a function of the decay parameter δ and the Euclidean distance x_{pr} in kilometers between parish p and r. Appendix D visually illustrates the forms of the weight function $e^{-\delta x_{pr}}$ for different values of δ and the shortest distance x. Given decay parameter δ reflects the extent to which the effects of a climate event can extend to neighboring parishes, I initially set δ to 0.06 which makes economic sense in the baseline measure [29] Finally, a firm's exposure to physical risks then corresponds to the physical risks of the parish where its main headquarters is located.[30]

There are three major advantages of using this risk indicator. First, it allows for incorporating the geographical spillover effects of extreme climate events. Specifically, those events often have consequences beyond the boundaries of one specific parish and can indirectly affect neighboring areas, depending on the magnitude of the events. Second, it measures risk exposure at a much smaller geographical area, i.e., for over 2000 Danish parishes. Third, it aggregates the risks at a level that can be safely considered exogenous, as the parish-level aggregation dates back to the Middle Ages.

Figure D.9 visually depicts substantial variations in physical risks across different geographical locations in the year 2009, as well as the time variation in physical risks in the past decades from 2009 to 2019. Notably, the west coast and southern part of Zealand have experienced higher physical risks and changes in physical risks compared to other areas.

[29] $\delta = 0.06$ indicates that neighboring parishes have a weight close to 1, while a parish at a distance of 10 km weights 0.55, and another parish at a distance of 100 km weighs 0.002. Considering the uncertainty surrounding an appropriate decay parameter, in refinement, I show the robustness of the results to varying decay parameter values, as shown in Table A2.

[30] I include a multi-establishment dummy to control for the fact that some firms have different establishments.

3.2.2 Transition risks data

Second, to measure firms' exposure to transition risks, I interact firm-level energy intensity with environmental tax. The assumption is that certain firms and industries with higher energy intensity (therefore higher emissions) are likely to be exposed to higher transition risks as climate policies and regulations tend to target them (Gu and Hale, 2023). The section below details the two important data sources that capture the firm emission intensity and climate policy stringency to measure transition risks.

Energy intensity data The starting point is to identify those polluting firms with higher energy intensity. Firm energy purchases and consumption data is from the FIRE register, which includes the expenses for energy purchases (for heating and production) and expenses for electricity, oil, gas, and district heating at the firm level.[31] This information enables me to measure scope 2 emissions at the firm level over an extensive sample period. Given banks' unique position as lenders, they likely have access to firm-specific information, such as energy data, through surveys or due diligence.[32] To account for size differences, I further normalize these emissions by the firm-level value added.[33] Specifically, the energy intensity for firm i in industry j at time t is calculated as follows:

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

In short, energy intensity measures a firm's total energy consumption, scaled by its value added for each year. To visually show the industry variations, I aggregate the average energy intensity at the industry level and depict the distribution of energy intensity across industries in 2019, as illustrated in Figure D.5. Notably, the manufacturing and transport sectors exhibit significantly higher energy intensity, while the information, communication, and technical service sectors display relatively lower energy intensity.

[31] The variable is called "KENE" in the FIRE register. The amount includes i.e. expenses for electricity, oil, gas, and district heating. However, fuel expenses for registered motor vehicles used for external transport must not be included. 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.

[32] There are two concerns about this measure. First, I cannot identify renewable energy sources from total energy consumption. Nevertheless, 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 D.6, and, therefore, are major sources of emissions. In addition, a large sample of firms are SMEs and lack the option to choose their energy source. Second, I cannot access direct greenhouse gas (GHG) emissions (scope 1 emissions) and indirect scope 3 emissions at the firm level. Nevertheless, I include scope 1 emissions at the industry level in refinement, and the results are robust to the main findings based on scope 2 emissions, as presented in Table A3.

[33] 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.

Climate-related policy stringency data To measure a climate-related policy stringency, I then use annual public environment-related tax (green tax) at a 2-digit sector level from StatBank Denmark as a proxy. Some examples of tax bases include greenhouse gas emissions and energy products such as fuel oil, coke, coal, and natural gas. For more examples, see Figure D.7.[34] This measure reflects industry-specific real costs or risks linked to the environment.[35] Similarly, to address the issue of some industries being larger and contributing to higher environmental tax, I scale the total environmental tax for each industry by its value added.[36]

To be specific, $\textit{Environmental tax}_{jt}$ is calculated as:

$$\textit{Environmental tax}_{jt} = \frac{\textit{Total environmental tax}_{jt}}{\textit{Value added}_{jt}}$$

for industry j, year t.

The distribution of environmental tax data across industries in 2019 is depicted in Figure D.8. Notably, the transport, electricity, and construction sectors exhibit comparatively higher environmental tax costs compared to other industries. In the robustness check, I also explore alternative measures for policy stringency, including changes in past climate policies within Denmark and the EU, as well as total energy taxes, as shown in Table A3. Given the environmental tax data offers more detailed variations at both the industry and year levels and includes wider scopes, I use this as my baseline analysis.

Transition risks Putting together, the main proxy for firms' exposure to transition risks for each firm i in the industry j at time t is $\textit{Transition risks}_{ijt}$ is an interaction term between firm-level energy intensity $\textit{Energy intensity}_{ijt}$ and industry-level environmental tax

[34] The detailed database can be found at `https://www.statbank.dk/MRS1`. For more information on environmental taxes, see Eurostat (2013) `https://ec.europa.eu/eurostat/documents/3859598/5936129/KS-GQ-13-005-EN.PDF`. The definition of green taxes emphasizes the effect of a given tax in terms of its impact on the cost of activities and the prices of products that negatively affect the environment. The environmental effect of a tax comes primarily through the impact it has on the relative prices of products and the level of activities, in combination with the relevant price elasticity.

[35] Two concerns may arise regarding this measure. First, environmental policies may not perfectly reflect climate change mitigation policies. However, as it serves as an essential policy tool to curb emissions, this measure allows me to proxy for the environmental policy-related costs imposed on each industry over time. Second, transition risks are also associated with future climate policies, making them hard to measure, especially due to their dependence on specific climate scenarios. Nevertheless, this measure captures those industries that pay higher environmental policy-related costs in the past and assumes those are likely to confront higher policy risks in the future.

[36] The industry gross value added data is obtained from Statistics Denmark: `https://www.statbank.dk/NABP117`. The results are also robust when I scale by industry real value added.

Environmental tax$_{jt}$:

$$\textit{Transition risks}_{ijt} = \textit{Energy intensity}_{ijt} \times \textit{Environmental tax}_{jt}$$

for firm i, industry j, year t.

This approach allows for capturing firms' vulnerability to the increasing stringency of climate-related policies targeted at emission-intensive firms.

4 Empirical Strategy and Identification

4.1 Empirical specification and identification

In this section, I provide the main empirical specification and identification strategy to investigate the effects of physical and transition risks on bank credit allocation. The identification exploits variations in physical risks across time and parish and transition risks across firms, time, and industries with saturated fixed effects models. 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 risk within narrowly defined geographic parish units over time is largely driven by nature and largely exogenous (Dell et al., 2014). On the other hand, given that transition risks are measured as the interaction of firms' energy intensity and incurred environmental taxes, they are firm and industry-specific and less exogenous to lending outcomes. To alleviate concerns about omitted variables, I include a comprehensive set of firm and bank-level confounding factors that may affect credit outcomes and a complete set of fixed effects to account for potential unobserved trends and factors, including industry-year, bank-year, and bank-firm fixed effects. By controlling for these variables and fixed effects, I can more carefully examine the effects of transition risks on credit outcomes.

The main dependent variable measures both the intensive and extensive margin of credit (lending) outcomes. On the one hand, the intensive margin is calculated as 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 the prior and current year. Specifically, the growth rate is calculated as $\frac{(loan_{ibt} - loan_{ibt-1})}{(0.5 \times loan_{ibt} + 0.5 \times loan_{ibt-1})} \times 100\%$, reflecting changes in the volume or amount of loan balance.[37] On the other hand, the extensive margin is calculated as a new loan 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.[38] It is equal to 1 when the loan growth rate is positive, capturing whether

[37] This method of growth calculation allows for incorporating the 0 in the loan outstanding balance.

[38] This is also conditional on firm-bank relations being present in both the prior and current year.

a firm gets any new credit at all, as opposed to how much credit it gets. In an extension, I also measure the firm bank relationship changes and interest rates as alternative outcomes.

In order to compare the individual effects of the two risks, I include both risk measures in the same regression model in the baseline analysis. To alleviate the potential reverse causality concern, I lag all climate risks variables by one year, given credit outcomes are measured annually. 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. I also consider firm and bank-level controls, such as size and leverage ratio, 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 I allow serial correlations within both firms and banks (See results in Table A6). Control variables, summarized in Table 1, generally have expected effects and vary in statistical significance, which is unsurprising given that different specifications include various sets of fixed effects. For brevity, I only report the main variables of interest.

Including too few fixed effects and controls may raise endogeneity concerns while including too many could lead to over-fitting. Therefore, I report the estimated outcomes for all specifications, allowing for a comparison of results from the most parsimonious to the most comprehensive model. I expect that as I add more granular fixed effects and controls, the estimated effects will decrease, with the most saturated model providing a lower bound for these estimates. Given the source of identification may vary depending on the set of fixed effects and controls I include, for illustrative purposes, I carefully outline each specification in the section below and discuss where the identification comes from in each empirical specification.

I start with parsimonious specification, where only the physical and transition risks variables and firm (α_i), bank(α_b), and time/year (α_t) fixed effects are included.

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

The key variables of interest 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 year, which captures the exposure to extreme precipitation and flood risk, while the second one measures firms' vulnerability to climate regulatory risks, varying by firm and year. Given both physical risks and transition risks are measured on different scales, I standardize climate risks variables in the regressions for a meaningful comparison of their relative magnitudes of the effects.

Only the most essential fixed effects α_i, α_b, and α_t are included in Equation (1). Specifically, the vector 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, the vector 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. The vector α_t is time-fixed effects that absorb all the time-varying trends or shocks to business cycles, for example, macroeconomic variables including GDP, unemployment rate, inflation, or policy rate. Finally, ϵ_{ibt} is the idiosyncratic error term.

Identification in Equation (1) thus rests on exploiting two sources of variation. First, within firm-bank variations, i.e., the credit differences over time within a given firm (borrower) bank pair, in response to the change of firms' climate risks over time, as shown in Figure D.10. Second, within bank-time variations, i.e., the credit differences over high-climate-risk firms relative to the low-climate-risk peers, when borrowing from the same bank in the same year, as shown in Figure D.11.

The main coefficients of interest, β_1 and β_2, indicate whether a bank is more or less likely to initiate a loan (for the extensive margin) or increase the loan amount (for the intensive margin) for a firm experiencing a change in exposure to climate risks over time. They also capture the credit differences between two comparable firms with different climate risks profiles borrowing from the same bank in a given year. The expected sign of β_1 and β_2 is not clear ex-ante, as there are both positive and negative forces that drive the bank and firm side, as explained in Section 2.2. A null coefficient will be consistent with the H1 hypothesis that no credit adjustment is observed. A negative coefficient would indicate that less credit is allocated to risky firms, this can be due to firms' lower growth and thus less credit demand (H3A) or banks may supply less credit due to high credit risks linked to physical and transition risks (H3B).

In Equation (2), I add firm-level and bank-level control variables X_{it-1} and Z_{it-1} to absorb those time-varying characters that capture firm credit demand and bank credit supply that might be correlated with variables as well as lending outcomes. The vector X_{it-1} denotes a set of firm-level variables including firm size, leverage ratio, and return on assets (ROA), while the vector Z_{it-1} consists of bank-level characteristics, such as bank size:

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

In the next specification Equation (3), I add location (parish) fixed effects to account for unobserved, time-invariant geographic characteristics, such as differences in productivity and firm size across locations, that may influence credit allocation and introduce estimation bias. Parish fixed effects also help address endogeneity arising from firms anticipating higher physical risks in certain areas, such as those near the sea, and consequently avoiding these areas or relocating from high- to low-risk zones. 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. This specification thus exploits the within-parish variation, i.e., comparing the credit differences by a given bank b to a given firm i in the same parish p over time:

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

Afterward, I saturate the model by adding industry-fixed effects α_j in Equation (4) to account for time-invariant industry-specific characters that may be correlated with both climate risks factors and credit outcomes. This also addresses the endogeneity concerns raised by firms that move from a brown to a relatively cleaner industry. Therefore, the expected magnitude of the coefficients is likely to be lower compared with Equation (2), as I control for firms moving in and out of industries and locations. 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 empirical specification is written as below:

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

The next specification in Equation (5) augments 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, I include a matrix of 2-digit industry-year dummies. I also include bank-year 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 including banks' financial health, internal policies regarding loan approval processes, changing regulatory environment, etc.[39]

[39] Note that I am not able to add bank-level control variables Z'_{bt-1} in this case as they are absorbed by bank-year fixed effects. Individual bank, industry, and year fixed effects are also absorbed by higher dimensional fixed effects. I do not add parish-year fixed effects and firm-year fixed effects as they will absorb the variations of the main variables of my interest.

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

Finally, thanks to the granularity of the data, I incorporate firm-bank fixed effects α_{bf} in Equation (6) 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 ensures that the identification relies on the same firm bank group, as shown in Figure D.10. In addition, adding those fixed effects allows me to control the bank credit supply shocks that are common across all firms with bank-year dummies and any shocks to firm-bank pair with bank-firm dummies, and thus control for credit demand in the spirit of Khwaja and Mian (2008), Jiménez et al. (2012), and Jiménez et al. (2014). While I cannot add firm-year fixed effects as this will absorb the variations in transition risks that are measured at the firm time level, I include as much firm-level time-varying control as possible to proxy for credit demand shocks that are common across all banks.[40]

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

4.2 Threats to identification

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

With respect to the exposure to future flood risk, with the variation largely coming from across locations, I 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. To address this concern, I consider a refinement in which I exclude those firms that relocate in order to compare the credit outcomes for firms that stay in the same locations, as presented in Table A7, in addition to adding location (parish)

[40]The state-of-the-art methodology to empirically identify credit supply shocks relies on the assumption that credit demand shocks can be accounted for using fixed effects that saturate all firm time variations. This method builds on recent literature that uses microdata to account for firm credit demand shocks that are common across all banks with firm-year dummies and for bank credit supply shocks that are common across all firms with bank-year dummies, as well as firm-bank dummies that control for all time-invariant unobserved shocks in the demand and supply of credit. For examples of recent papers, see Khwaja and Mian (2008); Paravisini et al. (2023); Jiménez et al. (2014); Chodorow-Reich (2014).

fixed effects in one of the specifications in Equation (3).

