Credit Allocation under Physical and Transition Climate Risks *

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Abstract

This paper studies how banks adjust credit allocation in response to firms' exposure to climate-related physical and transition risks, with a focus on non-listed SMEs. Using granular firm-level measures of both risk types matched to a universal bank–firm credit dataset from Danish administrative registers, I document that banks reduce credit growth to firms with higher exposure to either risk. A one standard deviation increase in physical (transition) risk is associated with a 1.1–1.4% (1.6–2.2%) decline in loan growth. Beyond average effects, I find evidence of credit reallocation across firms with heterogeneous risk profiles: more credit is allocated to firms with low joint exposure to physical and transition risks and to high-risk firms that engage in greening activities. Credit contractions are strongest when climate risks compound existing borrower vulnerabilities, such as financial constraints and asset exposure, and among banks with higher climate risk exposure and repeat lending relationships. Mechanism tests indicate that banks' credit risk considerations play an important role in driving these credit responses.

Keywords: Climate change, physical risks, transition risks, compound risks, credit allocation.
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1 Introduction

Over the past decades, banks have become increasingly exposed to two types of climate-related risks through their lending activities: (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. These risks may transfer to banks if banks' internal risk models cannot fully capture these two types of risks (Huang et al., 2021; Beyene et al., 2021), or if the risks cannot be fully insured (Marcoux and Wagner, 2024). It thus remains an empirical question whether banks respond by adjusting their credit outcomes to firms' climate risk exposures.

Existing studies provide evidence that global banks have begun to respond to either physical risks (Meisenzahl, 2023) or transition risks (Kacperczyk and Peydró, 2022; Mueller and Sfrappini, 2022; Degryse et al., 2023), primarily based on syndicated loans to large, listed firms. However, little is known about how banks adjust lending to non-listed small and medium-sized enterprises (SMEs). These firms tend to rely more heavily on bank credit and typically have less capacity to adapt to climate risks. Furthermore, it remains unclear whether banks primarily allocate credit away from high-risk firms or whether they also reallocate credit toward high-risk firms that engage in greening activities. Finally, the relative importance of physical and transition risks, as well as their potential interaction effects in bank lending, remains an open empirical question.

In this paper, I fill in the gaps by first confronting the question using novel, granular measures of both types of risks, merged with the universe of bank-firm matched Danish register data that are representative of all types of firms, ranging from listed large firms to a large sample of non-listed SMEs.[1] Second, I investigate whether banks reallocate credit to those high-risk firms that actively become greener (so-called "greening" firms) with credible emission reduction efforts, such as improving energy efficiency or investing in green innovation. Furthermore, given that banks are exposed to both physical and transition risks, I explore not only the individual effects of each type of risk but also how these risks interact. Finally, I explore the heterogeneity and test the mechanism on the supply and demand side, and highlight one possible channel: credit risk.

This paper studies these questions in the context of Denmark for two reasons. First, Danish register data make it possible to match universal credit account data with firms and banks, and to further link these records to employer–employee information. This allows me to trace the evolution of bank credit for nearly two decades across the full population of

[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.

banks and firms, including non-listed SMEs. Second, Denmark is exposed to substantial variation in both physical and transition climate risks. Due to its long coastline and low elevation, firms face increasing exposure to storms and coastal flooding associated with rising sea levels and extreme precipitation.[2] At the same time, firms operate in an environment with relatively ambitious climate policies at both the national and EU level, which increases their exposure to transition risks.

The main outcome variables in the empirical analysis capture the credit allocation outcomes at the firm-bank-year level, specifically, loan growth on the intensive margin and new loan initiation on the extensive margin. The key independent variables capture firms' exposure to two types of climate risks. To proxy for *physical risks*, I construct a novel indicator that varies over time at a fine geographical resolution, covering more than 2,000 Danish parishes.[3] This indicator combines projected flood risk with historical data on extreme precipitation and incorporates indirect geographic spillover effects using a geo-weighted model. To measure *transition risks*, I interact firm-level energy intensity with industry-level environmental taxes. This measure captures the relative vulnerability of high-emission firms to increasingly stringent environmental regulations over time.[4]

To identify the impact of climate risks on credit allocation, I exploit variation in physical risks across time and geographic location (parishes), and variation in transition risks across firms, time, and industries, using saturated fixed effects regression models. These models enable the estimation of credit supply effects by controlling for credit demand through a combination of saturated fixed effects and firm-level controls, following the approach of Khwaja and Mian (2008), Jiménez et al. (2012), and Jiménez et al. (2014). Both climate risk measures are included in the same regression to allow for a direct comparison of their individual effects. All climate risk variables and controls are lagged to address concerns about reverse causality. In the most saturated specification, I include parish fixed effects to absorb unobserved location-specific factors, 2-digit industry-year fixed effects to control for industry-level demand shocks, bank-year fixed effects to capture unobserved bank-specific supply shocks, and firm-bank fixed effects to account for endogenous matching between firms and banks.[5] Identification thus relies on within-firm-bank pair variation over time, within the

[2] According to the Danish Meteorological Institute, more than 40 storms have affected Denmark over the past three decades, several of which caused severe damage to infrastructure, housing, and agriculture.

[3] This represents a substantial improvement over the broader 50 km $\times$ 50 km grid cell resolution used in existing databases, which correspond to fewer than 50 geocodes in Denmark (e.g., GAME-LIGHTS). Moreover, the Emergency Events Database (EM-DAT) often lacks precise geo-location information for events in Denmark.

[4] As a robustness check, I also consider alternative emissions measures (e.g., industry-year level scope 1 emissions), as well as alternative proxies for policy stringency, such as energy-related taxes and documented changes in climate policy.

[5] Parish-year and firm-year fixed effects cannot be included, as they would absorb the variation in the

same location and industry, in response to changes in climate risks. As more granular fixed effects are introduced, the estimated coefficients tend to decline, with the most saturated specification providing a lower-bound estimate of the effects. To further address concerns related to omitted variables and simultaneity, I conduct robustness checks using alternative definitions, such as a base-year definition of transition risks and lag structures.[6]

The empirical results indicate that banks respond to climate risks by reallocating credit away from high-risk firms, though the magnitude and significance of these effects vary across credit margins. The analysis shows robust evidence on the *intensive margin*, indicating that firms more exposed to either physical or transition risks experience lower loan growth. A one standard deviation increase in a firm's exposure to physical risks is associated with a 1.1%–1.4% decline in loan growth, corresponding to an 8%–10% deviation from the sample mean and a reduction in loan amount of approximately 88,408–112,519 DKK.[7] The effect of *transition risks* is slightly larger: a one standard deviation increase is associated with a 1.6%–2.2% decrease in loan growth, equivalent to an 11%–16% deviation from the mean and a reduction in loan amount of approximately 128,593–176,816 DKK.[8]

Beyond the average effect, the empirical results also suggest a reallocation of credit across firms with heterogeneous climate risk profiles. First, more credit is allocated to high-risk but "greening" firms. These firms receive relatively more credit despite their high underlying risk exposure. Moreover, there is a different impact on firms with heterogeneous climate risk interaction: firms facing a lower degree of risk interaction, i.e., low joint exposure to physical and transition risks, receive more credit.[9] This suggests that banks account not only for the individual dimensions of climate risk but also for their interaction when making lending decisions.

This paper further documents substantial heterogeneity in the credit reallocation effects on both the firm and bank sides, leveraging rich firm- and bank-level data. On the firm side, the reallocation effect is stronger for more vulnerable firms, such as smaller and highly leveraged firms, as well as firms operating in the brownest industries and asset-intensive, which is consistent with banks avoiding the compounding of climate risks with existing credit risks (Dunz et al., 2023). On the bank side, reductions in credit growth are more

main explanatory variables.

[6]Another potential concern is that exposed firms may relocate. The paper mitigates this concern by excluding those firms in a refined model.

[7]Physical risks: mean = 0.99, SD = 1.162; loan growth: mean = -14.225%, SD = 117.261; loan amount: mean = 8.04 million DKK, SD = 132.84. For reference, 1 DKK ≈ 0.15 USD.

[8]Transition risks: mean = 26.678, SD = 150.140. The standard deviation and reference statistics for loan growth and loan amount are the same as above.

[9]For example, firms operating in the consulting industry (associated with low transition risk) and located in inland areas (low physical risk) have easier access to credit relative to the average firm.

pronounced among banks with repeat lending relationships and higher exposure to climate risks.[10] This finding is consistent with banks having an information advantage in relationship lending (Sharpe, 1990; Diamond, 1991; Rajan, 1992; Petersen and Rajan, 1994), and with more exposed banks adjusting lending more actively. Lastly, I find that banks specialized in "brown" industries, measured following the specialization measure in Paravisini et al. (2023), are more likely to increase lending. This result is consistent with Degryse et al. (2020) and Laeven and Popov (2023), suggesting that such banks expand lending in sectors where they retain comparative expertise.

Finally, I examine the mechanism underlying the observed credit reallocation and highlight one key channel: credit risk. On the supply side, I examine whether climate risks are associated with higher perceived credit risk. Firms with greater exposure to climate risks exhibit higher financial stress and lower profitability across multiple firm-level measures. These patterns are consistent with banks adjusting credit supply in response to heightened climate-related credit risk. On the demand side, I find no evidence that climate risks reduce firm-level credit demand. In particular, climate risk exposure is not significantly correlated with firm growth indicators commonly associated with credit demand, including investment growth, employment growth, fixed asset growth, or sales growth. Taken together, these results suggest that the observed credit reallocation is more likely driven by changes in banks' credit supply in response to increased climate-related credit risk, rather than by shifts in firms' credit demand. For an overview of the hypothesis-testing framework and results, see Figure A.1.

Related literature This paper contributes to the literature on empirical sustainable banking in distinct ways. First, while most existing studies rely on syndicated loans to large, publicly listed firms, this paper examines banks' responses using the universe of matched bank–firm credit data, allowing for a comprehensive analysis that includes non-listed SMEs. Second, the paper goes beyond average divestment effects by documenting how banks reallocate credit across firms with heterogeneous climate risk profiles, including firms that face high risk exposure but engage in credible greening activities. Third, unlike much of the existing work that focuses on either physical or transition risks separately, this paper jointly examines both types of climate risks and provides evidence that their interaction plays an important role in credit allocation.