Another concern is the reverse causality in the context of transition risks. As transition risks measure varies from year to year, it could be driven by firms' engagement in climate mitigation and adaptation and, thus, reduce risk exposure. One example is that firms with high energy intensity that are exposed to high emission tax 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, I include a refinement where I measure transition risks with a more exogenous base-year approach, i.e., measuring a firm's energy intensity in the first year in which a firm in the sample is observed. Specifically, transition risks, denoted as $\textit{Transition risks}_{ijt}$, is calculated as:

$$\textit{Transition risks}_{ijt} = \textit{Energy intensity}_{ij0} \times \textit{Environmental tax}_{jt}$$

for firm i, industry j, year t. I present the results with the base year approach in Table A4.

5 Empirical Results

In this section, I present the empirical results based on the specifications discussed above. The structure is as follows: I begin by presenting the baseline results for H1, examining whether banks adjust credit allocations to firms' exposure to climate risks (see Section 5.1) using gradually saturated fixed-effects specifications. Next, I test H2 to determine whether more credit is directed toward "greening" firms (Section 5.2). Finally, if a negative credit outcome is observed, I explore the heterogeneity (Section 5.4) and test the theoretical mechanisms discussed in H3A and H3B (Section 5.5) to identify the key driver.

5.1 Do banks adjust credit allocation?

5.1.1 Intensive margin of lending

I first report the baseline estimation results for the effects of physical and transition risks on the intensive margin of the lending, i.e., the loan growth rate in percentage points in Table 2.

In column 1 of Table 2, I estimate a simple model where I only include a set of dummy variables, namely firm, bank, and year dummies. 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 less credit to those firms located in high-physical-risk zones than they do for firms located in low-physical-risk zones in the same year. In addition, banks reallocate credit 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 risks of a firm's location results in about 1.368% reduction in credit growth in terms of absolute change.[41] This reduction per standard deviation change of physical risks represents about a 10% change relative to the sample mean loan growth, which represents a sizable reallocation of lending relative to the sample mean.[42]

Second, higher transition risks are also related to lower credit growth. The magnitude of the estimated coefficient is slightly larger than the physical risks. The coefficient of 2.208 suggests that if a firm's transition risks exposure increases by one standard deviation over time or relatively to another firm, the credit growth is reduced by about 2.208%.[43] This represents about a 16% change relative to the sample mean loan growth.[44]

I then advance the model with important control variables for firms and banks in column 2, parish fixed effects in column 3, and industry fixed effects in column 4. In column 5, I include high-dimensional fixed effects (industry-year fixed effects and bank-year fixed effects). Lastly, I add granular firm-bank fixed effects to address the endogenous matching in column 6. As I saturate the model with more restrictions, the estimated coefficients β_1 and β_2 overall decline as expected, but the coefficients remain negative and significant. Put together, a one standard deviation increase in a firm's exposure to physical risks, results in about 1.1%-1.4% reduction in loan growth, representing about 8%-10% deviation from the sample mean. The impact of transition risks is slightly larger, a one standard deviation increase in transition risks is associated with an about 1.6%-2.2% decrease in loan growth, representing 11%-16% deviation from the mean.

5.1.2 Extensive margin of lending

The estimation results for the extensive margin, defined as the probability of receiving new loans, are presented in Table 3. The new loans variable is 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 setup above, I begin with a simple model shown in column 1 (Equation (1)), then include additional controls in column

[41] Given that the mean and standard deviation of physical risks are 0.99 and 1.162 respectively (see Table 1), a one standard deviation increase implies that the mean average goes from 0.99 to 2.152 (0.99+1.162=2.152).

[42] The mean and standard deviation of loan growth is -14.225% and 117.261, therefore the change relative to the sample mean of loan growth is calculated as -1.368%/-14.225%= 10%, while the standard deviation change of loan growth is calculated as $(-1.368\% - (-14.225\%))/117.261 = 0.1$, indicating a modest effect relative to the overall variability of loan growth.

[43] A one standard deviation change in transition risks implies a considerable jump from an average of 26.678 to 176.818 (26.678 + 150.14 = 176.818), given the mean is 26.678 and standard deviation is 150.14.

[44] Given that the mean and standard deviation of loan growth is -14.225% and 117.261, the change relative to the sample mean is calculated as -2.208%/-14.225% = 16%. Regarding the standard deviation change of loan growth, it is about $(-2.208\% - (-14.225\%))/117.261 = 0.1$.

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 3 indicate that only higher physical risks are related to a lower likelihood of receiving new credit, and the results are no longer significant 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 and the quality of the firm's link with a particular bank, which plays a more important role in banks' decisions to allocate credit. Additionally, although the coefficients for transition risks are negative, they are not significantly associated with the probability of the firm receiving new credit 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 risk exposure. Instead, they could reduce the growth of the credit, as shown in Table 2, or ask for more collateral.

All in all, the evidence rejects the H1 hypothesis and indicates that firms' physical and transition risk exposure affect lending primarily on the intensive margin. Specifically, firms facing increased physical or transition risks over time experience reduced credit growth, suggesting that banks are cutting the growth of credit allocated to these firms. It is also important to highlight that the magnitude is relatively modest, given the rather large variability of loan growth.

5.1.3 Extension: alternative credit outcomes and extreme risks dummy

Firm-bank relationship changes and interest rate As an extension to the main credit outcomes, I further explore other aspects of interesting outcomes, including adjustment of firm-bank relationships and interest rates. To do so, I augment Equation (5), where the most complete set of fixed effects are included, replace the dependent variable with measures for relationship changes and interest rate, and present the estimation results in Table 4.

In column 1, I first estimate the effects of climate risks on entering into new relationships, where "enter" is a dummy variable set to 1 if a firm and bank establish a relationship for the first time. Specifically, it is defined as 1 if firm i borrows from bank b in year t but not in the previous year t-1, i.e., $(loan_{ibt} > 0 | loan_{ibt-1} = 0)$. Similarly, in column 2, "exit" is a dummy variable set to 1 if a previously existing firm-bank relationship discontinues, i.e., $(loan_{ibt-1} > 0 | loan_{ibt} = 0)$. The significant negative coefficients show that banks are cautious about entering into new relationships with firms exposed to high transition risks. Additionally, if the physical risks associated with existing clients become too large, banks may choose to exit those relationships. Put together, the results provide evidence that banks are adjusting their ties in response to climate risks: they are more cautious when it comes to initiating new relationships and may choose to cut their ties with firms when the risks become too high.

I then proceed by evaluating the interest rates (the loan prices) in column 3. Following Jensen and Johannesen (2017), I calculate the effective interest rate for a firm i borrowing from bank b in year t as $Interest\ rate_{ibt} = \frac{Interest\ payment_{ibt}}{0.5\times(Loans_{ibt}+Loans_{ibt-1})} \times 100$. This variable 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.[45] Column 3 shows that the cost of loans does not significantly show a direct correlation with physical and transition risks despite the estimated sign being positive.

Overall, the finding on alternative outcomes suggests that while banks may be cautious in forming new relationships and more likely to exit old relationships, they do not seem to adjust the pricing of existing loans yet.

Response to the tail of physical and transition risks In another extension for the baseline analysis, I focus on the tails of climate risks distribution, rather than the whole distribution. This is because the impacts of climate risks are typically related to the extreme ends of the risk distribution, often referred to as the "tail risks". By classifying firms into different extreme-risk groups, I can then decompose the credit allocation among different groups.

Specifically, I 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, where I define a high physical risks dummy variable (High PR) and a high transition risks dummy variable (High TR) that is set to 1 if the respective risk indicator falls into the top 25th percentile of the distribution in a given year.[46] Using the following specifications, I can compare the credit allocation among extreme-risk groups, relative to the medium-risk group.

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

[45] I adopt this approach as that loan maturity and the contractual interest rate are not systematically reported in the credit data. Nevertheless, the effective interest rate 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.

[46] Similarly, the low physical risks dummy variable (Low PR) and low transition risks dummy variable (Low TR) are then defined as 1 if the risk falls into the bottom 25th percentile of the distribution in a given year.

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

The estimated results are presented in Table 5. In columns 1-2, the dependent variable is the loan growth in percentage points as intensive margin while columns 3-4 measure the extensive margin, which is a 0/1 dummy variable indicating whether a given firm received new loans. The signs of the point estimates for the high physical risks (PR) dummy and high transition risks (TR) dummy are negative, whereas those for low PR and high TR are positive. This pattern confirms the baseline analysis and 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.

The results are robust to different definitions of extreme dummies and alternative measures of climate risks with a composite index. Specifically, I 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, as shown in the first panel of Table A9. I also consider a composite climate risks index that combines both dimensions of risks with equal weights into one metric, inspired by Bakkar (2023).[47] This index is essentially a discrete variable ranging from 0 to 8, where the highest value indicates the highest level of climate risks exposure for a firm. The second panel of Table A9 shows the results, which confirm the main findings.

5.1.4 Alternative tests and robustness checks

In the appendix, I present several alternative tests and robustness checks to make sure that my baseline result is not sensitive to specific choices of empirical proxies for climate risks and bank lending, as well as to particular choices of specifications and samples.

Alternative dependent variables In Table A1, I use different measures of dependent variables: 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 $\log(loan_{ibt}) - \log(loan_{ibt-1}) \times 100$. This helps to address potential concerns about the presence of zero values in the loan account balances. Taking the logarithm results, these observations are treated as missing data. In column 3, I focus on positive loan growth, setting negative loan growth to zero. This adjustment addresses the concern that my baseline measure of loan growth captures both the amount of the new loan origination and the repayment speed of

[47] Specifically, I divide the sample into four quartiles for both physical and transition risks metrics, assigning a score of 1 to firms in the lowest quartile, 2 in the second, and so on, with 4 for the highest quartile. This implicitly assumes that the risk distribution is stable over the sample period. I then construct a composite climate risks index by summing the scores for each risk dimension.

existing loans, leading to both positive and negative growth.[48] The results indicate that most of the point estimates for β_1 and β_2 remain negative, although some estimates lose significance.

Alternative climate risks variables I then look at robust definitions of the main empirical proxy for physical risks and transition risks. In Table A2, I modify physical risks measure using alternative levels of decay parameters, ranging from 0.01 to 0.1.[49] This decay parameter indicates how far-reach climate events can indirectly extend to firms located in the neighboring areas. A lower decay parameter implies that even firms located further away from the event locations will likely be indirectly affected. Conversely, a higher decay parameter captures local events where only directly affected firms in a given parish are reflected in the indicator. The results show that the sign of the estimated coefficients for physical risks are not sensitive to varying values of decay parameters. Notably, the magnitude of the estimated coefficients is larger for a lower decay parameter, which suggests that banks are more responsive to those impactful events that affect a larger area comprising several parishes.

In Table A3, I look at robust definitions of transition risks. In columns 1-2, as an alternative way to measure firms' exposure to climate policy changes, I leverage the data provided by Gu and Hale (2023), who count the total number of relevant climate policies that are either in force or announced and compute the annual change of policy counts.[50] I utilize the number of climate policies in Denmark and the EU and visually plot the changes in climate-related policy counts over time in Figure D.13, with policies related to climate mitigation and energy efficiency increasing significantly since the 2000s. A higher number of policy changes implies tighter government intervention and more aggressive political actions to combat climate change. I further interact with the change of policy data with firm-level energy intensity to obtain exposure at the firm level, i.e., $\textit{Transition risks}_{it} = \textit{Energy intensity}_{it} \times \textit{Climate policy change}_t$ for firm i, year t.

Given that my measure of firm-level energy intensity is based on energy consump-

[48] While the baseline measure estimates how climate risks may impact both the amount of new loans and existing loan repayments, in this alternative measure, I consider the scenario where only positive loan growth is analyzed, effectively ignoring the existing loan repayment.

[49] I choose the values range between 0.01 to 0.1, as these are the most economically reasonable choices given the average distance between measurement stations and the closest parishes, which is approximately 25 kilometers, varying from 10 kilometers in some areas to up to 40 kilometers in others. For example, when $\delta = 0, 1$, a parish 25 kilometers away has a weight of 0.08. If I choose a decay parameter that is too high, I will not be able to capture the spillover effects across parishes.

[50] The policy data is obtained from the International Energy Agency (IEA), which provides information on past, existing, and planned government policies to reduce emissions, support green energy technologies, and improve energy efficiency, over the period from 1975 to 2021.

tion, in columns 3-4, I alternatively measure transition risks as the interaction between energy intensity and total energy taxes at industry-year level, i.e., $\textit{Transition risks}_{it} = \textit{Energy intensity}_{it} \times \frac{\textit{Energy tax}_{jt}}{\textit{Value added}_{jt}}$ for firm i, industry j, and year t. The energy taxes include taxes on energy products for transport purposes (e.g., petrol and diesel), energy products for stationary purposes (e.g., fuel oils, natural gas, coal, and electricity), and taxes on greenhouse gases, i.e., carbon dioxide (CO2) taxes and emissions permits (e.g., EU Emissions Trading Scheme).

In columns 4-5, to address the concerns that firm-level energy intensity only captures scope 2 emission, I use scope 1 emissions (GHG emissions) at the industry level, and interact industry direct emissions with environmental taxes (both scaled by industry value added) to capture the exposure of climate policies or regulations for those emission-intensive industries, calculated as $\textit{Transition risks}_{jt} = \frac{\textit{GHG emissions}_{jt}}{\textit{Value added}_{jt}} \times \frac{\textit{Environmental tax}_{jt}}{\textit{Value added}_{jt}}$, for industry j, and year t.

In columns 7-8, I simplify my measure of transition risks by excluding policy stringency and only include firm-level energy intensity (scope 2) as a proxy. As shown in Table A3, the results using all of these alternative definitions of transition risks are consistent with those from my main analysis presented in Table 2 and Table 3.

Additional results reported in Table A4 also show that the impact of transition risks is still robust even when I use a more exogenous base year approach to measure the energy intensity variable in the construction of the transition risks to attenuate simultaneity issues, as explained in Section 4.2. All these refinements confirm the main findings that higher climate-related physical risks and transition risks are related to lower credit growth.