Specifically, this paper first contributes to the growing literature on climate risks and bank credit allocation. Most existing studies examine banks' responses to either transition

[10] Bank-level risk exposure is calculated as the loan-weighted average of climate risk across a bank's portfolio of client firms.

risks or physical risks using syndicated loans to large, publicly listed firms. In the context of transition risks, the existing literature has largely focused on pricing adjustments, with some evidence on banks systematically adjusting quantity to high-emission firms (Kacperczyk and Peydró, 2022; Mueller and Sfrappini, 2022; Reghezza et al., 2022). However, a smaller set of studies documents heterogeneity in banks' responses, including continued lending to carbon-intensive firms and concerns related to greenwashing (Giannetti et al., 2023; Mésonnier, 2021). Evidence on lending to non-listed firms and SMEs remains limited.

Related work on physical climate risks studies how extreme weather events and natural disasters affect credit provision and pricing. While some studies find that banks reduce lending in areas more exposed to climate physical risks (Faiella and Natoli, 2019; Aslan et al., 2022; Meisenzahl, 2023), others show that banks reallocate capital toward affected regions following disasters, reflecting post-shock demand dynamics (Cortés and Strahan, 2017; Koetter et al., 2020; Ivanov et al., 2022). Overall, the existing evidence is mixed.

More broadly, the paper relates to the literature on the implications of climate risks for the banking sector and firm behaviors. Previous studies show that climate risks affect banks' optimal capital structure, performance, and liquidity provision (Bakkar, 2023; Li and Pan, 2022; Barth et al., 2024), and increase financial and default risks at the firm level (Pankratz et al., 2019; Huang et al., 2022; Ginglinger and Moreau, 2023). This paper contributes by highlighting the bank lending channel as an important mechanism through which climate risks affect firms, while showing that access to credit is not uniformly reduced but depends on firms' exposure profiles and adaptation efforts.

The remainder of this paper is organized as follows: I begin with a discussion on the conceptual framework in Section 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 Conceptual Framework

Banks are indirectly exposed to climate-related risks through their lending portfolios. If physical or transition risks affect firms' expected cash flows, asset values, or default probabilities, banks may adjust credit allocation in response. However, the net effect of climate risks on lending is ex ante ambiguous.

Climate risks may lead to limited or no adjustment in bank lending. Banks may face high adjustment costs or maintain legacy exposures to carbon-intensive firms, resulting in little observable change in credit allocation (Degryse et al., 2020). Existing evidence also suggests that banks' stated sustainability objectives do not always translate into lending behavior

(Giannetti et al., 2023; Sastry et al., 2024).

Alternatively, banks may continue to lend to firms with high exposure to climate risks when these firms engage in credible adaptation or mitigation activities. Such behavior may reflect banks' incentives to maintain lending relationships or to support firms that reduce their exposure over time.

Climate risks may also be associated with a reduction in credit. Higher exposure to physical or transition risks may increase firms' probability of default or loss given default (Huang et al., 2018; Kabir et al., 2021), leading banks to reduce lending when climate risks are not fully priced (Beyene et al., 2021; Garbarino and Guin, 2021; Huang et al., 2021; Schubert, 2021). In addition, evidence suggests that insurance markets are not well developed to fully absorb climate risks (Wagner, 2022; Marcoux and Wagner, 2024), which may further restrict credit supply (Garmaise and Moskowitz, 2009). On the demand side, climate risks may adversely affect firms' operations, lowering investment and growth and thereby reducing credit demand (Huang et al., 2018; Bolton et al., 2019; Kacperczyk and Peydró, 2022). While clearly distinguishing between these channels is empirically challenging, examining firm- and bank-level outcomes can shed light on their relative importance.

Given these competing mechanisms, the empirical analysis first examines how bank credit allocation responds to firms' exposure to physical and transition risks, then tests whether banks reallocate credit across firms with heterogeneous risk profiles and across certain firm and bank characteristics, and finally assesses whether the observed effects are more consistent with changes in credit supply or credit demand.

3 Data and Descriptive Statistics

The data are 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.

While we obtain the credit data on the universe of bank loans that link firms and banks, we drop firms operating in the financial industry, micro firms with fewer than 10 employees, and micro banks with fewer than 50 employees for data accuracy.[11] This section below provides a detailed description of different data sources and descriptive statistics.

[11] During the merge, we only include firms with at least one bank account connection and non-negative account balance and interest payments. But we keep those firms when the account balance is zero.

3.1 Danish Administrative Data

3.1.1 Employer-employee data

The starting point is to construct matched employer–employee data from several registers administered by Statistics Denmark. Firm-level information is obtained from the General Firm Statistics (FIRM) and the Firm-Level Accounts 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 allows for measuring transition risks. 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. Using the Firm-Integrated Database for Labor Market Research (FIDA), workers in IDA can be linked to firms in the FIRM and FIRE datasets. These combined data allow for constructing several important control variables for the empirical analysis at the firm and bank level, such as firm size, return on assets (ROA), leverage ratio, firm age, and bank size.[12] The findings are reported 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 use 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 are 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 allows for merging credit information with employer-employee matched data. The resulting dataset allows for observing bank loans along with the characteristics of both the lending banks and the borrowing firms. The raw data are further collapsed from 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 and remove the unnecessary

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

noise.

Figure A.2 plots the average account balance data for 5 quantile bins, conditional on positive account balance, at the firm-bank level, at the beginning of the sample period (2003) to the end of the sample period (2019). This indicates that the loan account balance (outstanding) is highly skewed, where the top 20% of firms (Quantile 5) hold the majority of total balances. This disparity between Quantile 5 and others has widened from 2003 to 2019. Figure A.3 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 of credit outcomes, firm variables, and bank variables for the final sample are presented in Table 1. The final sample is a firm–bank–year panel from 2003–2019, covering 19,904 firms, 106 banks, and 220,890 observations.

3.2 Exposure to Climate Risks

Banks are indirectly exposed to physical and transition risks through the firms they lend to. This section details how I measure these two key independent variables: firms' exposure to physical risks and transition risks.[13]

3.2.1 Physical risks data

To measure firms' exposure to physical risks, I construct a time-varying risk indicator at the local parish level by combining historical extreme precipitation data with forward-looking flood risk projections. This indicator captures both direct effects and indirect geographic spillovers. The intuition behind the indirect effect is that climate events often have consequences that extend beyond a single parish, potentially impacting neighboring areas through updated risk perceptions or supply chain disruptions. In the following section, I document the two key data sources and the modeling approach used 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). As extreme weather occurrences, such as extreme rainfall and floods, reflect the impact of physical risks

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

more directly, they are more likely to update banks' perceptions or beliefs regarding climate risks. To capture these extreme events, I construct a dataset that measures the frequency of extreme precipitation using raw observation data from over 200 weather stations operated by the Danish Meteorological Institute (DMI).[14]

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

$$\nu_{cmdt}^{precip} = \frac{x_{cmdt}^{precip} - \overline{x}_{cm}^{precip}}{\sigma_{cm}^{precip}} \tag{1}$$

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, extreme precipitation events are defined as $\nu_{cmdt}^{precip} > 2$.[15]

In the next step, I count the occurrence of such extreme events for each parish p in year t, denoting it as $freq_{pt}$.[16] 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 provides a more exogenous measure compared to absolute extremes. This is because variations in relative precipitation shocks are identified within a given location and month, addressing concerns that some areas or seasons may naturally experience higher rainfall levels and volatility.[17]

Projected flood risk data Flood risk is a major source of physical climate risk for countries with extensive coastlines and low altitudes, such as Denmark. It can cause significant economic damage, as many investments, including firm facilities and properties, are located in flood-prone areas.

Flood risk data is obtained from the Technical University of Denmark (DTU) and the Danish Meteorological Institute (DMI), which provide forecasts of flood occurrences and

[14]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).

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

[16]In some parishes without a weather measurement station, each parish is assigned to the closest weather station using the geo-weighting indicator described in the Section 3.2.1.

[17]For example, the same volume of precipitation may be considered normal in one location but anomalous in another, even if occurring simultaneously. Firms may therefore endogenously anticipate such patterns and adapt strategically.

magnitudes across Denmark at a spatial resolution of 200×200 meter grid cells.[18]

For the baseline scenario, I aggregate this high-resolution data to the parish level by calculating the share of each parish area that is likely to be under the water, conditional on being exposed to 100-year flood events over a 20-year horizon under the IPCC RCP 4.5 scenario. This measure is denoted as fl_p (see the flood map in Figure A.6).[19] As expected, flood risk is concentrated in areas near the coast and around 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. The idea is that if a parish gets extreme rain in the past and at the same time is classified as very likely to be flooded given its geography, then it is assumed that the parish was likely to be flooded and is perceived to be exposed to high physical risks.

Physical risks indicator To account for geographic spillover effects, after interacting the static flood data with historical extreme precipitation ($fl_r \times freq_{rt}$), I construct a physical risks indicator for a parish p in year t using a distance-weighted sum of risk indicators from the parish's surrounding areas r, including p.[20]

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

$$Physical\ risks\ indicator_{pt} = \sum_{r=1}^{R} (fl_r \times freq_{rt})\, e^{-\delta x_{pr}} \tag{2}$$

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

This measure captures not only the climate physical risks originating from the local parish p but also spillovers from other parishes, using their distances to parish p as weights. 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. The decay parameter δ captures the spatial extent of spillovers from climate events to neighboring parishes. In

[18] Notably, the flood risk projections incorporate forward-looking perspectives, as the simulations are based on future climate scenarios. Specifically, these projections use geographic features, historical climate data, water level statistics, and sea level rise estimates; see Larsen et al. (2021).

[19] A 100-year flood event, or return period, refers to a flood of such magnitude being expected to occur, on average, once every 100 years. For further details, see Thomson et al. (2011).

[20] This method has become standard to measure the proximity of a given location to other locations and has its roots in agglomeration economies. See De Borger et al. (2019) as one example using a similar method with Danish data.

the baseline specification, I set $\delta = 0.06$, implying economically plausible spatial decay, with weights of 0.55 and 0.002 for parishes located 10 km and 100 km away, respectively.[21] Finally, a firm's exposure to physical risks then corresponds to the physical risks of the parish where its main headquarters are located.[22]

The physical risk indicator captures spatial spillovers from extreme climate events and is measured at a fine geographic level across more than 2,000 Danish parishes. Because parish boundaries have remained largely stable over time, this level of aggregation can be plausibly treated as exogenous.

Figure 1 visually depicts substantial variations in physical risks across different geographical locations in the year 2009, as well as the time variation in changes of physical risks in the past decades from 2009 to 2019. Notably, the west coast and southern part of Zealand have experienced higher and increasing physical risks.