Alternative specifications and clustering I then evaluate whether the impact of physical and transition risks on lending outcomes changes with different specifications in Table A5. First, to take into account banks' medium and long-run response to climate risks, I re-estimate Equation (2) by introducing a second lag climate risks variables in columns 1-2. The significant negative coefficients in the second lag of physical risks indicate the potential presence of long-term effects. Next, to explore the possible existence of non-linearity in the effects of climate risks, I also consider an additional specification in which I add the squares of climate risks variables, as reported in columns 3-4. The sign and magnitude of the estimated coefficients of physical and transition risks are similar to those from my main analysis. Furthermore, the positive coefficients in the square term of climate risks give suggestive evidence of a possible convex relationship between climate risks and lending. One potential explanation is that at a very high level of climate risks, the financing needs associated with firms' climate adaptation or mitigation could have a dominant effect and lead to a positive relationship between climate risks and lending. Lastly, I present the results with an alternative clustering scheme in Table A6, where I cluster the standard errors at the firm and bank levels and allow serial correlations within both firms and banks. The result suggests that the main result is not sensitive to how I cluster the standard errors.

Alternative sub-samples I proceed by repeating my main test using various robust samples to make sure that the results are not driven by specific groups of firms or banks. In Table A7, I look at various sub-samples at the firm level. Columns 1-2 present the main results using a sample of incumbent firms in the last 10 years (2009 to 2019). Columns 3-4 exclude new entrant firms that were formed in the sample period, while columns 4-5 exclude firms that exit during the sample periods to test the sensitivity of the results to firm dynamics. In columns 7-8, I address the potential concern that the results are driven by those highly productive firms, as those firms might have better access to credit or better risk management practices. Columns 9-10 exclude a sample of firms that relocate to address the concerns that firms may respond to increasing physical risks by relocating to other low-risk areas, as explained in Section 4.2. Finally, I exclude firms located in Copenhagen to address concerns that a large share of firms in the capital may drive my main results.[51]

I further explore the sensitivity of the results to different sub-samples of banks in Table A8. In columns 1-2, I exclude small banks with less than 200 employees as those small banks may be more focused on niche markets or local communities and have different risk profiles and less sophisticated risk management processes. In columns 3-4, only incumbent banks in the last 10 years (2009 to 2019) are included, while columns 5-6 exclude banks that exit during the sample periods to make sure that the results are not confounded by banks' entry and exit dynamics. In columns 7-8, I exclude banks in the capital region of Denmark to test whether the main findings are driven by regional factors specific to the capital areas. Columns 9-10 exclude a sample of banks with only one establishment to make sure the main results are influenced by the operational scale or geographic concentration of the banks.

All in all, I find that the main effect documented in this paper survives in all of those alternative samples and confirm that it is not driven by specific firm-level and bank-level sample characteristics.

5.2 Do banks allocate more credit to risky and "greening" firms?

So far, the empirical findings reject H1 and suggest that banks lower credit growth to firms with high exposure to physical or transition risks. However, these risky or initially "brown"

[51] I further explore the heterogeneity of the observed effects across different regions. The effects of physical risks are more pronounced in the capital city regions ("Region Hovedstaden") and Mid Jutland Region ("Region Midtjylland") among 5 regions of Denmark, as shown in Table A10.

firms may more intensively engage in climate adaptation or mitigation, such as green innovation activities (Miao and Popp, 2014; Gramlich et al., 2020; Liu et al., 2024), to hedge their risks, which may be viewed as positive signals by banks. Therefore, I proceed with testing H2 and see whether banks support those risky firms that show evidence of "greening". In other words, while firms with higher risk exposures generally experience lower credit growth, those that actively participate in climate adaptation and mitigation may be viewed more favorably by banks.

I identify "greening" firms with two proxies. First, a dummy variable equal to one if a firm shows reductions in energy intensity compared with the previous year. Second, a dummy variable equal to one if a firm applies for a green patent, to measure engagement in green innovation activities. The data is collected from a register of patent applications sent by Danish firms to the European Patent Office (PATSTAT), similar to Calel and Dechezleprêtre (2016) and Li et al. (2021). A patent application is defined as *green* if its Cooperative Patent Classification (CPC) is either in category *Y02* or *Y04S*. [52] Furthermore, a patent is classified as *green*, if its International Patent Classification (IPC) is under the categories that refer to climate change mitigation and adaptation technologies.[53]

In Table 7, I present estimation results based on versions of Equation (2), where I include an interaction of physical and transition risks with the proxies "greening" firms. In columns 1-2, I present the credit outcomes for those firms that show improvement in their energy intensity. The positive coefficients in the interaction terms indicate that improving energy intensity can partially offset the negative effects of their risk exposures. In columns 3-4, I show the credit outcomes for firms with green patent applications. Overall, the evidence supports the idea that while banks divest from firms with high climate risks exposure in general, they also consider those firms' engagement in climate risks adaptation or mitigation as a positive signal, leading them to allocate more credit toward these risky and "greening" firms.

[52] Category *Y02* covers selected technologies that control, reduce, or prevent anthropogenic emissions of greenhouse gases in the framework of the Kyoto Protocol and the Paris Agreement. It also includes technologies that allow adapting to the adverse effects of climate change. Category *Y04S* refers to systems integrating technologies related to power network operation, communication, or information technologies for improving the electrical power generation, transmission, distribution, or usage, i.e., smart grids. The detailed description of CPC can be found at `https://www.uspto.gov/web/patents/classification/cpc/html/cpc-Y.html#Y02`.

[53] The categories included are: 6A (Treatment, disposal, combustion and recycling of waste; cleaning of air and water pollution), 6B (Energy conservation and energy efficiency), 6C (Biofuels), 6D (Fuel cells and hydrogen technology), 6E (Solar Energy), 6F (Hydro Energy), 6G (Waste energy, energy from waste heat, fuel from waste), 6H (Wind Energy), 6I (Geothermal energy, and energy from natural heat), 6Z (Environment excluded in 6A), ZB (Automobiles), and ZC (Other transport technologies). The detailed description of these categories can be found at `https://www.dropbox.com/scl/fi/bek06qgq6eqgy26wbzl1f/Copy-of-green.xlsx?dl=0&rlkey=xah83onydyg7ywrri0uabb6yx`.

5.3 The role of interactions of physical and transition risks

While there is evidence of the individual effect of each type of risk on credit outcomes, how does the outcome respond to the interaction of the two risks? The idea is that physical and transition risks are often interrelated, interacting in complex ways (ECB, 2021b). Therefore, the observed negative effect of climate risks on credit allocation may be amplified or mitigated, depending on how the risks interact. For example, rising physical risks, such as those associated with extreme weather events, can trigger more stringent policies, thereby increasing transition risks.[54]

Given physical risks are mostly location-dependent, while transition risks are industry or firm-specific, firms may face varying degrees of exposure depending on their geographic location or industry. To visually show the interaction of the high (low) physical risks and transition risks exposure, I plotted them into a 2×2 matrix, as presented in Figure D.12.

To empirically investigate how banks respond to the interaction of the high (low) physical risks and transition risks exposure and reallocate credit among different groups, I estimate the following specifications:[55]

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

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

The main variables of interest are the four interaction dummies that capture the interaction of high (low) physical and transition risks, as defined in Section 5.1.3, with interaction effects represented by the coefficients β_1 through β_4. According to Table 6, 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 interacted (compounded risks). For firms with high interaction risks, I observe a negative impact on credit growth and the initiation of new loans, although these findings are not statistically significant. This indicates a modest response from banks, which appear to slightly favor firms with lower interacted risks while not significantly altering their credit

[54] Another example highlighting the importance of analyzing interacted (compounded) risks is that banks' climate-related scenario analyses have increasingly integrated both physical and transition risks. For instance, the Network for Greening the Financial System (NGFS) has developed four widely adopted scenarios featuring varying levels of physical and transition risks, including 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).

[55] I use the extreme risk dummy, instead of the continuous climate risk measure for the interaction analysis as the interaction of two continuous values is harder to intercept.

policies towards high-risk firms.

5.4 Heterogeneity analysis

In this section, the paper proceeds with the heterogeneity analysis and asks what factors on the borrower and bank sides might amplify the effect of physical and transition risks on lending patterns. Identifying these would also help to understand how different characteristics influence the sensitivity of the negative effects and shed light on some microeconomic mechanisms that could plausibly be behind the observed reallocation of credit, as I outlined in Section 2.2.

5.4.1 Borrower-level factors

Firm size As smaller firms are more informational opaqued, risky, and more likely to be 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 credit. To test this hypothesis empirically, I first categorize small and large firms based on their size distribution, then estimate a modified version of Equation (2), which includes an interaction with size dummy and climate risks variables.[56] As shown in columns 2 and 4 in Table 8, the empirical results support the idea that small firms appear to be more negatively affected by the effects of transition risks in terms of getting access to new loans, whereas large firms are positively impacted.

Financial leverage Firms with high leverage will likely 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, I examine the role of financial leverage in the observed reallocation of credit in response to heightened climate physical and transition risks. The findings are shown in Columns 1 and 2 of Table 9, where I augment the model from Equation (2) by adding an interaction term that combines a high financial leverage dummy (defined as one if the leverage ratio is above the median) with the key variables of interest. The significant negative coefficient for the interaction in column 2 indicates that highly leveraged firms are less likely to receive new loans when exposed to climate risks. This could be because banks are concerned about those firms' lack of financial cushion and lower financial flexibility to absorb adverse shocks related to climate disasters or policy.

[56] Given the skewed distribution of firm size in the sample, I define a large firm as a dummy variable equal to 1 if the firm's size falls within the top 25th percentile of the sample distribution, while a small firm is defined as 1 that falls within the bottom 25th percentile of the distribution.

Put together, the above evidence suggests that risky and constrained firms, such as smaller, more leveraged firms are more negatively affected. This is consistent with the notion that banks tend to avoid compounding different types of risks (Dunz et al., 2023).

Capital intensity and industry brownness I proceed by exploring other factors on the firm side that may play an important role: capital intensity and industry brownness, albeit the link is theoretically ambiguous.

First, capital intensity may play a role in affecting the observed bank lending decision. On the one hand, those firms with high capital intensity have substantial 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. Therefore, it is not clear ex-ante about the role of capital intensity. To test this, I include an 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 the median (50th percentile), with the physical and transition risks variables. The significant negative coefficients on the interaction terms between high capital intensity dummy and physical risks, as presented in columns 3 and 4 of Table 9, suggest 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 consistent with the notion that banks are more concerned about the direct exposure of tangible assets, i.e., machines and factories, to physical risks. However, the interaction term between transition risks and capital intensity shows different signs on the extensive and intensive margins, perhaps due to the different roles capital plays in response to climate risks.

Second, I explore the role of industry brownness. The question of how banks lend to firms within the brownest industry with extremely high scope 1 emissions (e.g., Coke & Refined Petroleum Products) is not clear ex-ante. On the one hand, banks might be more cautious in lending because those firms in the brownest industry are most exposed to transition risks. On the other hand, given that the brownest industry tends to give higher short-term returns, banks may continue to finance firms in brown industries to retain profits.[57] To empirically test for this, I first identify those brown industries if the industry energy intensity, calculated

[57]For example, Fossil fuel finance reports stated the world's 60 largest banks have financed \$4.6 trillion in fossil fuel since 2015, with \$742 billion in 2021 alone (Alliance et al., 2022). Additionally, those brownest industries. such as power generation, oil refining, and steel manufacturing—are typically participants in the EU ETS. This involvement may be viewed as a positive signal by banks that these industries are actively engaging in regulated carbon emissions management.

as the total GHG emission divided by industry value added ($\frac{GHG\ emissions_{j,t}}{Value\ added_{j,t}}$) is above the 95th percentile of the entire sample distribution over time. Those are, therefore, the brownest industries that contribute to high scope 1 emissions in the sample, including the manufacture of coke and refined petroleum products, air transport, and the manufacture of other non-metallic mineral products. In the next step, I refine Equation (2) with an interaction term between climate risks variables and brown industry dummy, as shown in the estimation results reported in Table 10. The estimated coefficient of -5.683 and -6.072 for interaction terms in column 1 suggests that for firms in the brownest industries, the negative impacts of physical risks and transition risks on loan growth (the intensive margin), is even larger, reducing loan growth by an additional 5-6%. However, when it comes to the extensive margin, there is a mixed pattern for the effects of physical and transition risks.

Overall, the empirical results suggest mixed evidence for the role of capital intensity and industry brownness in the observed credit allocation outcomes, consistent with the previous theoretical hypothesis.

5.4.2 Bank-level factors

Next, I explore the different roles that bank-level factors may play in the observed relationship between firms' exposure to climate risks and credit allocations.

Lending familiarity Given the firm bank fixed effects play an important role in the estimation of baseline results, i.e., the effects of physical risks on the extensive margin of lending drop and become insignificant (see Table 3), this further raises the question of how the relationships between banks and borrowers may influence the banks' decisions. My hypothesis is that banks are more likely to adjust lending to existing clients, compared with the first-time lender for two reasons. First, banks have an information advantage when dealing with borrowers who have obtained loans in the past, particularly in the context of SMEs (Petersen and Rajan, 1994; Diamond, 1991; Sharpe, 1990; Rajan, 1992). They can therefore more efficiently acquire climate-related information from these repeat borrowers. Second, given Danish bank-firm relationships tend to be quite "sticky" (Hviid et al., 2022), banks are in a better position to adjust lending to repeat borrowers, knowing that it may be difficult for firms to shift lenders.[58] However, when it comes to first-time lending, they might lift their credit restrictions and give more new loans to build relations with new borrowers, regardless of their climate risks exposure.

In Table 11, I take the question to the data and augment Equation (2) with an interaction term between climate risks variables and a bank-borrower measure of lending relationships or

[58]The average firm maintains connections with only about two banks.

familiarity. Specifically, "Repeat Lending" is a 0/1 dummy variable indicating whether the same bank has previously allocated loans from the same firm, while "First Time Lending" is a dummy variable equal to 1 if a given bank has never initiated loans to a given firm in the past. The point estimates on the interaction between repeat lending and climate risks are mostly negative and significant (columns 1 and 2), while the interaction between first-time lending and climate risks are largely positive and significant (columns 3 and 4). The interpretation is that banks tend to adjust lending to existing clients with high exposure to climate risks while not necessarily lending to new customers. This confirms the hypothesis and supports the theoretical notion that relationship lending plays an important role in the observed reallocation of credit in response to climate risks. It also echoes the idea that sticky banking relationships can be costly to borrowers who switch lenders (Chodorow-Reich, 2014).