To illustrate differences in credit allocation across firms with high versus low physical risk exposure, Figure A.4 plots average account balances across five quantile bins of the physical risk indicator. In addition, Figure A.5 shows the evolution of total credit balances for firms with high physical risk exposure (top 25th percentile within each year) and low physical risk exposure (bottom 25th percentile within each year). Both figures indicate that, over time, a larger share of credit is allocated to firms with lower physical risk exposure relative to firms facing higher physical risk.

3.2.2 Transition risks data

To measure firms' exposure to transition risks, I construct an interaction between firm-level energy intensity and industry-level environmental taxes. The measure captures the idea that firms with higher energy intensity are more exposed to transition risks when climate-related policies impose higher costs on emission-intensive industries (Gu and Hale, 2023). This section describes the data sources used to construct firm-level energy intensity and industry-level policy stringency.

Energy intensity data Firm-level energy consumption data are obtained from the FIRE register, which reports firms' expenditures on electricity, oil, gas, and district heating used

[21] Results are robust to alternative values of δ (see Table B.2). Figure A.7 shows the implied spatial decay of the weighting function $e^{-\delta x_{pr}}$ for alternative values of δ.

[22] It is because the headquarters' location is theoretically the most relevant location for assessing exposure to physical risks, given that headquarters typically centralize strategic decision-making and resource allocation. For a robustness check, I include a multi-establishment dummy to control for the fact that some firms have different establishments.

for production and heating purposes.[23] These expenditures capture energy use corresponding broadly to scope 1 and scope 2 emissions. To account for firm size, energy consumption is normalized by firm-level value added.

Specifically, the energy intensity for firm i in industry j at time t is calculated as follows:

$$Energy\ intensity_{ijt} = \frac{Energy\ consumption_{ijt}}{Value\ added_{ijt}} \tag{3}$$

In short, energy intensity measures a firm's total energy consumption scaled by its value added. To illustrate variation across industries, I aggregate firm-level energy intensity to the industry level and plot the distribution across industries in 2019 in the left panel of Figure 2. Manufacturing and transport exhibit relatively high energy intensity, whereas information, communication, and technical service industries display lower energy intensity.

Climate-related policy stringency data Climate-related policy stringency is proxied using annual environmental taxes at the two-digit industry level from StatBank Denmark. These taxes apply to activities and products with documented negative environmental impacts, including greenhouse gas emissions and energy products such as fuel oil, coal, and natural gas. This measure reflects industry-specific real costs or risks linked to the environment. To account for differences in industry size, total environmental taxes are scaled by industry-level value added.

To be specific, $Environmental\ tax_{jt}$ is calculated as:

$$Environmental\ tax_{jt} = \frac{Total\ environmental\ tax_{jt}}{Value\ added_{jt}} \tag{4}$$

for industry j, year t.

The distribution of environmental tax data across industries in 2019 is depicted in the right plot in Figure 2. Notably, the transport, electricity, and construction sectors exhibit higher environmental tax costs compared to other industries. In the robustness check, I also explore alternative measures for policy stringency, including changes in climate policies within Denmark and the EU, as well as total energy taxes, as shown in Table B.3. Given that the environmental tax data offer more detailed variations at both the industry and year

[23] The variable *KENE* excludes fuel expenses for external transport and is reported in 1,000 DKK. Given that it is only available for the period 2000-2016, I therefore impute the missing emission intensity in years 2017-2019 based on the mean energy consumption at the firm level over a 3-year rolling window, including the current observations.

levels and include wider scopes, it is used in the baseline analysis.

Transition risks indicator The resulting transition risk measure for firm i in industry j at time t is defined as the interaction between firm-level energy intensity and industry-level environmental taxes:

$$\textit{Transition risks}_{ijt} = \textit{Energy intensity}_{ijt} \times \textit{Environmental tax}_{jt} \tag{5}$$

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.

In the online appendix, Figure A.8 plots average account balances across five quantile bins of the transition risk measure, while Figure A.9 shows the evolution of total credit balances for firms in the top and bottom quartiles of transition risk. These figures illustrate descriptive patterns in credit allocation across firms with different exposure to transition risks.

4 Empirical Strategy and Identification

4.1 Empirical Specification

This section outlines the empirical specification and identification strategy used to assess the impact of physical and transition risks on bank credit allocation. Identification exploits variation in physical risks across time and geographic locations (parishes), and variation in transition risks across firms, industries, and time, using saturated fixed effects regressions.

To identify the effect of physical risks, I leverage variation in abnormal precipitation patterns and projected flood risk at the parish level over time, which are plausibly exogenous to bank lending outcomes (Dell et al., 2014). To mitigate concerns about firms adapting through relocation, parish fixed effects are included in the most saturated specifications.

Transition risks are measured as the interaction between firm-level energy intensity and sector-level environmental taxes. To address potential confounding, I include a comprehensive set of firm- and bank-level controls and fixed effects, including industry-year, bank-year, and bank–firm fixed effects. Controlling for these variables and fixed effects allows for careful examination of the effects of transition risks on credit outcomes. Furthermore, the saturated fixed effects model allows for identification of credit supply effects in the spirit of Khwaja and Mian (2008).

The main dependent variables capture both the intensive and extensive margins of bank credit. The intensive margin is measured as the growth rate of loans from bank b to firm i in year t, conditional on an active lending relationship in $t-1$ and t. Loan growth is defined 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 of the loan balances.[24] 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.[25] In an extension, I also measure the firm bank relationship changes and interest rates as alternative outcomes.

Both risk measures are included simultaneously in the baseline specification and lagged by one year. Firm- and bank-level controls are also lagged by one year. Standard errors are clustered at the firm level. 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.

I begin with a parsimonious specification that includes physical and transition risks, along with firm (α_i), bank (α_b), and year fixed effects (α_t):

$$Lending_{ibt} = \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + \alpha_i + \alpha_b + \alpha_t + \epsilon_{ibt} \tag{6}$$

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 thus relies on within-firm variation in climate risk exposure over time and cross-firm differences in exposure among firms borrowing from the same bank in a given year, as shown in Figure A.10.

In Equation (7), I add firm- and bank-level control variables X_{it-1} and Z_{bt-1}. The vector X_{it-1} includes firm size, leverage, and return on assets (ROA), while Z_{bt-1} includes bank

[24] This definition accommodates zero loan balances.

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

characteristics such as bank size:

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} \\ &+ X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \alpha_i + \alpha_b + \alpha_t + \epsilon_{ibt} \end{aligned} \tag{7}$$

In Equation (8), I add parish fixed effects to control for time-invariant geographic characteristics that may affect credit allocation. This specification exploits within-parish variation in lending over time:

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} \\ &+ X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \alpha_i + \alpha_b + \alpha_t + \alpha_p + \epsilon_{ibt} \end{aligned} \tag{8}$$

I then include industry fixed effects α_j in Equation (9) to control for time-invariant industry characteristics correlated with climate risks and credit outcomes. Identification relies on within-firm variation over time within the same location and industry:

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} \\ &+ X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \alpha_i + \alpha_b + \alpha_t + \alpha_p + \alpha_j + \epsilon_{ibt} \end{aligned} \tag{9}$$

In Equation (10), I further include industry-year and bank-year fixed effects to absorb time-varying demand and supply shocks at the industry and bank levels:[26]

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} \\ &+ X'_{it-1}\gamma_1 + \alpha_i + \alpha_p + \alpha_{jt} + \alpha_{bt} + \epsilon_{ibt} \end{aligned} \tag{10}$$

Finally, I include firm–bank fixed effects α_{ib} in Equation (11) to control for time-invariant unobserved heterogeneity in endogenous bank-firm matching, including relationship lending.[27] Firm-level time-varying controls together with granular fixed effects are included to proxy for common credit demand shocks:

$$\begin{aligned} Lending_{ibt} =& \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} \\ &+ X'_{it-1}\gamma_1 + \alpha_p + \alpha_{jt} + \alpha_{bt} + \alpha_{ib} + \epsilon_{ibt} \end{aligned} \tag{11}$$

[26] Bank-level controls are absorbed by bank-year fixed effects.

[27] This approach follows the literature that identifies credit supply shocks using fixed effects; see, for example, Khwaja and Mian (2008); Jiménez et al. (2014); Paravisini et al. (2023).

4.2 Threats to Identification

Two additional threats to identification are considered. First, firms may respond to physical risks by relocating away from high-risk areas. To address this concern, I conduct a robustness analysis that excludes relocating firms and compare credit outcomes for firms that remain in the same location. In addition, parish fixed effects are included in the baseline specifications (see Equation (8)). Results are reported in Table B.7.

Second, transition risk exposure may change endogenously if firms adjust energy use over time. To mitigate this concern, I construct an alternative transition risk measure using the firm's energy intensity in the first year the firm appears in the sample. Specifically, it is denoted as

$$\textit{Base transition risks}_{ijt} = \textit{Energy intensity}_{ij0} \times \textit{Environmental tax}_{jt} \tag{12}$$

for firm i, industry j, year t. The results with the base year approach are presented in Table B.4.

5 Empirical Results

This section presents the empirical results based on the specifications outlined above. I begin by examining whether banks adjust credit allocation in response to firms' exposure to physical and transition risks. I then analyze whether credit is reallocated across firms with heterogeneous risk profiles, including firms that engage in greening activities, firms in the tails of the risk distribution, and firms with varying degrees of risk interaction. Finally, I examine heterogeneous effects across firm and bank characteristics and explore mechanisms underlying the baseline results.

5.1 Baseline Results: Credit Allocation and Climate Risks

This subsection examines whether banks adjust credit allocation in response to firms' exposure to physical and transition risks.

5.1.1 Intensive margin of lending

Baseline estimates for the effects of physical and transition risks on the intensive margin of lending, measured by loan growth in percentage points, are reported in Table 2. The corresponding coefficient estimates across specifications are illustrated in the left panel of the online appendix Figure A.11.

Column 1 of Table 2 reports estimates from a specification including firm, bank, and year fixed effects (Equation (6)). Firms exposed to higher physical risks experience significantly lower credit growth relative to firms facing lower physical risks within the same year, as well as lower credit growth when physical risk exposure increases over time. A one standard deviation increase in physical risk is associated with a 1.368 percentage point reduction in loan growth, corresponding to roughly a 10% decline relative to the sample mean.[28] In levels, this implies an average reduction of approximately 110,000 DKK in outstanding loans.

Higher transition risks are also associated with lower credit growth, with somewhat larger magnitudes. A one standard deviation increase in transition risk is associated with a 2.208 percentage point decline in loan growth, equivalent to about 16% of the sample mean and an average reduction of roughly 178,000 DKK in loan amounts.