Banks' exposure to climate risks Given banks' exposure to climate risks primarily arises indirectly through their loan portfolios (Faiella and Natoli, 2019), I then proceed by examining banks' own exposure to climate risks, calculated based on their loan portfolio and their client firms' exposure to physical and transition risks. My hypothesis is that banks with higher exposure to climate risks may be more aware of these risks and, thus, more proactive in incorporating them into their credit allocation.

To test this channel, I construct an empirical proxy for the banks' exposure to climate risks. In particular, I calculate, for each bank year, the loans-weighted average of physical risks (transition risks) of their client firms. Specifically, banks' exposure to physical risks $\textit{Banks' physical}_{bt}$ for bank b at time t are defined as:

$$\textit{Banks' physical}_{bt} = \frac{\sum_{i \in I} \textit{Loans}_{ibt} \times \textit{Physical risks}_{pt}}{\sum_{i \in I} \textit{Loans}_{ibt}}$$

where $\textit{Loans}_{ibt}$ is the total loan balance bank bank b extend to firm i at time t. The numerator is the sum of the loan amounts weighted by the physical risks exposures of client firms. Specifically, for each bank b, I first multiply the amount of loans $\textit{Loans}_{ibt}$ with the physical risks exposure $\textit{Physical risks}_{pt}$ of for the given firm i located at parish p. Then, I summarize the amount for all the firm i if it belongs to bank b's clients base I. The denominator is the total loan balance provided by each bank b at time t. Essentially, the banks' physical risks exposure is the weighted average of the physical risks indicator from their client firms, with weights being the proportion of each loan relative to the total loans.

Similarly, banks' exposures to transition risks are defined as:

$$\textit{Banks' transition}_{bt} = \frac{\sum_{i \in I} \textit{Loans}_{ibt} \times \textit{Transition risks}_{i,t}}{\sum_{i \in I} \textit{Loans}_{ibt}}$$

I then define high exposure banks to be those for which *Banks' physical*$_{bt}$ or *Banks' transition*$_{bt}$ are above the 75th percentile. Those are the banks that are extremely exposed to physical or transition risks. "High Exposure Bank" is a dummy variable equal to 1 if a bank falls into the category. I then interact this variable with physical and transition risks and augment Equation (2) with this interaction, as reported in column 1-2 of Table 12. The evidence confirms that those high-exposure banks are more cautious in lending to those high-exposure firms, as indicated by the negative coefficients of the interaction terms.

Banks' specialization in brown industry Another prominent bank-level factor that might play a role is bank specialization (Paravisini et al., 2023), albeit the relations are ambiguous. On the one hand, banks that have already built experience or expertise in lending to brown industries may have a higher incentive to continue this trend to obtain higher short-term profit margins (Laeven and Popov, 2023).[59] In addition, banks with high exposure to a particular industry are more informed and have lower information acquisition costs (Sharma, 2024; Giometti and Pietrosanti, 2022), as they have more interaction with the borrowers and have an information advantage. As a result, specialized banks are better positioned to manage those risks, such as in the event of sudden implementation of carbon taxes. On the other hand, as those banks are likely to face higher regulatory, reputation, or financial risks associated with climate risks, they might be more proactive in managing the risks and, therefore, more cautious in lending, as discussed in Section 5.4.2.

Following banks' specialization measure in the spirit of Paravisini et al. (2023), I construct an empirical proxy $Share_{b,t,j}$ as the share of total lending bank b in a given year t extended to 2-digit industry j, calculated as the ratio of total loans by bank b extended in year t to industry j ($Loan_{b,t,j}$) to total lending by bank b in year t to all industries ($Loan_{b,t}$). Specifically, the share of total lending to industry j by bank b in year t is given by:

$$Share_{b,t,j} = \frac{Loan_{b,t,j}}{Loan_{b,t}}$$

A bank is considered to be specialized in an industry j in year t if the share falls in the 75th percentile of the sample distribution for that industry j, i.e., $S_{b,t,j} \geq P_{75}(S_j)$. I then identify those banks specialized in brown industries if the specialized industry j falls in brown industry.[60]

To empirically test this channel, I interact a dummy "Brown Industry Specialization",

[59] For instance, Degryse et al. (2020) show banks with legacy positions of brown firms continue to lend to brown firms and create a barrier in credit supply to newer, greener firms.

[60] This is defined if the industry emission intensity, calculated as the total GHG emission divided by value added ($\frac{GHG_{j,t}}{VA_{j,t}}$) is above the 95th percentile of the entire sample distribution, as explained in Section 5.4.1.

which is a dummy equal to 1 if banks specialized in brown industry, with climate risks variables, as reported in columns 3 and 4 of Table 12. The evidence is consistent with the idea that banks specializing in brown industries are prone to continue to initiate new loans, as indicated by the significantly positive coefficients of the interaction terms in column 4. In other words, banks with specialization in brown industries are more likely to increase lending to those exposed firms, perhaps due to lower information acquisition costs and long-term established ties, consistent with the findings of Laeven and Popov (2023) and Degryse et al. (2020).

5.5 Mechanisms

Since the observed credit outcomes represent the equilibrium between bank lending and firm borrowing, I explore whether the supply-side (banks) or demand-side (firms) effects play a more important role and examine the motivations behind the driver. As suggested in Section 2.2, 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 have slower growth, deleverage, and initiate divestment in response to uncertainties and external shocks, resulting in reduced credit demand (H3A). On the supply side, banks may choose to allocate less credit to firms with high climate risks due to the increased perceived risk of default (H3B). While I acknowledge the inherent challenge of separating supply-side effects from demand-side factors in a clean way, as discussed in the empirical banking literature (Khwaja and Mian, 2008; Jiménez et al., 2020; Degryse et al., 2019). Nevertheless, leveraging rich firm-level data, I empirically test H3A and H3B to examine both the demand and supply sides, in order to have an idea of which side is more important.

5.5.1 Climate risks and credit demand

To empirically test for H3A that lower firm growth can drive the observed negative effects, I begin by examining whether climate risks variables are linked to a range of firm-level indicators that reflect firm growth and credit demand, as detailed in Equation (7). Specifically, I use investment growth and employment growth as proxies for credit demand from firm expansion. Additionally, I consider fixed asset growth as an indicator of funding needs for capital expenditure and sales growth as a measure of credit demand for working capital.

$$Firm\ Growth_{it} = \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + \alpha_i + \alpha_p + \alpha_{jt} + \epsilon_{it} \quad (7)$$

A significant negative coefficient would suggest that higher climate risks are associated with lower firm growth and thus reduced credit demand, implying that credit demand factors could be driving the observed results. However, my analysis does not find evidence supporting this channel stated in H3A, because 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 and banks' risk perceptions, may be more influential in the observed credit reallocation in the context of climate risks.

An alternative way to test for H3A is to examine the effects of climate risks on lending outcomes for a subset of firms that exhibit positive credit demand, inspired by Takahashi and Shino (2023). The rationale behind this approach is that if the negative effects of climate risks on loan growth remain even among firms with high credit demand, it would suggest that the demand effect is not the primary driver. To do so, I re-estimate the baseline regression from Equation (5) using a different sample of firms that are likely to have positive credit demand. The estimation results are presented in Table 14. In columns 1-4, I focus on firms with positive investment growth and employment growth, using these metrics as proxies for growing firms. Columns 5-6 include firms with positive fixed asset growth as an indicator of funding needs for capital expenditure, while columns 7-8 use a sample of firms with positive sales growth to measure the demand for working capital.[61] The evidence that negative effects persist among firms with positive credit demand rejects H3A and suggests that these effects may be attributed to the supply side, rather than a lack of demand.

5.5.2 Climate risks and credit supply

To support the credit supply side explanation, I apply a method developed by Degryse et al. (2019), where I include high dimensional ILST fixed effects to better proxy for local credit demand variations.[62] They argue that by grouping firms of similar size, operating within the same industry and geographic location in the same year, it is possible to reduce

[61] I acknowledge that a strong credit supply can also stimulate firm growth and, in turn, generate greater 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.

[62] While the most saturated model in my baseline analysis includes fixed effects such as industry-year and bank-firm to control for the credit demand, there are concerns they may not fully capture the credit demand.

the variability in credit demand that is not related to supply-side factors, as those granular groups of firms are likely to exhibit comparable credit demands within a given year. I present the results in Table 15, where I gradually saturate the model with Industry-Location-Size Fixed Effects (ILS) in column 1, Industry-Location-year fixed effects (ILT) in column 2, and Industry-Location-Size-year fixed effects (ILST) in column 3. The evidence indicates a robust negative relationship between transition risks and loan growth, which further supports the supply-side explanations.[63]

Credit risk channel So far, my empirical evidence suggests that a shift in credit supply is likely to play a more important role in the observed outcomes. A follow-up question is: what is driving banks' motivation? One hypothesis is banks may be concerned about the perceived increasing credit risk associated with climate risks, as stated in H3B.

To empirically examine H3B whether exposure to climate risks is associated with increased credit risk, I run a firm-level regression to test the correlation between climate risks and three proxies for high credit risks: firms' likelihood of exiting the sample, negative EBIT, and financial distress. The estimation results are presented in Table 16. Specifically, the exit variable is a binary indicator that equals one if a firm exits the sample, thereby providing an upper bound estimate of the default rate.[64] Second, negative EBIT is a dummy if a firm's EBIT is negative, an indicator of low profit and high credit risk, as shown in column 2. Finally, financial distress is a dummy equal to 1 if a firm has a low interest coverage ratio (ICR), shown in column 3.[65] The positive coefficients for transition risks in both columns 2 and 3 provide suggestive evidence firms exposed to higher transition risks are more likely to experience negative EBIT and high financial stress, which are perceived as having higher credit risk and are relevant in a bank's conventional credit risk assessment matrix.

Overall, my evidence rejects H3A and supports H3B, suggesting that banks' credit supply may play a more important role in the reduction of credit allocation, and this is due to the financial consideration that those firms exposed to high climate risks are likely to experience higher credit risk.[66]

[63] One caveat of using too many fixed effects is that it may also absorb significant variations of interest, so the result is likely to be a lower bound of my estimates.

[64] To visually see the time trend, Figure D.14 in the appendix details the number of firms that left the sample. Notably, there is a surge of firms exiting during the global financial crisis of 2007-2009.

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

[66] While banks may also have other non-financial incentives such as a taste for green firms, I do not test this channel here as this requires other data sources such as surveys.

6 Conclusion and Discussion

Existing empirical research on banking has shown evidence that large global banks are beginning to respond to physical and transition risks, typically through syndicated loans to large publicly listed firms (Kacperczyk and Peydró, 2022; Degryse et al., 2023; Meisenzahl, 2023). However, there is limited understanding of how banks adjust their credit allocation to non-listed firms which are usually small and medium-sized enterprises (SMEs). Furthermore, existing studies often consider the impacts of physical and transition risks separately, despite their interconnected nature and potential for compounding effects.

This study adds to the empirical sustainable banking by providing evidence on how climate risks affect bank credit allocation, using comprehensive firm-bank matched data from Denmark, that are representative of all types of firms. The empirical evidence suggests that firms exposed to high physical risks and transition risks receive lower credit growth, which echoes the evidence found in the syndicated loan markets. In addition, more credit is allocated to these risky but "greening" firms and firms with low interacted risks.

This paper further documents a large heterogeneity of observed credit allocation within different groups of borrowers and banks. On the borrower side, more constrained firms (small firms and highly leveraged firms) are more negatively affected. On the bank side, the observed reductions are stronger for banks with repeat lending relationships with high-risk exposure, while banks specializing in the brown industry continue to increase their lending. Furthermore, I empirically test the relations between climate risks and firm-level outcomes to shed light on the channels. The evidence suggests that the credit supply side is likely to play a bigger role in the observed effect, as firms facing higher climate risks are observed to experience higher credit risk.

This paper responds to the concerns from policymakers about the potential financial stability risks posed by climate change (ECB, 2021b; Fed, 2021) and has several policy implications. First, I provide positive evidence that banks are responding to rising climate risks in credit allocation. This is particularly interesting for banking supervision authorities and central banks. Given the modest magnitude of the effects, future policies should develop clear guidelines for banks to assess and manage both physical risks and transition risks comprehensively, and provide training to better integrate these risks into credit assessments. Second, given that the results suggest more constrained firms are more negatively affected in accessing credit, there may be a need for targeted policies to help those smaller and more marginalized firms in the green transition. For example, providing them with targeted financial assistance, access to external financing, insurance schemes, and subsidies. Third, future policies could be introduced to further encourage banks to support firms engaging in “greening” efforts and consider the potential interaction of two types of climate risks.

The results also have implications for firms and banks. From the firms’ perspective, I document that exposure to high climate risks may incur additional costs through the bank financing channel. Small and highly leveraged firms are particularly vulnerable to these credit constraints. In addition, given that “greening” firms have easier access to finance, firms might have more incentives to engage in green transition to ensure easier access to credit. For banks, given the modest effect of climate risks on credit allocation and the large heterogeneity among banks, they need to enhance their climate risks management practices and accelerate the shift toward more sustainable lending.

Finally, I highlight a few crucial caveats in light of all these results. First, while the empirical results provide evidence that high-risk exposure firms receive lower credit growth, it is important to emphasize the magnitude of this effect is relatively modest. However, given the anticipated heightened climate-related risks and banks’ internalizing climate risks under their rational expectations, a stronger effect may be observed in the future. Second, this study does not directly evaluate the real effect of the credit reallocation on actual emission reductions (Hartzmark and Sussman, 2019; Apicella and Fabiani, 2023), emission pledges (Gormsen et al., 2024) or green innovations (Accetturo et al., 2022). However, our work may open doors for future research on banks’ real impact on green transition. Lastly, despite my efforts to test the relative importance of the supply and demand factors, I acknowledge the inherent challenges and advocate future research to leverage possible shocks or credible IV to further disentangle credit supply and demand in the context of rising climate risks.