Columns 2 through 6 progressively introduce firm- and bank-level controls, parish fixed effects, industry fixed effects, high-dimensional industry-year and bank-year fixed effects, and firm–bank fixed effects. Across specifications, the estimated coefficients on both physical and transition risks remain negative and statistically significant.

Put together, a one standard deviation increase in physical risk is associated with a 1.1%–1.4% reduction in loan growth, corresponding to an 8%–10% decline relative to the sample mean. The effect of transition risk is slightly larger: a one standard deviation increase is associated with a 1.6%–2.2% reduction in loan growth, equivalent to an 11%–16% decline relative to the mean.

5.1.2 Extensive margin of lending

Results for the extensive margin, measured by the probability of receiving new credit, are reported in Table 3 and illustrated in the right panel of Figure A.11. Higher physical risk is associated with a lower likelihood of receiving new credit, although the effect attenuates once firm-bank fixed effects are included. Transition risk is not significantly related to the probability of receiving new credit in any specification. Taken together, these results suggest that climate risks primarily affect credit allocation along the intensive margin rather than through loan initiation.

5.1.3 Extension results: alternative credit outcomes

I next examine whether banks adjust other credit margins, including firm-bank relationship dynamics and loan pricing. Using the specification in Equation (10), I replace the dependent

[28] See Table 1 for summary statistics.

variable with indicators for relationship entry, relationship exit, and effective interest rates. Results are reported in Table 4 and plotted in Figure A.12.

Banks are less likely to enter new relationships with firms exposed to higher transition risks and more likely to exit existing relationships when physical risks increase. In contrast, loan pricing does not respond significantly to either physical or transition risks.

Put together, this pattern suggests that banks primarily manage climate-related risks through quantity adjustments and relationship dynamics rather than through interest rate changes. One explanation is that climate risks are difficult to price precisely and tend to materialize over long horizons, making quantity adjustments a more effective tool than marginal price changes.

5.1.4 Alternative tests and robustness checks

This section summarizes a set of robustness checks conducted to assess whether the baseline results are sensitive to alternative definitions of credit outcomes, climate risk measures, model specifications, and sample selection. Detailed results are reported in the Online Appendix.

Alternative dependent variables To assess the sensitivity of the results to the measurement of credit outcomes, I consider alternative definitions of loan growth. In Table B.1, I replace the baseline growth measure with (i) the log level of outstanding loans, (ii) log changes in loan balances, and (iii) positive loan growth only to separate loan origination from repayment dynamics. Across these specifications, the estimated effects of both physical and transition risks remain negative, though some coefficients lose statistical significance.

Alternative climate risk measures I next examine the robustness of the results to alternative definitions of physical and transition risks. For alternative physical risks (reported in Table B.2), I vary the decay parameter, capturing geographic spillovers across a wide range of values. The estimated coefficients remain stable in sign, with larger magnitudes for lower decay parameters, consistent with banks responding more strongly to events affecting broader areas.

For transition risks, I consider alternative policy-based measures, emission measures, and a base-year approach to firm energy intensity to mitigate simultaneity concerns. Across these alternatives, the results summarized in Table B.3 and Table B.4 are consistent with the baseline findings.

Alternative specifications I further examine whether the results depend on model specification choices. The results are robust when allowing for a second lag of climate risks and

potential nonlinearities by including squared risk terms, which provide suggestive evidence of convex effects at high levels of climate risk (Table B.5). Finally, the results are robust to alternative clustering schemes, as shown in Table B.6.

Alternative samples Finally, I re-estimate the main specifications across a range of firm- and bank-level subsamples to address sample selection concerns. At the firm level, I consider incumbent firms, exclude entrants and firms that exit, exclude high-productive firms, and remove firms that relocate during the sample period (Table B.7). At the bank level, I exclude small banks, restrict the sample to incumbent banks, remove banks located in the capital regions, and remove banks that exit during the sample period (Table B.8). The main results remain robust across all subsamples considered.

5.2 Reallocation across Firms with Heterogeneous Risk Profiles

This subsection examines how banks reallocate credit across firms with heterogeneous climate risk profiles. While the baseline results document an average reduction in credit to high-risk firms, banks may differentiate across firms depending on the level, extremity, and composition of climate risk exposure. I therefore study three dimensions of heterogeneity: whether banks engage with high-risk firms that undertake credible greening efforts, whether lending responses are concentrated in the tails of the risk distribution, and whether banks consider the joint exposure to physical and transition risks.

5.2.1 High-risk and "greening" firms

So far, the results indicate that banks reduce credit to firms with high exposure to physical or transition risks, particularly along the intensive margin. While such divestment may mitigate banks' risk exposure, it may also be counterproductive for the green transition if it restricts high-emission firms' ability to finance cleaner technologies (Hartzmark and Shue, 2022). This raises the question of whether banks also engage with high-risk firms that undertake credible efforts to reduce their climate exposure. In this section, I take this question to the data and examine whether firm-level "greening" efforts attenuate the adverse relationship between climate risks and lending.

"Greening" firms are defined using two outcome-based proxies that are less susceptible to greenwashing: (i) reductions in firm-level energy intensity and (ii) green innovation activity. The first proxy is a dummy indicating whether a firm reduces its energy intensity relative to the previous year. The second proxy captures green patent applications, based on Danish firms' filings to the European Patent Office, following Calel and Dechezleprêtre (2016) and

Li et al. (2021). Detailed patent classification criteria are described in the Online Appendix.

Table 6 reports results from specifications interacting physical and transition risks with the greening indicators. Firms that reduce energy intensity or apply for green patents experience a significantly weaker negative relationship between climate risks and credit growth. These interaction effects suggest that banks view observable greening efforts as positive signals, partially offsetting the adverse impact of high climate risk exposure.

5.2.2 Firms in the tail of the risk distribution

To assess whether banks respond more strongly to extreme climate risk exposure, I examine credit allocation across the tails of the physical and transition risk distributions. Firms in the top (bottom) quartile of the annual risk distribution are classified as high-risk (low-risk).

Using the following empirical specifications, I compare credit allocation to firms in the high- and low-risk groups relative to those in the medium-risk group.

$$\begin{aligned} Lending_{ibt} =& \boldsymbol{\beta_1}\, High\ PR_{it-1} + \boldsymbol{\beta_2}\, High\ TR_{it-1} + \boldsymbol{\beta_3}\, Low\ PR_{it-1} + \boldsymbol{\beta_4}\, Low\ TR_{it-1} \\ &+ X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \text{FEs} + \epsilon_{ibt} \end{aligned} \tag{13}$$

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

Results in Table 5 and Figure A.13 show that firms in the high-risk tails experience significantly lower credit growth relative to firms with medium risk exposure, while firms in the low-risk tails receive more credit. The estimated effects are larger than those obtained using continuous risk measures, consistent with the idea that banks respond more strongly to extreme climate risks and indicate a non-linear response to tail risk. These results are robust to alternative definitions of tail exposure and to the use of a composite climate risk index (see Table B.9).

5.2.3 Firms with joint exposure to physical and transition risks

Physical risks are primarily location-based, while transition risks are firm- or industry-specific, implying that firms may face compounded exposure depending on their geographic and sectoral characteristics (ECB, 2021). As a result, banks may respond not only to individual risk dimensions but also to their interaction.

To examine this channel, I classify firms into high- and low-risk groups for each risk

dimension and estimate specifications interacting with physical and transition risk indicators:

$$\begin{aligned} Lending_{ibt} =& \boldsymbol{\beta_1}\, Low\ PR_{it-1} \times Low\ TR_{it-1} + \boldsymbol{\beta_2}\, High\ PR_{it-1} \times Low\ TR_{it-1} \\ &+ \boldsymbol{\beta_3}\, Low\ PR_{it-1} \times High\ TR_{it-1} + \boldsymbol{\beta_4}\, High\ PR_{it-1} \times High\ TR_{it-1} \\ &+ X'_{it-1}\gamma_1 + Z'_{bt-1}\gamma_2 + \text{FEs} + \epsilon_{ibt} \end{aligned} \tag{14}$$

for firm i, bank b, year t.

Results are reported in Table 7 and visualized in Figure A.14. Banks allocate slightly more credit to firms with low joint exposure to both physical and transition risks, driven primarily by firms with low physical risk exposure. In contrast, firms facing high exposure to both risk dimensions experience lower credit growth, although these effects are imprecisely estimated. Overall, the evidence suggests that banks respond modestly to compounded climate risks, favoring firms with jointly low exposure while not penalizing firms facing high interaction risks beyond the average individual effects.

Taken together, these results show that banks reallocate credit across firms in a non-linear way and respond to both the level and composition of climate risk exposure.

5.3 Reallocation across Firm and Bank Characteristics

This section examines whether the risk-based reallocation documented above varies across borrower and bank characteristics. On the borrower side, if banks internalize climate risks and treat them as credit risk, the effects should be stronger for those vulnerable firms with limited capacity to absorb shocks and high credit risk, such as smaller, financially constrained borrowers. On the bank side, this credit adjustment does not happen uniformly across all banks. It could vary depending on relationship lending, banks' own balance-sheet exposure to climate risk, or bank specialization. This heterogeneity analysis provides evidence on these mechanisms.

5.3.1 Borrower-level heterogeneity

I begin by examining whether certain firm characteristics may amplify the lending response to climate risks.

Firm size Smaller firms are typically more informationally opaque, riskier, more financially constrained, and have higher default risk (Hadlock and Pierce, 2010). I proceed with testing whether the adverse effects of climate risks on credit allocation are more pronounced for small firms. Firms are classified as small or large based on the bottom and top quartiles

of the size distribution, and I interact these indicators with the climate risk measures in a modified version of Equation (7).

As shown in columns 2 and 4 of Table 8, small firms experience a significantly larger reduction in access to new credit in response to transition risks, whereas large firms are less affected and, in some cases, benefit from relative reallocation. These results suggest that banks have higher sensitivity to climate risk when lending to constrained borrowers. This further indicates that banks tighten credit more strongly when climate risks are compounded with existing information frictions and default risk.

Financial leverage Financially leveraged firms face higher credit risk and have limited buffers against adverse shocks, which may further constrain bank lending under climate risk exposure (Jiménez et al., 2014; Laeven and Popov, 2023). To assess this channel, I interact climate risk measures with a high-leverage indicator in Equation (7).