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7 Tables

Table 2: 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 Effects						Yes
Firm Variables		Yes	Yes	Yes	Yes	Yes
Bank Variables		Yes	Yes	Yes		
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 estimated from Equation (1) to Equation (6). 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 1: Descriptive statistics

Variables	**Definition**	**Mean**	**Sd**
Loan growth	The loan growth in percentage points of firm i received from bank b in a given year t	-14.225	117.261
New loans	A 0/1 dummy variable indicating whether a given firm received new loans	0.383	0.486
Physical risks indicator	Geo-weighting indicator of the interaction term between flood and extreme precipitation with delta = 0.06, standardized	0.990	1.162
Transition risks indicator	Interaction term between firm-level emission intensity and scaled environmental tax, standardized	26.678	150.140
Firm variables			
Log (assets)	Log of total assets	10.577	1.56
Fixed assets ratio	The proportion of a firm's fixed assets relative to its total assets	0.33	0.241
Leverage ratio	The proportion of a firm's total debt relative to its total assets	0.502	4.453
ROA	Return on assets, calculated as a firm's profit as a ratio of total assets	-0.642	273.100
Log (size)	Log of total number of employees	3.541	1.031
Multi-establishment	A a 0/1 dummy variable indicating if a firm is a multi-establishment company	0.381	0.486
Log (firm age)	Log of firm age	3.277	0.467
Bank variables			
Log (size)	Log of total number of employees in the bank	7.219	1.791
Multi-establishment	A 0/1 dummy variable indicating if the bank is a multi-establishment company	0.033	0.023
Foreign	Foreign employees as a proportion of all employees in the bank, as a proxy for foreign ownership	0.839	0.368
Number of observations			**220890**
Number of firms			**19904**
Number of banks			**106**

Notes: All descriptive statistics are calculated as averages from 2003-2019. Accounting variables are in real Danish Kroner (using 2015 as the base year). 1 Danish krone is approximately 0.15 US Dollars

Table 3: Climate Risks and New Loans (Extensive Margin)

	New Loans					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Physical Risks	-0.005**	-0.005**	-0.004**	-0.004**	-0.004*	-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 Effects						Yes
Firm Variables		Yes	Yes	Yes	Yes	Yes
Bank Variables		Yes	Yes	Yes		
R-sq	0.139	0.140	0.148	0.148	0.171	0.265
N	220,963	220,890	219,228	219,225	219,167	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) based on Equation (1) to Equation (6). 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 20l9. The detailed firm-level and bank-level control variable definitions are described in Table 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 4: Climate Risks and Bank Lending: Relationship Changes 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
R-sq	0.377	0.368	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 $\frac{Interest\ payment_{ibt}}{0.5\times(Loans_{ibt}+Loans_{ib,t-1})} \times 100\%$, 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 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 5: 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	
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 25th percentile 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 percentile 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 6: 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	
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 25th percentile 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 percentile 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 7: Lending to Risky and "Greening" Firms

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**
	(1)	**(2)**	**(3)**	**(4)**
Physical Risks	-2.029***	-0.007***	-1.490***	-0.005**
	(0.591)	(0.002)	(0.490)	(0.002)
Transition Risks	-3.089***	-0.007**	-2.203***	-0.001
	(0.810)	(0.003)	(0.574)	(0.001)
Reduction energy intensity x Physical Risks	1.116*	0.005**		
	(0.657)	(0.002)		
Reduction energy intensity x Transition Risks	1.126	0.006*		
	(0.929)	(0.003)		
Green patent application x Physical Risks			12.125	0.045*
			(9.000)	(0.027)
Green patent application x Transition Risks			-7.899	-0.057
			(10.663)	(0.090)
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
R-sq	0.087	0.140	0.087	0.140
N	189,142	220,890	189,142	220,890

Notes: The table presents the estimation results for banks' lending to risky and "greening" firms. The estimation is based on versions of Equation (2), where we include an interaction of physical and transition risks with a proxy for "greening" firms. 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. Reduction energy intensity is a dummy variable equal to one if a firm reduces its energy intensity compared with the previous year. Green patent application is defined as one if a firm applies for green patents. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 8: Climate Risks and Lending: Firm Size Heterogeneity

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**
	(1)	**(2)**	**(3)**	**(4)**
Physical Risks	-0.532	-0.005	-1.770***	-0.005**
	(0.841)	(0.003)	(0.526)	(0.002)
Transition Risks	-3.471**	0.000	-2.031***	-0.007***
	(1.620)	(0.000)	(0.564)	(0.001)
Small Firm x Physical Risks	-1.237	0.000		
	(0.872)	(0.003)		
Small Firm x Transition Risks	1.460	-0.007***		
	(1.703)	(0.001)		
Large Firm x Physical Risks			1.224	0.000
			(0.868)	(0.003)
Large Firm x Transition Risks			-1.313	0.006***
			(1.671)	(0.001)
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
R-sq	0.087	0.140	0.087	0.140
N	189,142	220,890	189,142	220,890

Notes: The table presents the estimation results for the firm size 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. Large firm is a dummy variable that equals to 1 if firm size is in the top 25th percentile of the sample distribution; Small firm is defined as those falls into the bottom 25th percentile of the sample distribution; 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 9: Climate Risks and Lending: Financial Leverage and Capital Intensity

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**
	(1)	**(2)**	**(3)**	**(4)**
Physical Risks	-0.944	-0.001	-0.393	0.000
	(0.639)	(0.002)	(0.598)	(0.002)
Transition Risks	-2.306**	-0.001	-1.541***	-0.006***
	(0.930)	(0.001)	(0.525)	(0.002)
High Leverage x Physical Risks	-1.101	-0.007***		
	(0.695)	(0.003)		
High Leverage x Transition Risks	0.212	-0.005**		
	(1.130)	(0.002)		
High Capital Intensity x Physical Risks			-2.138***	-0.010***
			(0.696)	(0.003)
High Capital Intensity x Transition Risks			-1.540*	0.005***
			(0.798)	(0.002)
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
R-sq	0.087	0.140	0.087	0.140
N	188,934	220,615	188,934	220,615

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 the 50th percentile, while high capital intensity is defined if the share of fixed assets as a fraction of total assets is above the 50th percentile. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 10: Climate Risks and Lending: Firms within the Brownest Industry

	Loan Growth	**New Loans**
	(1)	**(2)**
Physical Risks	-1.453***	-0.005**
	(0.491)	(0.002)
Transition Risks	-2.015***	-0.007***
	(0.534)	(0.001)
Brown Industry x Physical Risks	-5.683*	-0.049**
	(3.374)	(0.021)
Brown Industry x Transition Risks	-6.072***	0.007***
	(2.068)	(0.001)
Firm Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes
Firm Variables	Yes	Yes
Bank Variables	Yes	Yes
R-sq	0.087	0.140
N	189,066	220,805

Notes: The table presents the estimation results for banks' lending to firms within the brown industry. The estimation is based on versions of Equation (2), where we include an interaction of physical and transition risks with a proxy for firms in the brown industry. The brown industry is a dummy equal to 1 if a firm belongs to an industry where the industry emission intensity, calculated as the total GHG emission divided by industry value added ($\frac{GHG_{j,t}}{VA_{j,t}}$) is above the 95th percentile of the entire sample distribution over time. Those are, therefore, the brownest industries that contribute to high scope 1 emissions in our sample, including the manufacture of coke and refined petroleum products, air transport, and the manufacture of other non-metallic mineral products. 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. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 11: Climate Risks and Lending: Lending Familiarity

	Loan Growth **(1)**	**New Loans** **(2)**	**Loan Growth** **(3)**	**New Loans** **(4)**
Physical Risks	-0.331	0.001	-1.492***	-0.006***
	(0.815)	(0.002)	(0.488)	(0.002)
Transition Risks	-1.183	0.000	-2.521***	-0.010***
	(0.866)	0.000	(0.523)	(0.002)
Repeat Lending x Physical Risks	-1.161	-0.008***		
	(0.770)	(0.002)		
Repeat Lending x Transition Risks	-1.338*	-0.010***		
	(0.772)	(0.002)		
First Time Lending x Physical Risks			1.161	0.008***
			(0.770)	(0.002)
First Time Lending x Transition Risks			1.338*	0.010***
			(0.772)	(0.002)
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
R-sq	0.112	0.187	0.112	0.187
N	189,142	220,890	189,142	220,890

Notes: The table presents the estimation results for the role of banks' lending familiarity in the observed relations between climate risks and lending. The estimation is based on versions of Equation (2), where we augment the model with interaction terms. 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. 'Repeat Lending" is a 0/1 dummy variable indicating whether the same bank has previously extended loans from the same firm, while "First Time Lending" is a dummy variable equal to one if a given bank has never initiated loans to a given firm in the past. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 12: Climate Risks and Lending: Banks' Exposure and Specialization Lending

	Loan Growth (1)	**New Loans** (2)	**Loan Growth** (3)	**New Loans** (4)
Physical Risks	-0.608	-0.004*	-1.818***	-0.008***
	(0.631)	(0.002)	(0.557)	(0.002)
Transition Risks	-1.648	0	-1.951***	-0.006***
	(1.024)	0.000	(0.545)	(0.001)
High Exposure Bank x Physical Risks	-1.699**	-0.002		
	(0.720)	(0.003)		
High Exposure Bank x Transition Risks	-0.736	-0.007***		
	(0.974)	(0.001)		
Brown Industry Specialization x Physical Risks			0.795	0.007***
			(0.673)	(0.003)
Brown Industry Specialization x Transition Risks			-1.157	0.006***
			(1.089)	(0.001)
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
R-sq	0.088	0.140	0.087	0.140
N	189,142	220,890	189,142	220,890

Notes: The table presents the estimation results for the role of banks' own exposure to climate risks and specialization lending in the observed relations between climate risks and lending. The estimation is based on versions of Equation (2), where we augment the model with interaction terms. 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 Exposure Bank" is a dummy variable equal to one if a bank's exposure to physical or transition risks, calculated as the loans-weighted average of physical or transition risks, are above 75th percentile of the sample. "Brown Industry Specialization" is a dummy equal to 1 if banks specialized in brown industry, defined if the share of total lending of a given bank in a given year extended to the brown industry is in the 75th percentile of the brown industry. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 13: 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
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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 14: Climate Risks and Credit Demand: Firms with Positive Credit Demand

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**
Included Sample	Positive Investment Growth		Positive Employment Growth		Positive Fixed Assets Growth		Positive Sale Growth	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Physical Risks	-2.245***	-0.008**	-0.317	-0.004	-1.276	-0.002	-1.817**	-0.008***
	(0.856)	(0.003)	(0.705)	(0.003)	(0.816)	(0.003)	(0.747)	(0.003)
Transition Risks	-3.683***	-0.001	-2.113**	-0.008***	-2.543**	-0.001	-1.827	-0.001
	(1.021)	(0.001)	(0.847)	(0.002)	(1.029)	(0.001)	(1.158)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2-digit Industry-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.18	0.212	0.14	0.185	0.169	0.206	0.145	0.188
N	81,051	95,796	108,614	127,182	80,071	93,992	103,634	121,371

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 in columns 1, 3, 5, 7 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 columns 2, 4, 6, 8 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. Firms with positive credit demands tend to be those experiencing growth and requiring substantial funding for capital expenditures or working capital. In columns 1-4, we focus on firms with positive investment and employment growth as proxies for growing firms. Columns 5-6 include firms with positive fixed asset growth as an indicator of funding needs for capital expenditure, while columns 7-8 use 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 15: Climate Risks and Lending: Adding ILST Fixed Effects

	Loan Growth			New Loans		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Physical Risks	-0.587	-0.001	-0.606	-0.002	-0.785	-0.006
	(0.625)	(0.002)	(0.898)	(0.003)	(1.139)	(0.004)
Transition Risks	-1.573***	-0.007***	-1.601***	-0.008***	-1.580*	-0.009***
	(0.426)	(0.001)	(0.484)	(0.002)	(0.913)	(0.003)
Parish Fixed Effects	Yes	Yes		Yes	Yes	
2-digit Industry-Time Fixed Effects	Yes			Yes		
Bank-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Bank-Firm Fixed Effected	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Location-Size Fixed Effects (ILS)	Yes			Yes		
Industry-Location-Time Fixed Effects (ILT)		Yes			Yes	
Industry-Location-Size-Time Fixed Effects (ILST)			Yes			Yes
Firm Variables	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.235	0.303	0.327	0.379	0.421	0.461
N	176,635	206,903	167,697	198,441	151,469	182,448

Notes: The table presents the estimation results for the climate risks and lending with granular high-dimensional fixed effects, in addition to the fixed effects included in Equation (6). The dependent variable in column 1 to 3 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 4 to 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. We saturate the model with Industry-Location-Size Fixed Effects (ILS) in column 1 and 3, Industry-Location-Time Fixed Effects (ILT) in column 2 and 4, and Industry-Location-Size-Time Fixed Effects (ILST) in column 3 and 6. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table 16: Climate Risks and Credit Risk 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
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 risk 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 20l9. The detailed firm-level variable definitions are described in Table 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

APPENDIX

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

The findings overall suggest that banks divest from firms with high exposure to physical or transition risks. To rationalize this, I 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), I assume that banks perceive that the green firm has a higher expected return and lower volatility than the brown firm. While not directly empirically tested, I also incorporate a green preference parameter for the bank's non-financial motives in prioritizing green investments (Pedersen et al., 2021; Pástor et al., 2021).

Specifically, I 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. I assume that $\mu_g > \mu_b$ while $\sigma_g < \sigma_b$. The bank's risk aversion parameter is denoted as λ, and α is the green preference parameter, where a higher value of α indicates a stronger preference for the green firm (I 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.1, I 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, I 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 $\mu_g > \mu_b$, $\sigma_g < \sigma_b$ and $\alpha > 0$, I can infer $w_g - w_b > 0$. 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 a taste for investing in green firms.

A.1 Additional proof

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

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

I 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, I 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, I get the closed-form solutions:

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

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

B Additional Literature Review

B.1 Climate risks and other financial markets

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.

Regarding physical risks, 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).

B.2 Climate risks and the pricing of loans

Studies have so far found mixed evidence regarding the pricing of transition risks in bank loans. On the one hand, there is positive evidence that banks price stringent environmental regulations (Fard et al., 2020b), 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., 2024). 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). On the other hand, 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.

Mixed evidence is also found in the price of physical risks 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 risk and track the impact of floods ex-post closely.

C Additional tables

Table A1: Climate Risks and Loan Growth: Dependent Variable Robustness

	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
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 dependent variable 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A2: Climate Risks and Loan Growth: Alternative Decay Parameters

	Loan Growth	**New Loans**
	(1)	**(2)**
Decay Parameter: 0.01	-2.526*	-0.011**
	(1.307)	-(0.005)
Decay Parameter: 0.02	-2.681***	-0.009***
	(0.910)	-(0.003)
Decay Parameter: 0.03	-2.392***	-0.007***
	(0.731)	-(0.003)
Decay Parameter: 0.04	-2.004***	-0.006***
	(0.628)	-(0.002)
Decay Parameter: 0.05	-1.687***	-0.005**
	(0.566)	-(0.002)
Decay parameter: 0.06	-1.448***	-0.005**
	(0.529)	-(0.002)
Decay parameter: 0.07	-1.264**	-0.004**
	(0.505)	-(0.002)
Decay parameter: 0.08	-1.119**	-0.004**
	(0.489)	-(0.002)
Decay parameter: 0.09	-0.998**	-0.003*
	(0.479)	-(0.002)
Decay parameter: 0.1	-0.895*	-0.003*
	(0.472)	-(0.002)
Firm Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes
Firm Variables	Yes	Yes
Bank Variables	Yes	Yes
R-sq	0.087	0.14
N	189,142	220,890

Notes: The table presents the estimation results for Equation (2), using alternative levels of decay parameter to construct physical risks indicator (**??**). For the sake of brevity, only the estimated coefficients for physical risks are reported. In column 1, 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 column 2 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. 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 1. 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: Alternative Definitions of Transition Risks

	Loan Growth (1)	New Loans (2)	Loan Growth (3)	New Loans (4)	Loan Growth (5)	New Loans (6)	Loan Growth (7)	New Loans (8)
Energy Intensity (Scope 2) X Climate Policy Change	-0.615***	-0.002***						
	(0.227)	-(0.001)						
Energy Intensity (Scope 2) X Energy Tax			-2.255***	-0.001				
			(0.680)	-(0.001)				
Emission Intensity (Scope 1) X Enviromental Tax					-0.715***	0.001		
					(0.078)	(0.000)		
Energy intensity (Scope 2)							-0.005**	-0.000**
							(0.002)	(0.000)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.085	0.138	0.086	0.139	0.085	0.139	0.085	0.138
N	198,997	232,357	192,923	225,334	200,274	234,194	198,997	232,357

Notes: The table presents the estimation results for banks' lending response to transition risks from OLS regressions, with alternative definitions of transition risks. In columns 1-2, we measure transition risks as $\textit{Transition risks}_{it} = \textit{Energy intensity}_{it} \times \textit{Climate policy change}_t$ for firm, i, year t, to capture firms' exposure to changes in policy related to climate mitigation and energy efficiency in Denmark and the EU, documented in the IEA database. In columns 3-4, transition risks are proxied by the interaction between energy intensity and total energy taxes at the industry-year level, i.e., $\textit{Transition risks}_{it} = \textit{Energy intensity}_{it} \times \frac{\textit{Energy tax}_{jt}}{\textit{Value added}_{jt}}$ for firm i, industry j, and year t. To address the concerns that firm-level energy intensity only captures scope 2 emission, in columns 4-5, we use scope 1 emissions at the industry-year level and calculate transition risks as $\textit{Transition risks}_{jt} = \frac{\textit{GHG emissions}_{jt}}{\textit{Value added}_{jt}} \times \frac{\textit{Environmental tax}_{jt}}{\textit{Value added}_{jt}}$, for industry j, and year t. In columns 7-8, we simplify our measure of transition risks by excluding policy stringency and only include firm-level energy intensity (Scope 2) as a proxy. The dependent variable in column 1, 3, 5, and 7 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 2, 4, 6, 8 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. 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 1. 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: Base Year Approach

	Loan Growth **(1)**	**New Loans** **(2)**
Physical Risks	-1.589***	-0.005**
	(0.488)	(0.002)
Transition Risks (Base Year Approach)	-0.318*	0.001
	(0.169)	(0.000)
Firm Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
Bank Fixed Effects	Yes	Yes
Firm Variables	Yes	Yes
Bank Variables	Yes	Yes
R-sq	0.084	0.137
N	188,851	220,214

Notes: The table presents the estimation results for climate risks and banks' lending, using a base year definition for transition risks to alleviate the reserve causality concerns, i.e., measuring a firm's emission intensity in the first year in which a firm in the sample is observed. Specifically, $\textit{Transition risks}_{ijt}$ is calculated as: $\textit{Transition risks}_{ijt} = \textit{Emission intensity}_{ij0} \times \textit{Environmental tax}_{jt}$. The dependent variable in column 1 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 column 2 is a 0/1 dummy variable indicating whether a given firm received new loans from a given bank b in a given year. 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 1. 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: Alternative Specification

	Loan Growth (1)	**New Loans** (2)	**Loan Growth** (3)	**New Loans** (4)
Physical Risks, Lag 1	-0.721	-0.003	-1.979***	-0.008***
	(0.640)	(0.002)	(0.758)	(0.003)
Transition Risks, Lag 1	-1.464***	-0.001	-3.914***	-0.008***
	(0.445)	(0.001)	(1.230)	(0.002)
Physical Risks, Lag 2	-1.206*	-0.002		
	(0.693)	-(0.003)		
Transition Risks, Lag 2	-0.549	-0.001		
	(0.688)	-(0.001)		
Physical Risks, Squared			0.144	0.001
			(0.162)	-(0.001)
Transition Risks, Squared			0.033*	0.000***
			(0.017)	(0.000)
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
R-sq	0.097	0.149	0.087	0.140
N	140,004	161,204	189,142	220,890

Notes: The table presents the estimation results for banks' lending response to transition risks from OLS regressions, with alternative specifications. In columns 1-2, we re-estimate Equation (2) by introducing a second lag climate risks variables to consider banks' medium and long-run response to climate risks. In columns 3-4, we add the squares of climate risks variables in Equation (2) to explore the possible existence of non-linearity in the effects of climate risks. The dependent variable in column 1 and 3 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 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. 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 1. 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: Alternative Clustering Scheme

	Loan Growth					
	(1)	(2)	(3)	(4)	(5)	(6)
Physical Risks	-1.368***	-1.448***	-1.237**	-1.238**	-1.279***	-1.124**
	(0.504)	(0.506)	(0.485)	(0.485)	(0.445)	(0.550)
Transition Risks	-2.208**	-2.183***	-2.079***	-2.125**	-1.782**	-1.630**
	(0.866)	(0.828)	(0.789)	(0.818)	(0.713)	(0.751)
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 Effects						Yes
Firm Variables		Yes	Yes	Yes	Yes	Yes
Bank Variables		Yes	Yes	Yes		
R-sq	0.086	0.087	0.096	0.097	0.123	0.190
N	189,200	189,142	187,764	187,760	187,700	179,374

	New Loans					
	(1)	(2)	(3)	(4)	(5)	(6)
Physical Risks	-0.005**	-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 Effects						Yes
Firm Variables		Yes	Yes	Yes	Yes	Yes
Bank Variables		Yes	Yes	Yes		
R-sq	0.139	0.140	0.147	0.148	0.171	0.265
N	220,963	220,890	219,228	219,225	219,167	209,659

Notes: The table presents the estimation results for the effects of physical and transition risks on lending from OLS regressions, clustering at both the firm and bank levels (multi-way clustering). The dependent variable in the first panel 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 the second panel 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. 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 1. Robust standard errors clustered at the firm and the bank level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A7: Climate Risks and Lending: Alternative Sub-samples, Firm Level

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**
Included Sample	Include incumbent firms in the last 10 years		Exclude entrant firms		Exclude firms exiting the sample	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Physical Risks	-2.080***	-0.006**	-1.474***	-0.005**	-1.383***	-0.004**
	(0.702)	-(0.003)	(0.494)	-(0.002)	(0.493)	(0.002)
Transition Risks	-2.794***	-0.006**	-2.157***	-0.001	-2.229***	-0.001
	(0.807)	-(0.003)	(0.565)	(0.001)	(0.585)	(0.001)
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
R-sq	0.071	0.124	0.086	0.139	0.085	0.138
N	80,258	93,875	186,087	216,991	185,425	216,551

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**
Included Sample	Exclude highly productive firms		Exclude firms that relocate		Exclude firms in Copenhagen	
	(7)	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Physical Risks	-1.528**	-0.005**	-1.865***	-0.010***	-1.325***	-0.004**
	(0.595)	(0.002)	(0.695)	(0.003)	(0.506)	(0.002)
Transition Risks	-3.931***	-0.009**	-2.200***	-0.001	-1.988***	-0.001
	(1.308)	(0.004)	(0.620)	(0.001)	(0.512)	(0.001)
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
R-sq	0.093	0.148	0.092	0.145	0.090	0.144
N	129,517	151,862	123,980	144,362	169,305	196,559

Notes: The table presents the firm-level sample robustness checks for estimation results for the effects of physical and transition risks on lending from OLS regressions, based on Equation (2). In columns 1-2, only incumbent firms in the last 10 years (2009 to 2019) are included. Columns 3-4 exclude entrant firms that were formed in the sample period, while columns 4-5 exclude firms that exit during the sample periods. In columns 7-8, we exclude those highly productive firms, defined if firm productivity ($\frac{revenue}{firm\ size}$) is above the 75th percentiles of the entire sample. Columns 9-10 exclude a sample of firms that relocate to different municipalities, while columns 11-12 exclude firms located in the capital city. The dependent variable in columns 1, 3, 5, 7, 9, 11 is the loan growth in percentage points of firm i received from bank b in a given year t, for the 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 2, 4, 6, 8, 10, 12 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. 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 1. Robust standard errors clustered at the firm and the bank level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A8: Climate Risks and Lending: Alternative Sub-samples, Bank Level

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**	**Loan Growth**	**New Loans**
Included Sample	Exclude small banks		Include incumbent banks		Exclude banks exiting the sample		Exclude banks located in the capital region		Exclude banks with single establishment	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Physical Risks	-1.447**	-0.003	-1.374**	-0.005**	-1.383***	-0.004**	-1.444**	-0.004	-1.350**	-0.004*
	(0.629)	-(0.002)	(0.636)	-(0.002)	(0.493)	(0.002)	(0.657)	(0.002)	(0.578)	(0.002)
Transition Risks	-3.244***	-0.002	-1.635***	-0.001	-2.200***	-0.001	-1.996***	-0.001	-2.454***	-0.002
	(0.618)	-(0.001)	(0.550)	(0.001)	(0.576)	(0.001)	(0.765)	(0.001)	(0.547)	(0.001)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-sq	0.129	0.190	0.103	0.156	0.088	0.142	0.156	0.208	0.132	0.188
N	133,448	163,470	103,527	120,328	184,571	215,538	118,346	143,307	152,263	183,257

Notes: The table presents the bank-level sample robustness checks for estimation results for the effects of physical and transition risks on lending from OLS regressions, based on Equation (2). In columns 1-2, we exclude small banks with less than 200 employees. In columns 3-4, only incumbent banks in the last 10 years (2009 to 2019) are included. Columns 5-6 exclude banks that exit during the sample periods. In columns 7-8, we exclude banks in the capital region of Denmark. Columns 9-10 exclude a sample of banks with only one establishment. The dependent variable in columns 1, 3, 5, 7, and 9 is the loan growth in percentage points of firm i received from bank b in a given year t, for the 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 2, 4, 6, 8, and 10 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. 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 1. Robust standard errors clustered at the firm and the bank level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A9: Climate Risks and Lending: Response to the Tail Risks, Fixed Distribution and Climate Risks Index

	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	
R-sq	0.087	0.123	0.140	0.171
N	189,142	187,700	220,890	219,167

	Loan Growth		**New Loans**	
	(1)	**(2)**	**(3)**	**(4)**
Climate Risks Index	-2.207**	-1.977**	-0.005	-0.004
	(0.969)	(0.973)	(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	
R-sq	0.087	0.123	0.140	0.171
N	189,142	187,700	220,890	219,167

Notes: In the first panel of the table, we present the estimation results for banks' lending response to the tail physical and transition risks, with the tail risks defined based on a fixed distribution. High PR and Low TR are set to 1 if the respective risk indicator for physical or transition risks falls into the highest quantile of the distribution *for the entire sample.* Low PR and Low TR are then defined as one if the risk falls into the lowest quantile of the distribution *for the entire sample.* In the second panel of the table, we present the estimation results using the alternative composite climate risks index. Specifically, we divide the sample into four quintiles for both physical and transition risk metrics, assigning a score of 1 to firms in the lowest quintile, 2 in the second, and so on, with 4 for the highest quintile. We then construct a composite climate risk index by summing the scores for each risk dimension. 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. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

Table A10: Climate Risks and Lending: Region Heterogeneity

	Loan Growth				
Included Sample	Capital Region of Denmark	Central Denmark Region	North Denmark Region	Region Zealand	Region of Southern Denmark
	(1)	(2)	(3)	(4)	(5)
Physical Risks	-4.266*	-2.177**	-0.165	-2.07	2.395
	(2.555)	(1.015)	(1.455)	(1.699)	(1.491)
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes
Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Variables	Yes	Yes	Yes	Yes	Yes
Bank Variables	Yes	Yes	Yes	Yes	Yes
R-sq	0.169	0.18	0.199	0.232	0.192
N	46,434	52,213	32,786	15,662	34,496

Notes: The table presents the estimation results for the region heterogeneity on banks' credit growth in response to climate physical risks. We re-estimate Equation (3) with sub-samples of firms located in 5 regions of Denmark: the Capital Region of Denmark, the Central Denmark Region, the North Denmark Region, the Region Zealand, and the Region of Southern Denmark. 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. 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 1. Robust standard errors clustered at the firm level are reported in parentheses in all columns. Significance levels: ***1%, **5%, *10%.