Columns 1 and 2 of Table 9 show that highly leveraged firms are significantly less likely to receive new loans when exposed to climate risks. This is consistent with banks avoiding the compounding of financial risks and climate-related risks when assessing credit exposure.

Taken together, these results indicate that smaller firms facing tighter financial constraints and therefore higher credit risks are more likely to experience climate-related credit tightening, consistent with the notion that banks avoid compounded risk exposure (Dunz et al., 2023).

Capital intensity Capital intensity may affect lending responses to climate risks through two opposing channels. On the one hand, firms with large stocks of physical assets are directly exposed to climate-related damage. On the other hand, tangible assets may serve as collateral, potentially mitigating credit constraints.

To examine these channels, I interact climate risks with a high capital-intensity indicator. Columns 3 and 4 of Table 9 show that banks reduce lending growth and are less likely to initiate new loans to capital-intensive firms exposed to high physical risks. This evidence suggests that concerns about asset vulnerability dominate potential collateral benefits when physical risks are high. This is consistent with the idea that climate risks may increase expected losses given default through the exposure of tangible assets.

Industry brownness I next examine whether lending responses differ for firms operating in the most emission-intensive ("brown") industries. Banks may be more cautious due to their high transition risk exposure, but may also continue lending given high short-term profitability and informational advantages.

Brown industries are defined as those in the top 5% of the industry-level emission intensity distribution. As shown in Table 10, firms in these industries experience substantially larger reductions in loan growth when exposed to high physical and transition risks, with an additional 5–6% decline along the intensive margin.

Overall, borrower-side heterogeneity indicates that climate-related credit contraction is strongest among firms that combine high climate exposure with limited capacity to absorb shocks, particularly firms that are smaller, financially constrained, asset-intensive, and operate in emission-intensive industries. This pattern is consistent with the notion that banks tend to avoid exacerbating climate risks by compounding them with pre-existing financial or operational vulnerabilities, which tends to be linked to credit risk.

5.3.2 Bank-level heterogeneity

I next turn to bank characteristics that may amplify or attenuate how climate risks are incorporated into lending decisions. The analysis focuses on three channels: relationship lending, banks' own exposure to climate risks, and specialization in carbon-intensive industries.

Relationship lending Relationship lending may influence how banks adjust credit in response to climate risks. Banks possess informational advantages over repeat borrowers, particularly among SMEs (Diamond, 1991; Sharpe, 1990; Rajan, 1992; Petersen and Rajan, 1994), and lending relationships in Denmark are typically persistent (Hviid et al., 2022). These features suggest that banks may be more willing, or better equipped, to adjust credit within established relationships.

Using interaction terms between climate risks and indicators for repeat versus first-time lending, Table 11 shows that banks significantly reduce lending to existing clients exposed to climate risks, while lending to first-time borrowers is less negatively affected. This pattern suggests that banks primarily adjust credit within established relationships, where borrowers' switching costs are highest (Chodorow-Reich, 2014).

Banks' exposure to climate risks Banks' exposure to climate risks arises primarily through their loan portfolios. Banks with greater aggregate exposure may be more aware of climate-related risks and therefore more proactive in adjusting lending.

I construct bank-level exposure measures as loan-weighted averages of client firms' physical and transition risk exposures. Banks' physical risk exposure is defined as:

$$Banks'\ physical_{bt} = \frac{\sum_{i \in I} Loans_{ibt} \times Physical\ risks_{pt}}{\sum_{i \in I} Loans_{ibt}}, \tag{15}$$

with an analogous measure for transition risks.

I define *High-exposure banks* as those above the 75th percentile of the respective exposure distributions. Interacting this indicator with firm-level climate risks in Equation (7), the results reported in Columns 1–2 of Table 12 show that high-exposure banks reduce lending more strongly to high-risk firms.

These findings indicate that banks internalize climate risks at the portfolio level and respond by tightening credit where climate risks compound existing balance-sheet exposure. This also highlights the importance of the credit supply channel.

Banks' specialization in brown industries Another bank-level factor that may affect lending responses is specialization. Banks that specialize in emission-intensive ("brown") industries may face competing incentives. On the one hand, specialization may generate informational advantages and lower monitoring costs (Giometti and Pietrosanti, 2022; Sharma, 2024), allowing banks to better assess and manage climate-related risks. Such banks may also have stronger incentives to continue this pattern in order to obtain a higher short-term profit margins (Laeven and Popov, 2023). On the other hand, those banks are likely to face higher regulatory, reputation, or financial risks associated with climate risks. Therefore, they might be more proactive in managing the risks and more cautious in lending.

Following Paravisini et al. (2023), a bank is classified as specialized in an industry if the share of a bank's total lending allocated to a given two-digit industry lies above the 75th percentile of the industry-specific distribution. Banks specialized in brown industries are defined as those whose specialized industry falls within the brown industry category.[29]

To test this channel, I interact a dummy for brown-industry specialization with climate risk measures. The results, reported in columns 3–4 of Table 12, indicate that banks specializing in brown industries are more likely to continue initiating new loans to climate-exposed firms. The positive and significant interaction terms suggest that information advantages and legacy exposure may attenuate the negative effects of climate risks on credit allocation, consistent with the findings of Degryse et al. (2020) and Laeven and Popov (2023).

Put together, the heterogeneity analysis shows credit tightening is more pronounced when climate risks compound existing borrower vulnerabilities, such as financial constraints, asset exposure, or industries with high emission intensity. On the bank side, the effect is stronger when banks themselves face high portfolio exposure and lending to existing borrowers with high switching costs. At the same time, lending to first-time borrowers and industry specialization attenuate these effects. A summary of the key results in this section is in Table 13.

[29]Brown industries are identified as those with industry emission intensity above the 95th percentile of the sample distribution.

5.4 Mechanisms

As outlined in Section 2, banks may reduce lending to firms with high climate risk exposure due to heightened perceived credit risk, while firms facing increasing climate risks may reduce borrowing by slowing growth, deleveraging, and divesting (Huang et al., 2018; Kacperczyk and Peydró, 2022; Bolton et al., 2019).

Given that the observed credit outcomes reflect both firm-level demand and bank-level supply, identifying the dominant driver can be empirically challenging. However, leveraging the rich firm-level data, this section provides a set of tests that shed light on the relative importance of each channel.

5.4.1 Climate risks and credit supply

Industry–Location–Size–Time (ILST) fixed effects While the most saturated specification in the baseline analysis includes fixed effects such as industry-year and bank-firm to control for credit demand, concerns remain that these may not fully capture demand-side heterogeneity, particularly when climate risks affect firms asymmetrically within narrowly defined markets. To further support a supply-side interpretation, I follow Degryse et al. (2019) and introduce high-dimensional Industry–Location–Size–Time (ILST) fixed effects, which more finely control for local credit demand conditions.

The underlying assumption is that firms operating in the same industry, location, and size category within a given year are likely to exhibit similar borrowing needs. Accordingly, in Table 14, I gradually saturate the regression model with increasingly granular fixed effects: Industry–Location–Size (ILS) in column (1), Industry–Location–Time (ILT) in column (2), and the most saturated Industry–Location–Size–Time (ILST) in column (3).

Across all specifications, the estimated relationship between transition risks and loan growth remains negative and statistically significant. The persistence of these estimates under increasingly restrictive demand controls points to an important role of credit supply.[30]

Credit risk channel If credit responses reflect credit supply adjustments, one possible mechanism is banks' perceived heightened credit risk associated with climate exposure. To examine this channel, I estimate a set of firm-level regressions that relate climate risks to three proxies commonly associated with high credit risk, reported in Table 15.

Specifically, *Exit* is a binary indicator equal to one if a firm exits the sample, serving

[30] One caveat of using highly saturated fixed effects is that they may absorb a substantial portion of the variation of interest. The resulting estimates, therefore, likely represent a lower bound of the true effect.

as an upper-bound proxy for default risk.[31] The second proxy, *Negative EBIT*, is a dummy variable indicating whether a firm's earnings before interest and taxes are negative, signaling low profitability (column 2). Finally, *Financial Distress* is defined as a dummy equal to one if a firm's interest coverage ratio falls below a given threshold (column 3).[32]

The positive and statistically significant coefficients on transition risks in columns 2 and 3 indicate that firms exposed to higher transition risks are more likely to experience low profitability and financial distress. These outcomes are associated with banks' conventional credit risk assessment matrix and are consistent with banks internalizing climate risks via standard credit risk channels.

5.4.2 Climate risks and credit demand

Next, I examine whether reduced firm growth, and therefore lower credit demand, can account for the observed credit reallocation.

Firm growth and climate risks To explore this, I examine whether exposure to climate risks is associated with a range of firm-level indicators that proxy for firm growth and credit demand, as presented in Equation (16). Specifically, investment growth and employment growth are used as proxies for credit demand related to firm expansion. In addition, fixed asset growth is included to capture funding needs for capital expenditure, and sales growth as a measure of working capital demand.

$$Firm\ Growth_{it} = \beta_1 Physical\ risks_{pt-1} + \beta_2 Transition\ risks_{it-1} + X'_{it-1}\gamma_1 + \alpha_i + \alpha_p + \alpha_{jt} + \epsilon_{it} \tag{16}$$

As shown in columns 1 through 4 of Table 16, climate risks are not systematically associated with any of these firm-level growth measures. This lack of evidence suggests that reduced credit demand is unlikely to be the primary driver. This further supports that supply-side factors, such as banks' risk perceptions and preferences, are more likely to explain the observed reallocation of credit in response to climate risks.

Subsample test on firms with positive credit demand As an alternative approach, I examine lending responses within subsamples of firms exhibiting positive credit demand,

[31] Figure A.15 in the appendix reports the number of firm exits per year and shows a notable spike during the 2007–2009 global financial crisis.

[32] The interest coverage ratio reflects a firm's ability to service its debt; lower values indicate greater financial fragility.

following Takahashi and Shino (2023). The rationale is that if the negative impact of climate risks on loan growth persists even among firms with strong credit demand, then demand-side factors are unlikely to be the primary driver.

I re-estimate the baseline regression from Equation (10), based on samples restricted to firms with positive credit demand. The results are reported in Table 17. Columns 1–4 focus on firms with positive investment and employment growth, proxies for firm expansion. Columns 5–6 consider firms with positive fixed asset growth, indicating capital expenditure needs, while columns 7–8 analyze firms with positive sales growth as a measure of working capital demand.[33]

Across all subsamples, the negative effects of climate risks on loan growth persist. This provides further evidence that the observed credit reallocation is unlikely to be driven primarily by demand-side factors.

Overall, the evidence indicates that supply-side forces play a more important role in the observed lending responses to climate risks. While multiple channels may contribute to this, this paper highlights one possible channel behind banks' motivation: credit risk.

6 Conclusion and Discussion

Existing studies document that large global banks are beginning to respond to physical and transition climate risks, primarily through adjustments in syndicated lending to large publicly listed firms (Kacperczyk and Peydró, 2022; Degryse et al., 2023; Meisenzahl, 2023). However, there remains limited evidence on how banks adjust credit allocation to non-listed firms, which are predominantly small and medium-sized enterprises (SMEs), or on whether banks condition lending on firms' credible greening efforts rather than simply divesting. In addition, most existing research examines physical and transition risks separately, despite their potential interaction and compounding effects.

Using comprehensive matched bank–firm credit data from Denmark, covering a large sample of non-listed firms, this paper provides empirical evidence of an average reduction in credit to firms exposed to higher physical or transition risks, primarily through quantity adjustments on the intensive margin (i.e., lower credit growth) and relationship dynamics. However, I find no systematic evidence of pricing adjustments.

At the same time, banks differentiate across firms depending on the level and composition of climate risk exposure. Specifically, they allocate more credit to high-risk firms that engage in credible greening activities, as well as toward firms with low joint exposure to physical

[33] While strong credit supply can itself stimulate firm growth and thus increase credit demand, these proxies originate from firms' internal operations and can serve as reasonable indicators of inherent credit demand.

and transition risks.

The analysis further documents heterogeneous responses across firm and bank characteristics. On the borrower side, credit contractions are stronger for more vulnerable firms, such as smaller, highly leveraged, capital-intensive firms, as well as firms operating in the brownest industries, which is consistent with banks avoiding the compounding of climate risks with existing credit risk. On the bank side, lending reductions are more pronounced when banks themselves face high portfolio exposure within repeat lending relationships, while banks specialized in brown industries tend to maintain or expand lending, reflecting the role of legacy exposure and industry expertise. Mechanism tests suggest that these patterns are primarily driven by the credit supply side, as higher climate risk exposure is associated with high indicators of perceived credit risk.

These findings speak to policymakers' concerns regarding the financial stability implications of climate change (ECB, 2021; Fed, 2021). First, the results provide evidence that banks are already incorporating climate risks into credit allocation for non-listed SMEs, primarily through quantity adjustments. This is of direct relevance for banking supervisors and central banks. However, given the modest magnitude of the effects and their heterogeneity across credit margins and firms' risk profiles, future regulatory guidance may focus on improving banks' capacity to consistently assess and manage physical and transition risks. Second, because more constrained firms are disproportionately affected, targeted policies may help mitigate unintended distributional results during the green transition.

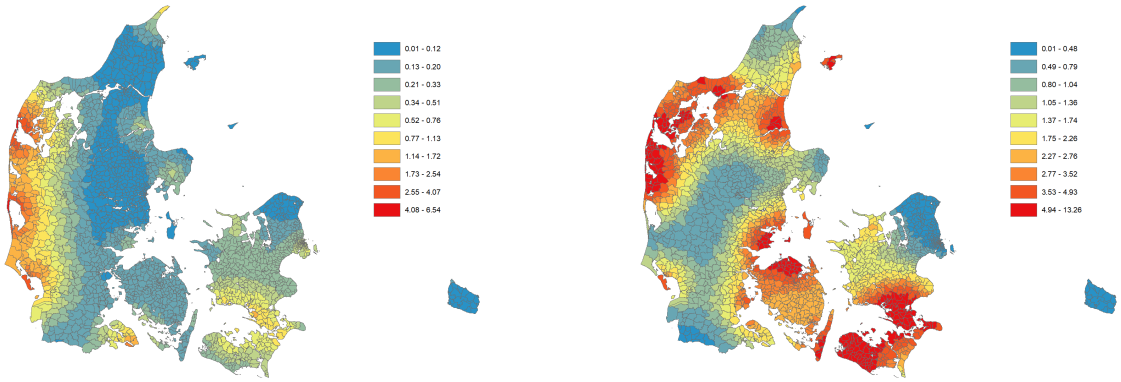
Several caveats are worth noting. First, while the results indicate an average reduction in loan growth for firms with higher climate risk exposure, the magnitude of the effect is modest and conditional on the intensive margin as well as firm and bank survival. As climate risks intensify and banks further internalize these risks, stronger effects may be observed over time. Second, this study does not directly assess the real effects of credit reallocation on actual emission reductions (Hartzmark and Sussman, 2019; Apicella and Fabiani, 2023), emission pledges (Gormsen et al., 2024), the green transition (Gu et al., 2026), firms' real outcomes (Miguel et al., 2024), or green innovation (Accetturo et al., 2022). Finally, despite extensive tests, fully disentangling credit supply from credit demand remains challenging. Future research exploiting exogenous shocks or credible instruments could further improve identification in this setting.

Figures

Figure 1: Physical Risks Indicator by Parish over Time

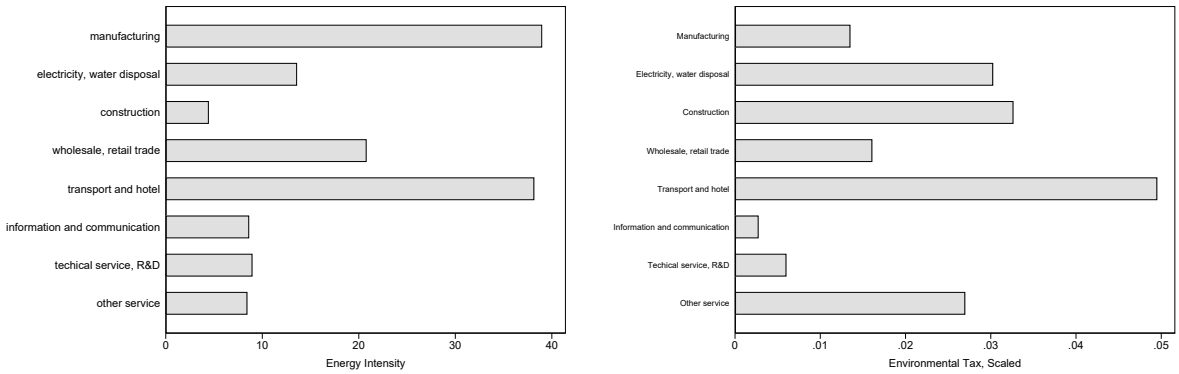
(a) Physical risks indicator, 2009

(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 flood events on the 20-year horizon under the IPCC RCP 4.5 scenario; extreme precipitation is based on weather data from DMI.

Figure 2: Energy Intensity (Left) and Environmental Tax (Right) Across Industry



Tables

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 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 (6) to Equation (11). 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 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 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 (6) to Equation (11). 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	**Exit**	**Interest Rate**
	(1)	**(2)**	**(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 (10). 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 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 6: Credit Allocation to High Risk and "Greening" Firms

	Loan Growth (1)	**New Loans (2)**	**Loan Growth (3)**	**New Loans (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 (7), 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 7: 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 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 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 (1)	**New Loans** (2)	**Loan Growth** (3)	**New Loans** (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 (1)	**New Loans** (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 (7), 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 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 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 (7), 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 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 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 (7), 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: Summary of Credit Reallocation across Firm and Bank Characteristics

Characteristics	**Credit Allocation Response**
Borrower characteristics	
Firm size	Small firms: ↓↓↓ new loans under transition risks Large firms: ↑↑↑ new loans under transition risks
Financial leverage	High leverage: ↓↓↓ new loans under both risks
Capital intensity	High capital intensity: ↓↓↓ new loans & growth under physical risks; ♦ under transition risks
Industry brownness	Brown industries: ↓↓ new loans & growth under physical risks; ♦ under transition risks
Bank–firm relationship	
Relationship lending	Repeat borrowers: ↓↓↓ new loans under physical risks; ↓ growth under transition risks First-time borrowers: ↑↑↑ new loans under both risks; ↑ growth under transition risks
Bank characteristics	
Bank climate exposure	High-exposure banks: ↓↓↓ new loans under transition risks; ↓↓ growth under physical risks;
Bank specialization	Brown-industry specialized bank: ↑↑↑ new loans under both risks

Notes: Arrows summarize the direction and relative strength of estimated interaction effects. Red arrows indicate credit tightening or reallocation away from firms; green arrows indicate increasing credit allocation.

Table 14: 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 (11). 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 15: 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 2019. 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 16: 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 (16). 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 17: Climate Risks and Credit Demand: Firms with Positive Credit Demand

Included Sample	**Loan Growth** Positive Investment Growth	**New Loans** Positive Investment Growth	**Loan Growth** Positive Employment Growth	**New Loans** Positive Employment Growth	**Loan Growth** Positive Fixed Assets Growth	**New Loans** Positive Fixed Assets Growth	**Loan Growth** Positive Sale Growth	**New Loans** 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 (10) 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 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%.

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Online Appendix for "Credit Allocation under Physical and Transition Climate Risks"

22 January 2026

Appendix A: Additional Figures

Figure A.1: Overview of Hypotheses Testing Results

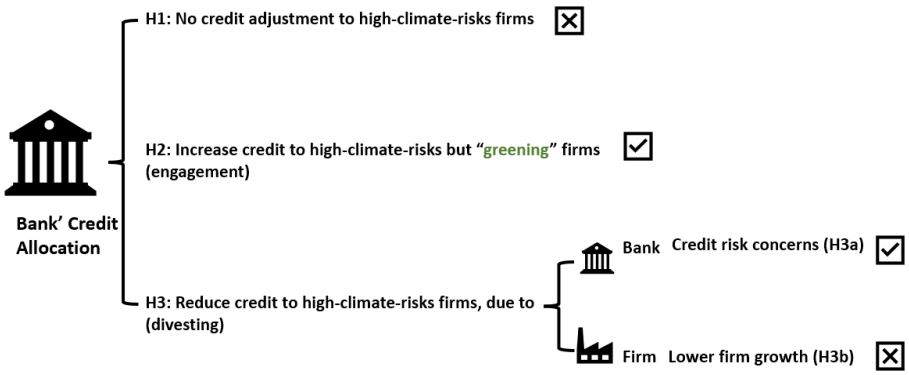


Figure A.2: Average Firm-Bank Account Balance for Each Quantile Bin by Account Balance, 2003 vs 2009