D Additional figures

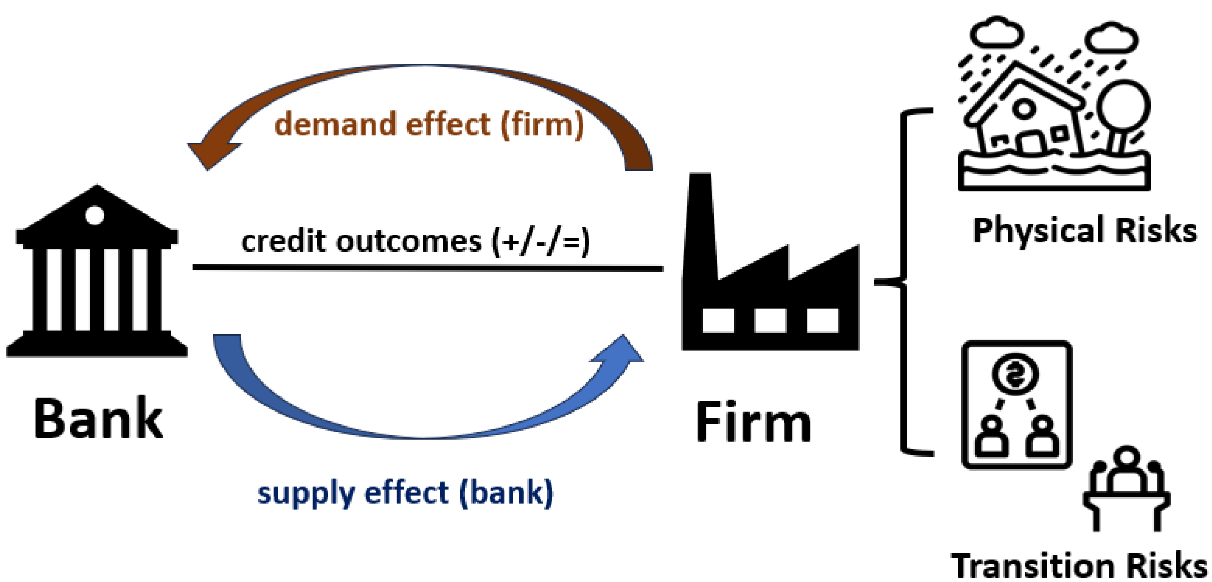


Figure D.1: Illustration

Figure D.2: Number of Firms and Banks

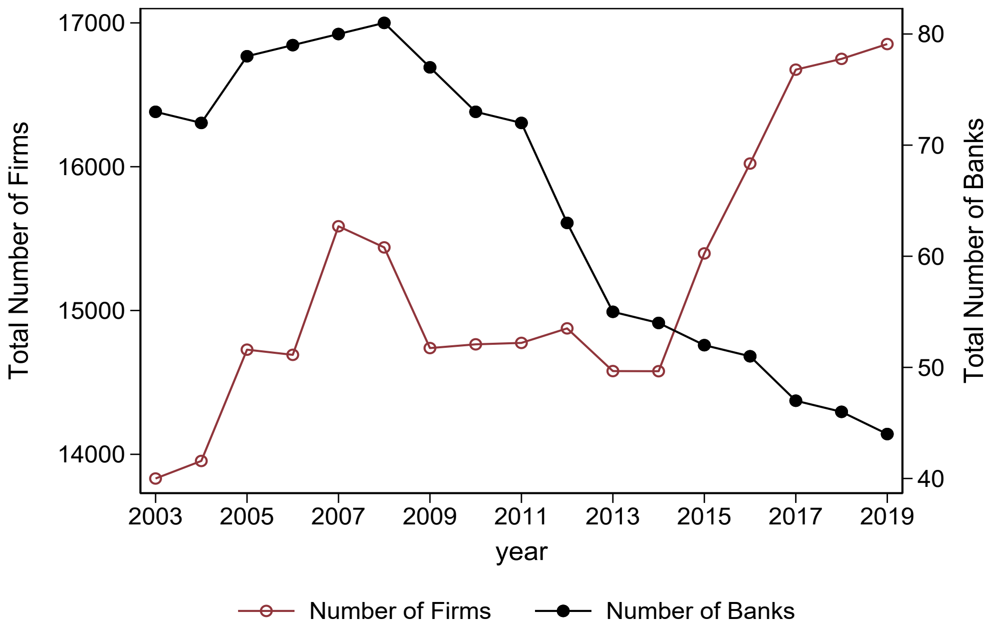
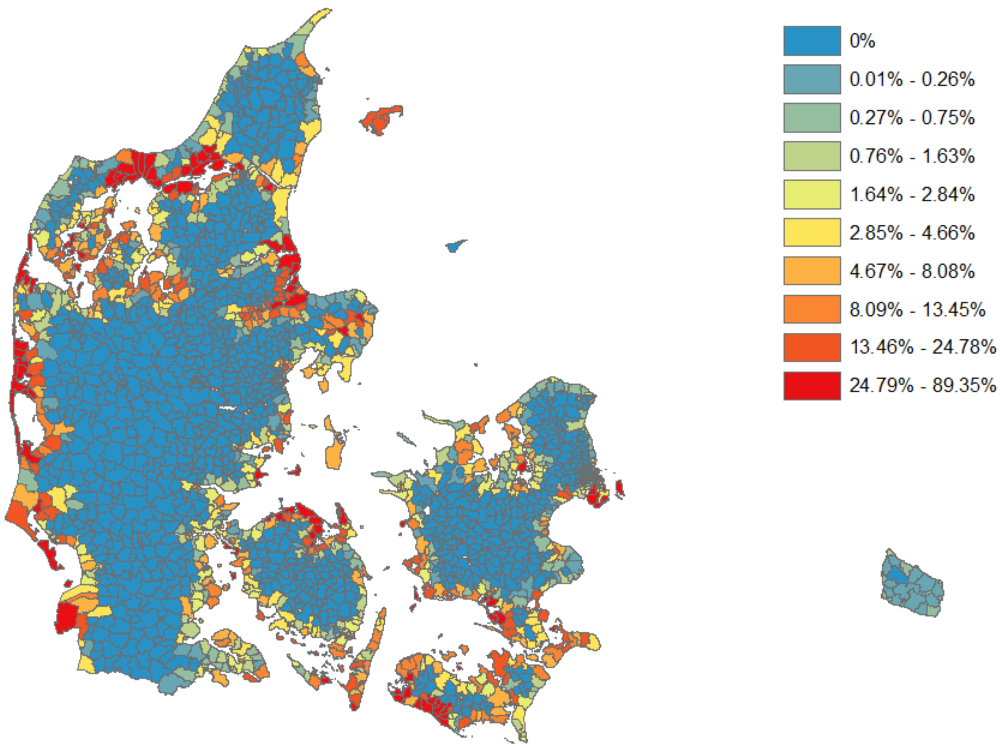
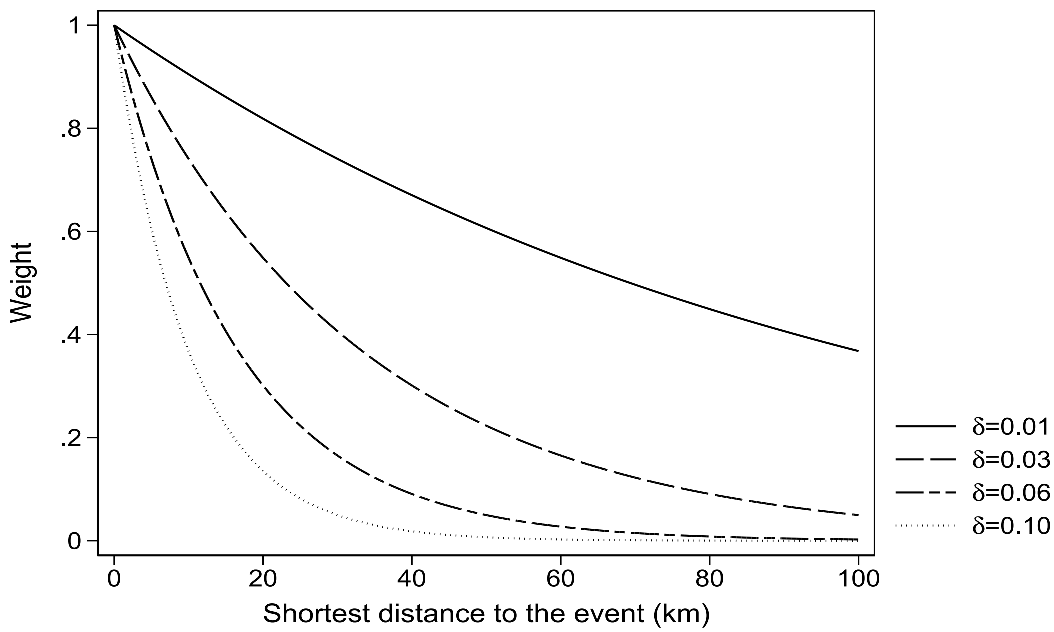


Figure D.3: Share of Flood Risk by Parish



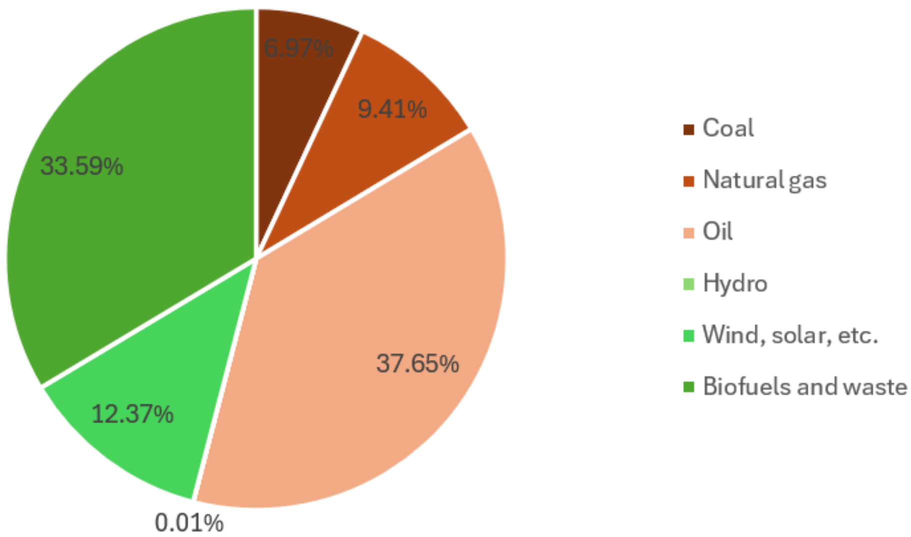
Notes: Based on flood risk in 20 years under IPCC RCP 4.5 scenario with a 100-year return period aggregated at the parish level. The grey outlines are the boundaries for each small administrative district. Source: author's calculations, data provided by DTU management

Figure D.4: The Weight Functions $\boldsymbol{e^{-\delta x_{pr}}}$ 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. The average distance between measurement stations is about 25 kilometers, varying from 10 kilometers in certain areas to as much as 40 kilometers.

Figure D.6: Energy Mix in Denmark, 2022



Source: IEA and author's own calculation

Figure D.5: Energy Intensity Across Industry, 2019

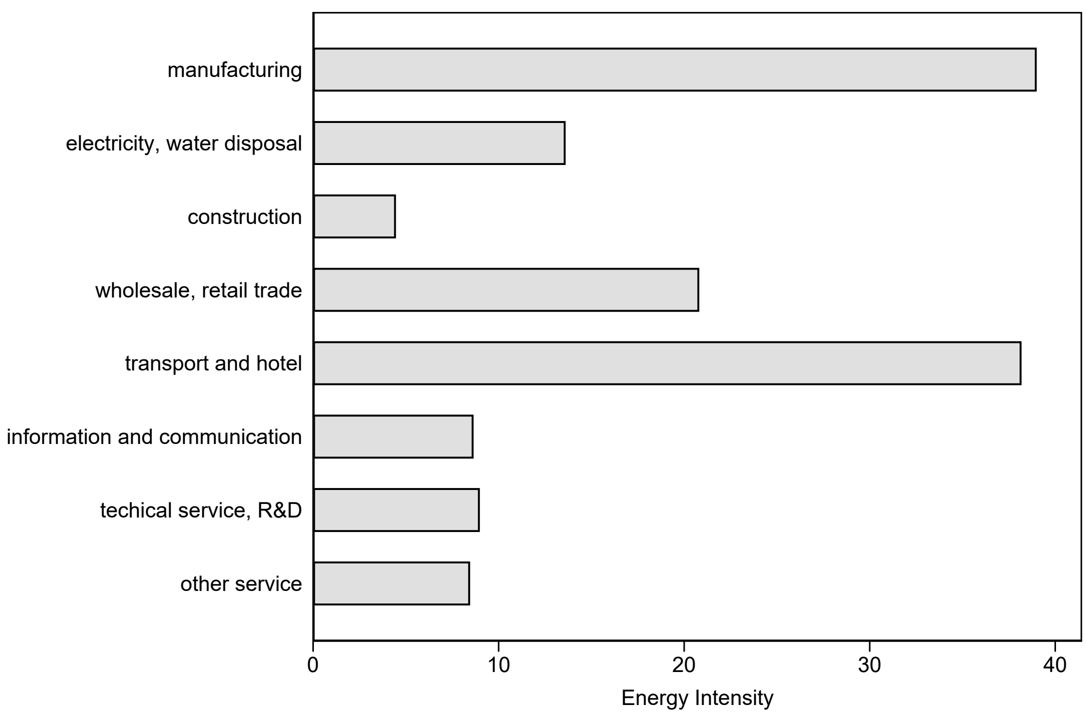


Figure D.7: Examples of Environmental Tax Bases

Energy (including fuel for transport)

— Energy products for transport purposes

- Unleaded petrol
- Leaded petrol
- Diesel
- Other energy products for transport purposes (e.g. LPG, natural gas, kerosene or fuel oil)

— Energy products for stationary purposes

- Light fuel oil
- Heavy fuel oil
- Natural gas
- Coal
- Coke
- Biofuels
- Electricity consumption and production
- District heat consumption and production
- Other energy products for stationary use

— Greenhouse gases

- carbon content of fuels
- emissions of greenhouse gases (including proceeds from emission permits recorded as taxes in the national accounts)

Transport (excluding fuel for transport)

— Motor vehicles import or sale (one off taxes)

— Registration or use of motor vehicles, recurrent (e.g. yearly taxes)

— Road use (e.g. motorway taxes)

— Congestion charges and city tolls (if taxes in national accounts)

— Other means of transport (ships, airplanes, railways, etc.)