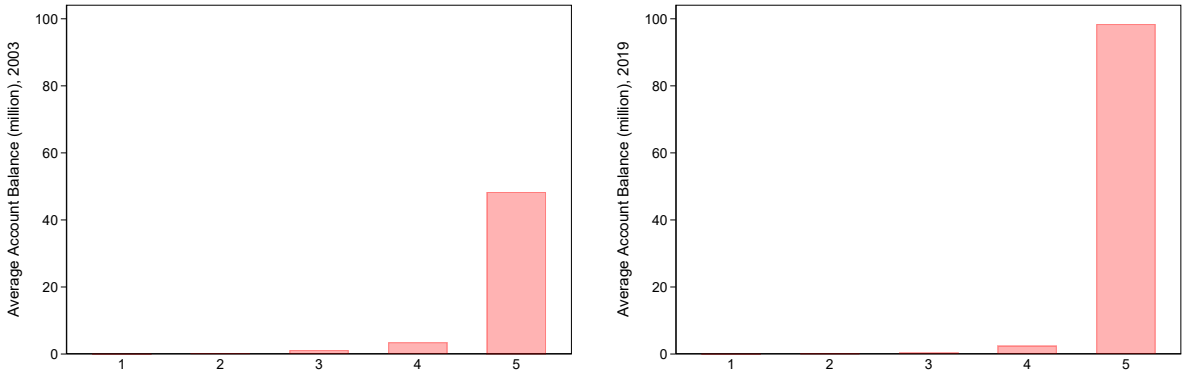


Figure A.3: Number of Firms and Banks

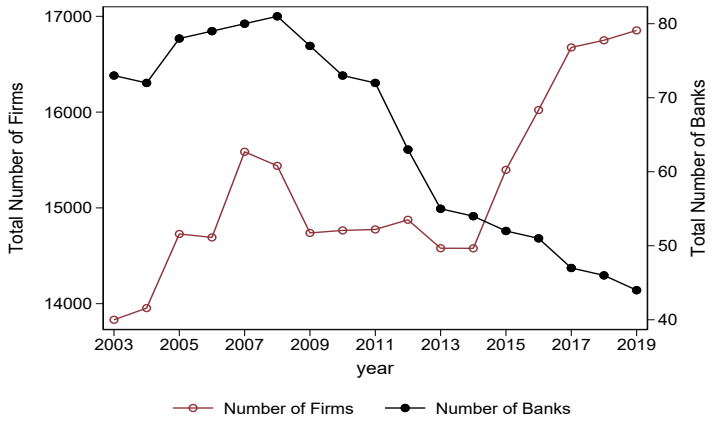


Figure A.4: Average Firm-Bank Account Balance for Each Quantile Bin by Physical Risks, 2003 vs 2009

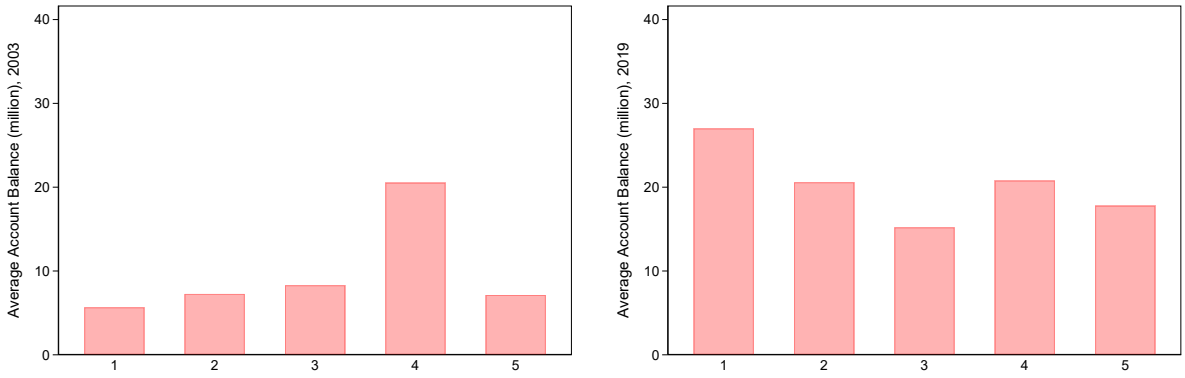


Figure A.5: Aggregate Account Balance to High PR Firms (Top 25%) vs Low PR Firms (Bottom 25%) over Time

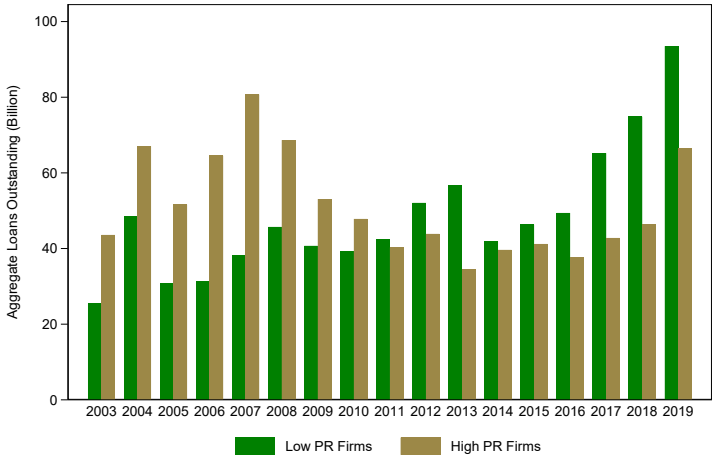
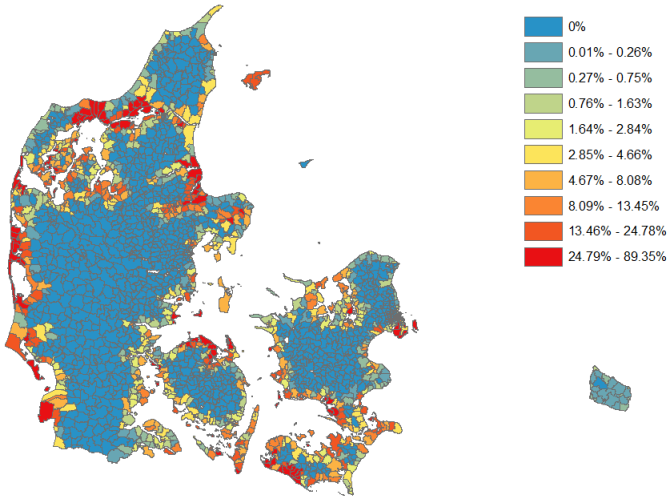
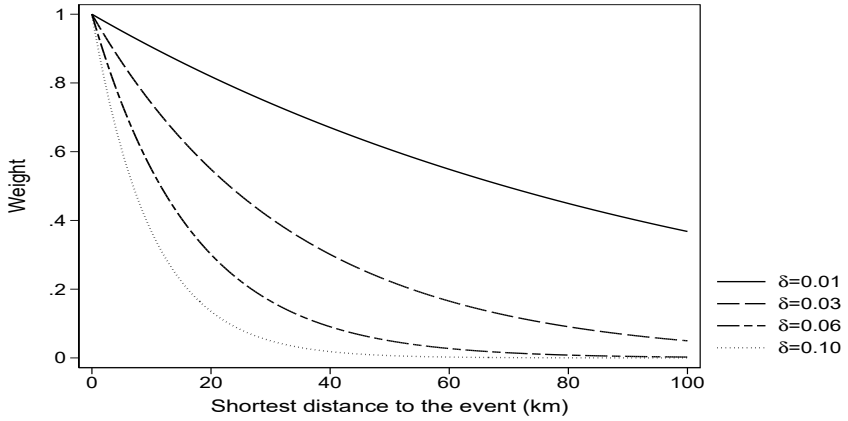


Figure A.6: Share of Flood Risk, by Parish



Notes: Based on flood risk in 20 years under the 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 A.7: The Weight Functions $e^{-\delta x_{pr}}$ 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 A.8: Average Firm-Bank Account Balance for Each Quantile Bin by Transition Risks

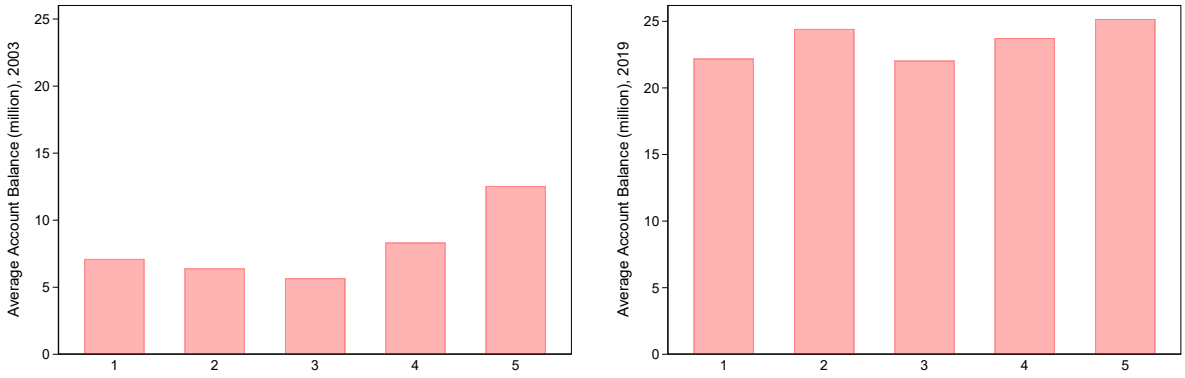


Figure A.9: Aggregate Account Balance to High TR Firms (Top 25%) vs Low TR Firms (Bottom 25%) over Time

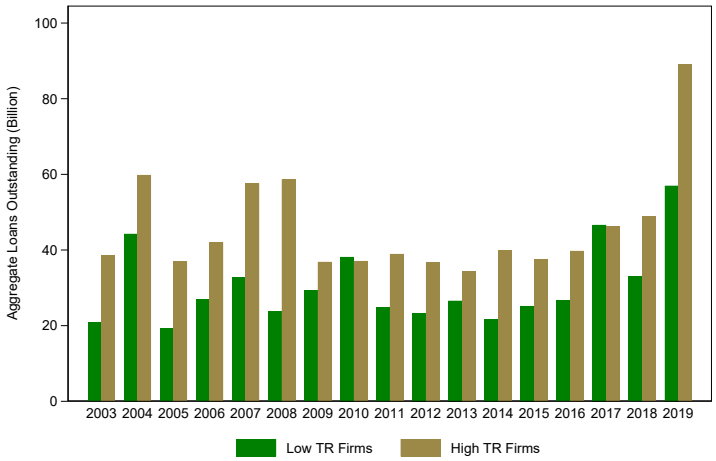


Figure A.10: Sources of Identification: Variation Within Firm (left), Variation Between Firm (right)

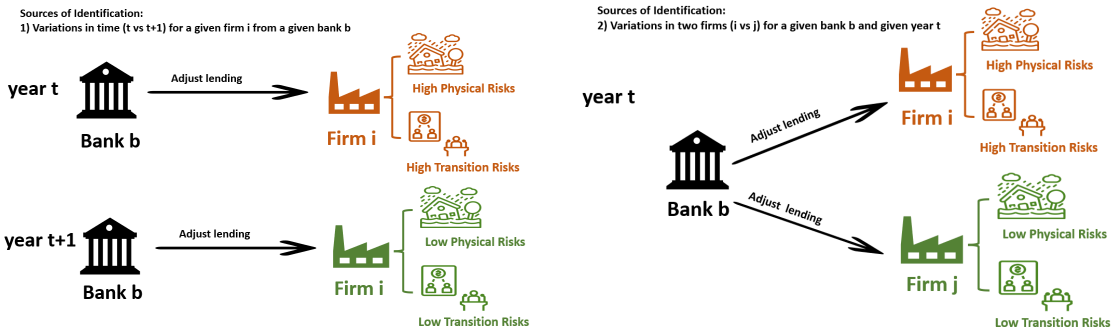


Figure A.11: Climate Risks and Loan Growth (Left), New Loans (Right)

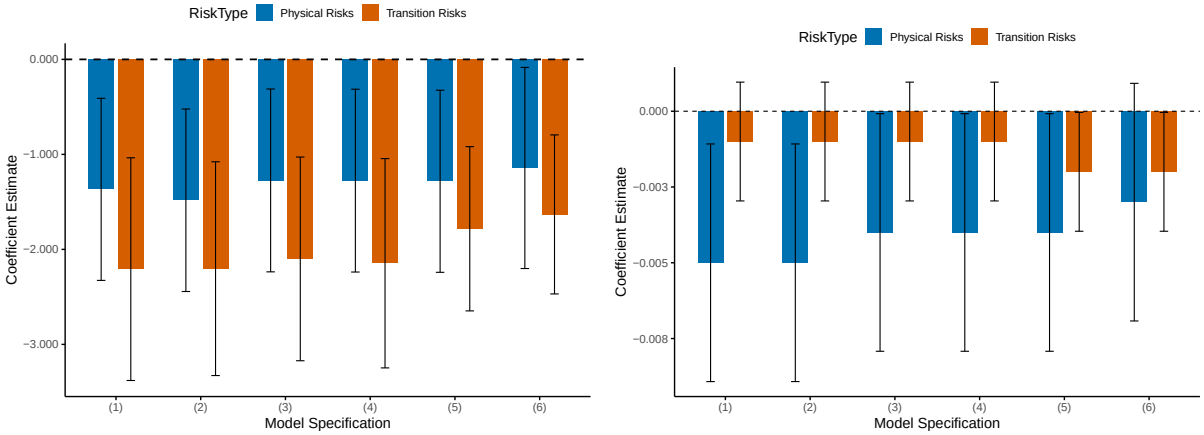


Figure A.12: Alternative Credit Outcomes: Relation Changes and Interest Rate

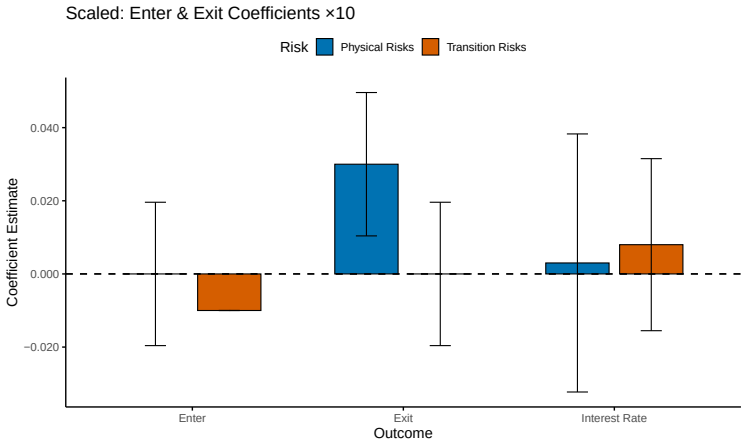


Figure A.13: Credit Response to the Tail Risks

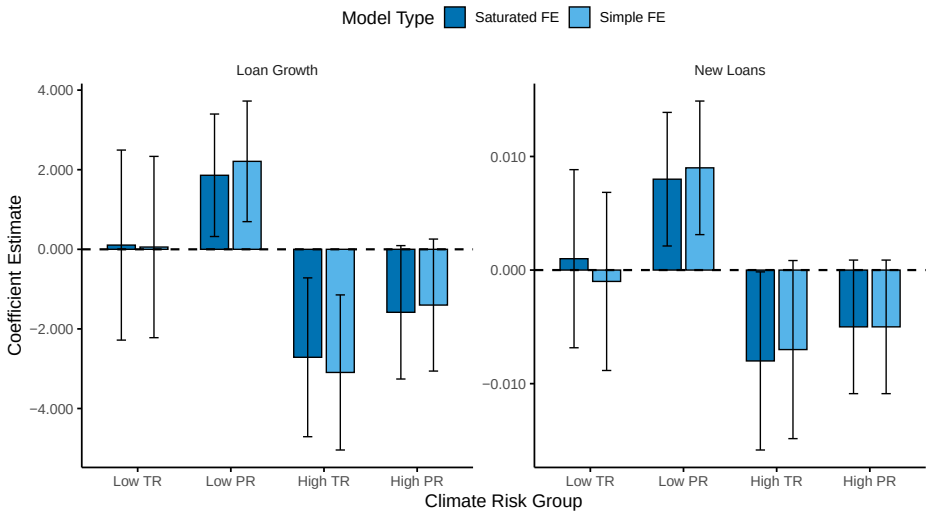


Figure A.14: Interaction Effects of Physical and Transition Risks

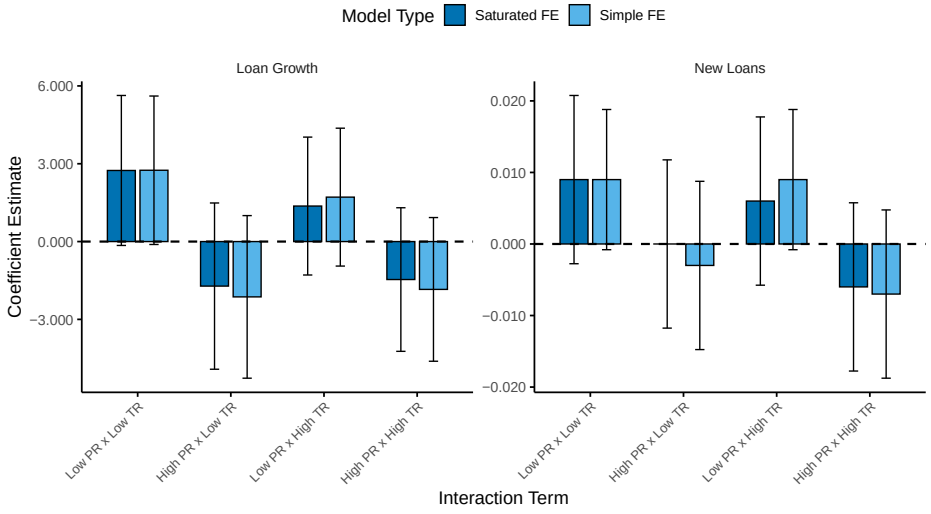
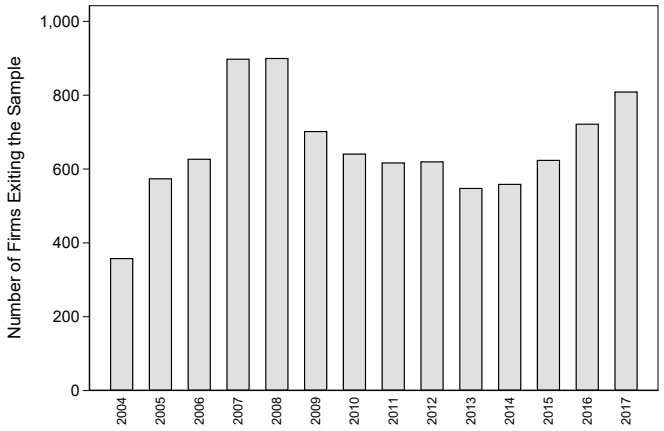


Figure A.15: Number of Firms that Exit the Sample



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

Appendix B: Additional Tables

Table B.1: 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 B.2: 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 (7), 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 B.3: 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 B.4: 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, *Transition risks*$_{ijt}$ is calculated as: *Transition risks*$_{ijt}$ = *Emission intensity*$_{ij0}$ × *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 B.5: Climate Risks and Lending: Alternative Specification

	Loan Growth	**New Loans**	**Loan Growth**	**New Loans**
	(1)	**(2)**	**(3)**	**(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 (7) 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 (7) 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 B.6: 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 2019. 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 B.7: Climate Risks and Lending: Alternative Sub-samples, Firm Level

Included Sample	**Loan Growth** Include incumbent firms in the last 10 years	**New Loans**	**Loan Growth** Exclude entrant firms	**New Loans**	**Loan Growth** Exclude firms exiting the sample	**New Loans**
	(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

Included Sample	**Loan Growth** Exclude highly productive firms	**New Loans**	**Loan Growth** Exclude firms that relocate	**New Loans**	**Loan Growth** Exclude firms in Copenhagen	**New Loans**
	(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 (7). 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 2019. 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 B.8: Climate Risks and Lending: Alternative Sub-samples, Bank Level

Included Sample	**Loan Growth** Exclude small banks	**New Loans** Exclude small banks	**Loan Growth** Include incumbent banks	**New Loans** Include incumbent banks	**Loan Growth** Exclude banks exiting the sample	**New Loans** Exclude banks exiting the sample	**Loan Growth** Exclude banks located in the capital region	**New Loans** Exclude banks located in the capital region	**Loan Growth** Exclude banks with single establishment	**New Loans** 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 (7). 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 2019. 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 B.9: 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 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 B.10: 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 (8) 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 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%.

Appendix C: Additional Data Description

Definition of green patent application *Green patent application* is a dummy variable equal to one if a firm applies for a green patent, to measure engagement in green innovation activities. The patent 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* 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.

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. 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).