— Flights and flight tickets

— Vehicle insurance (excludes general insurance taxes)

Pollution

— Measured or estimated emissions to air

- Measured or estimated NO_x emissions
- Measured or estimated SO_x emissions
- Other measured or estimated emissions to air (excluding CO_2)

— Ozone depleting substances (e.g. CFCs or halons)

— Measured or estimated effluents to water

- Measured or estimated effluents of oxydisable matter (BOD, COD)
- Other measured or estimated effluents to water
- Effluent collection and treatment, fixed annual taxes

— Non-point sources of water pollution

- Pesticides (based on e.g. chemical content, price or volume)

Source: Environmental taxes - A statistical guide (Eurostat, 2013)

Figure D.8: Environmental Tax Across Industry (Scaled), 2019

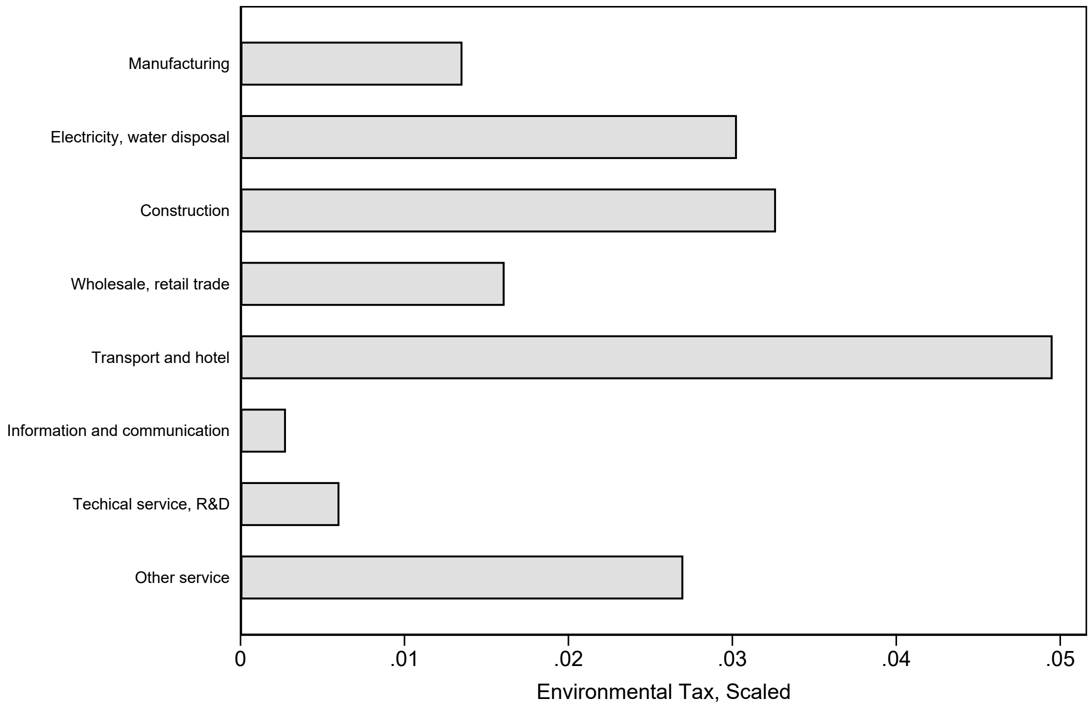
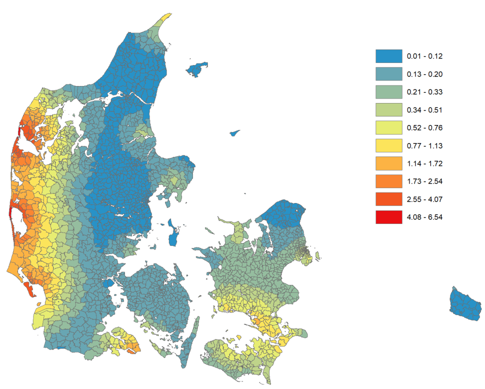
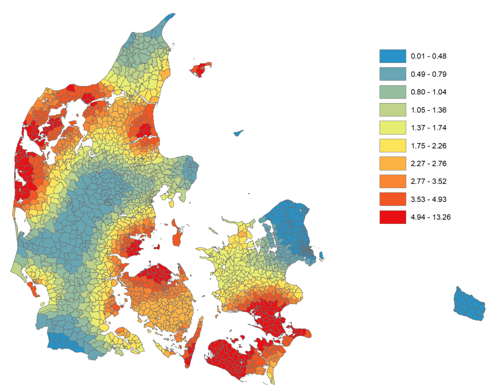


Figure D.9: Physical Risks Indicator by Parish over Time

(a) Physical risks indicator, 2009



(b) Change from 2009 to 2019



Notes: Physical risks indicator is an interaction between projected flood risk and historical extreme precipitation event frequency 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 D.10: Sources of Identification: Variation Across Time

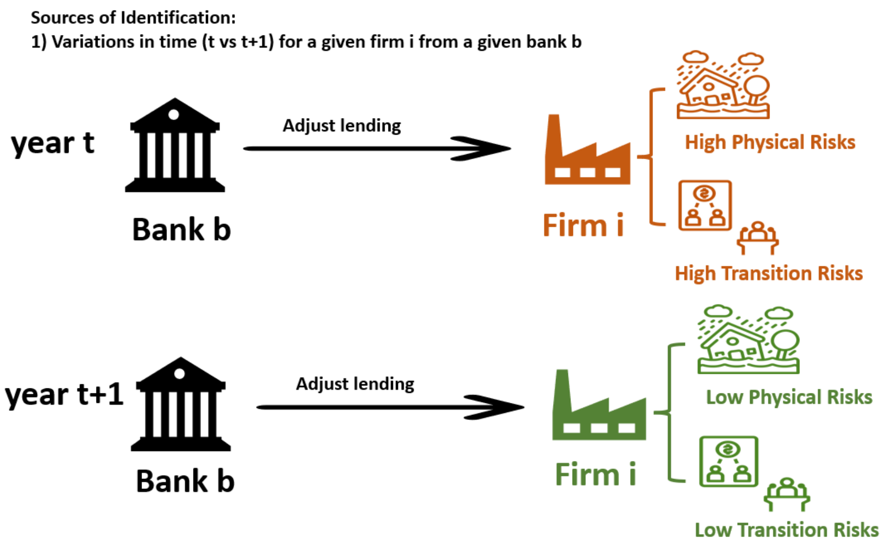


Figure D.11: Sources of Identification: Variation Across Firm

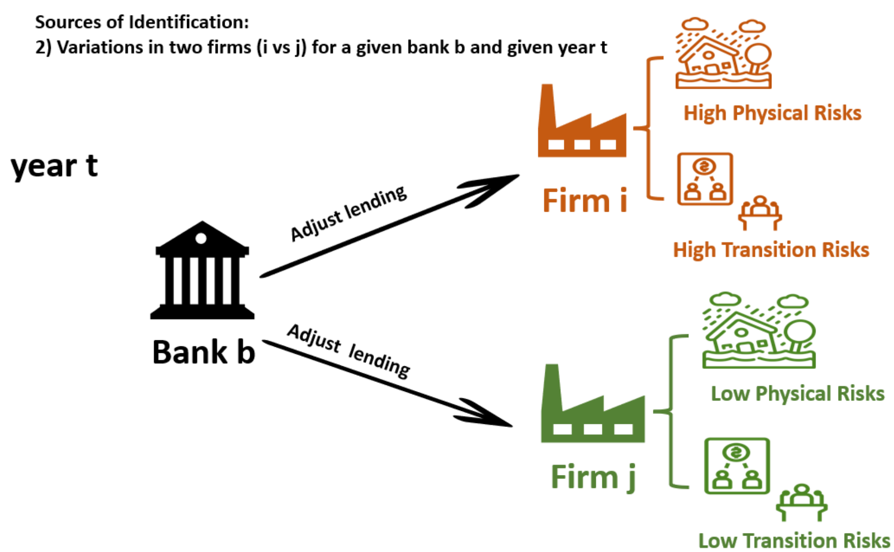


Figure D.12: Interaction of Physical and Transition Exposure

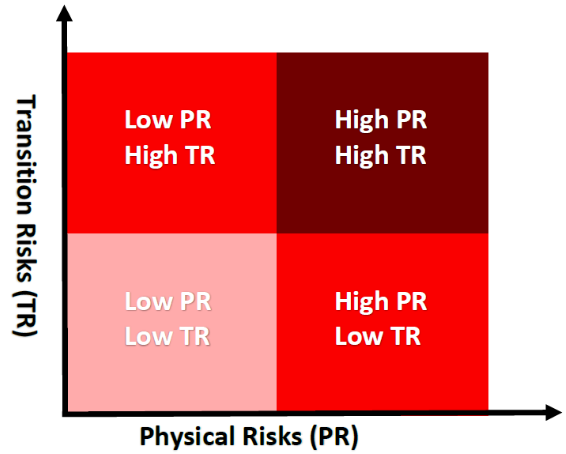


Figure D.13: IEA climate policy changes over time

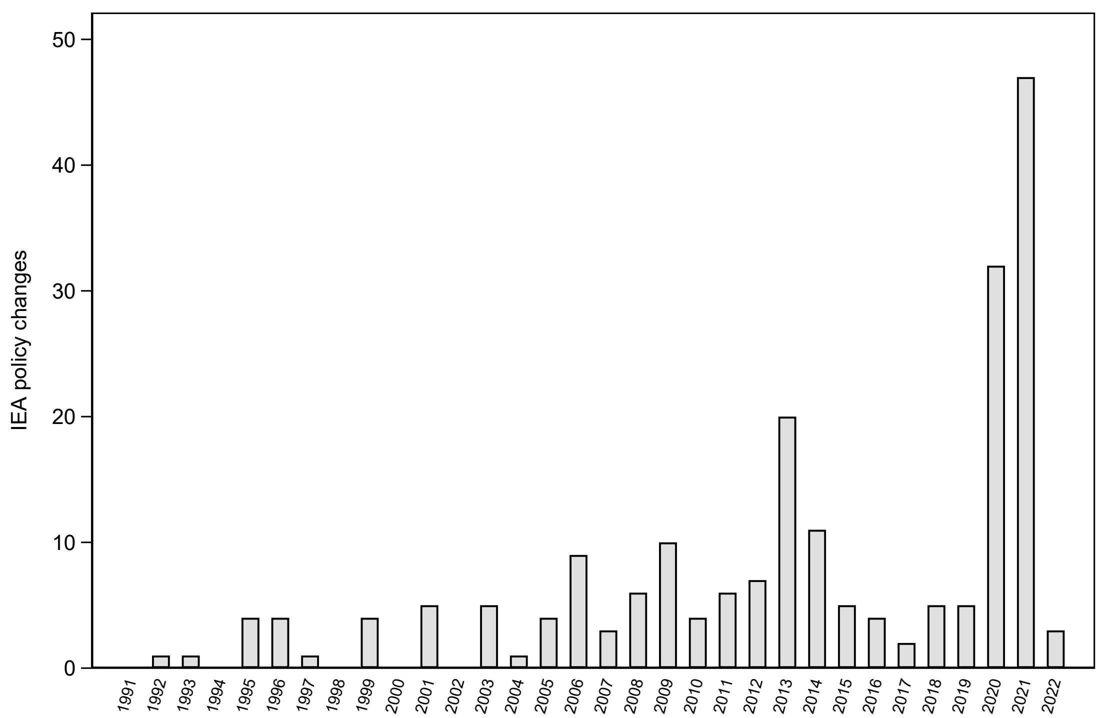
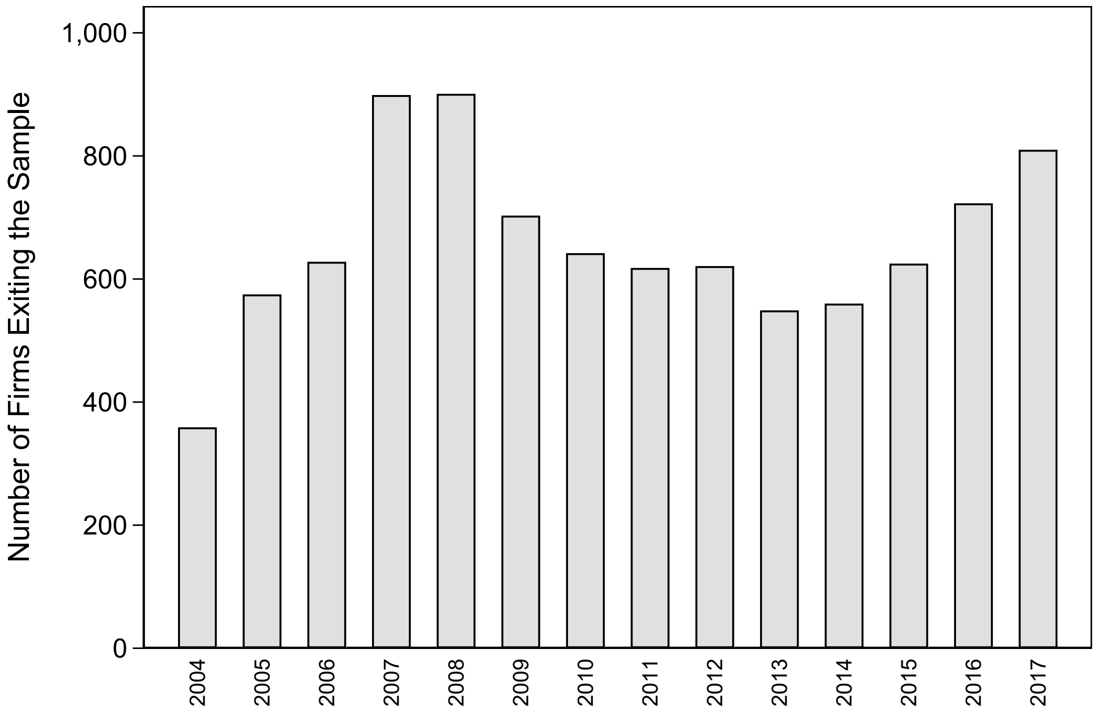


Figure D.14: Number of Firms that Exit the Sample



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