Climate Risk, Soft Information, and Credit Supply *

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Abstract

We study the impact of climate risk on credit supply using a unique loan-firm-bank-level dataset on all wildfires and corporate loans in Spain. Our findings reveal a significant decrease in credit following climate-driven events. This result is driven by diversified (outsider) banks, which reduce lending significantly to firms in affected areas. In contrast, geographically concentrated (local) banks, with superior soft information access, reduce credit to opaque firms to a significant lesser extent without increasing risk. Moreover, employment declines in affected areas where local banks are absent.

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Keywords: Climate Risk; Bank Lending; Soft Information; Local Banks; Credit Supply.

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1 Introduction

In recent years, climate-related disasters have increased in number and severity[1], escalating the challenges for the financial system. Beyond the transition risks associated with the shift to a lower-carbon economy, it is essential to assess the financial sector's response to the rising physical risks of climate change. Understanding these responses allows the assessment of the impact of climate risks on the economy. This paper asks whether local or outsider diversified banks are better equipped to keep credit flowing to the local economy, which has suffered the shock (a wildfire in our case).

A common assumption is that well-diversified outsider banks are better equipped to absorb localized shocks—such as the climate-related events in our case—and sustain credit provision, because they benefit from geographic and sectorial diversification, stronger liquidity positions, and access to advanced hedging instruments. As a result, optimizing an outsider bank's loan portfolio may involve reallocating capital away from affected regions, a strategy that local banks cannot as easily implement. At the same time, local banks may hold a competitive advantage through their superior access to soft information about local firms, including insights into their business models and resilience to shocks—information that large, diversified banks, reliant on hierarchical structures and standardized risk assessment, often lack.[2] The ability to leverage soft information may allow local banks to better assess loan risks and enhance their screening and monitoring of local firms' projects, potentially offsetting their relative lack of diversification.

We explore the mechanisms underlying bank credit allocation in a theoretical framework with asymmetric information and firm-specific climate shocks. We consider two types of banks at the province level—local banks (geographically concentrated) and outsider banks—and two types of firms —transparent and opaque—. A local bank in a province presents a high fraction of its credit balance in this province.[3] Local banks can better screen, monitor,

[1]See Smith and Katz (2013); Hulme (2014); Zscheischler et al. (2018); Zscheischler et al. (2020); and Tebaldi et al. (2021) for evidence on the increase in frequency and intensity of climate-driven disasters around the world. See Pechony and Shindell (2010); Moritz et al. (2012); Pausas and Keeley (2021) for studies that focus on wildfires.

[2]Throughout this paper, we refer to soft information as qualitative, non-standardized data that is inherently challenging to quantify, verify, or transfer. This type of information often relies on subjective judgment and personal interactions, such as assessments of a borrower's character, reputation, or trustworthiness.

[3]In our empirical analysis, we define and use the variable $LocalBank_{b,p,t}$ as the fraction of bank b's credit balance in province p where firm f in year t.

and calibrate the risk of opaque firms because they have better access to soft information than outsider banks.

Our theoretical framework shows that the differential use of soft information by local and outside banks in their lending decisions is a primary mechanism influencing bank credit allocation following a climate-related disaster. Specifically, after a climate event such as a wildfire, there is a decline in the credit extended to the affected firms by both outsider and local banks, but the latter reduce credit less than the former. Moreover, we observe that local banks decrease lending to opaque firms–for which soft information plays a critical role in lending decisions–to a lesser extent compared to outsider banks.

We conduct a comprehensive empirical analysis using data on firms, banks, and wildfires in Spain. We focus on corporate loans in Spain because we can construct a unique dataset—with monthly detailed information on all companies, all banks, and all bank-firm credit relationships—that covers a long period (i.e., 2004-2017) and we can geolocate. Besides, we focus on wildfires in Spain because it is one of the countries most affected by wildfires in Europe (European Commission et al. (2020a)).[4] The total area burned annually in Spain has been greater than 50,000 hectares in 13 of the last 18 years and at least 46.35% of its municipalities are located in areas of high wildfire risk (see Vega (2021)). Overall, our dataset comprises monthly data on an average of 769,983 firms per year, covering all bank-firm relationships exceeding €6,000, as reported by all credit institutions operating in Spain to the Bank of Spain.

Our empirical design is based on a quasi-experimental design provided by wildfires. The combination of geolocalized data on loan-firms-banks that are merged with the geolocalized wildfires enables us to implement a precise identification strategy. Then, we identify all firms that were located within a wildfire-affected area on the date. These wildfire-treated firms are assigned a dummy variable *Fire* that takes the value one if the firm is located within the affected area and zero otherwise. The control group consists of those firms located within a ring outside the treatment delimitation. First, we confirm that wildfires have adverse effects on the business activities of affected firms. Our estimates point to a drop in sales of firms in those areas relative to their total assets of 7 pp as compared to similar firms in unaffected

[4]Spain accounted for 40% of EU land lost to forest fires in 2022 and the number of days per year with high to extreme wildfire risk is increasing significantly due to higher temperatures and increasing drought (European Commission et al. (2020b)).

areas the year after a fire.

Our empirical findings indicate that firms impacted by fire experience a reduction in outstanding credit that is approximately 6% greater than that of comparable firms in the same municipality that were not affected by fire.[5] We exploit the variation in the credit supply of banks with different exposures to the province where a specific affected firm is located relative to firms with similar characteristics that are not affected by fire. We show that firms affected by fire obtain more credit from local banks (i.e., banks with a higher proportion of their credit within a given province) than from outsider banks, which contract their credit supply to a greater extent. In fact, local banks with a relatively high concentration of credit in a given province could even increase the credit balance of fire-affected firms. This would be consistent with the portfolio reallocation of outsider banks. However, local banks tend to provide more credit to affected firms when they have sufficient lending opportunities to reallocate credit to non-affected firms. These findings highlight the superior access of local banks to soft information, enabling them to continue lending in affected areas. In fact, our analysis shows that the geographic proximity of local banks to their borrowers facilitates the collection of more comprehensive soft information. Additionally, characteristics that typically define outsider banks, such as larger size, and higher quality risk management processes, do not result in a statistically significant difference in credit supply to firms impacted by fire.

Consistent with the soft information mechanism, we find that local banks provide more loans to affected firms with stronger credit relationships and to those that are more opaque compared to outsider banks. The effect of relationship lending is related to local banks' superior ability to use soft information effectively, given that these banks are more likely to extend more credit to existing affected clients after a disaster. However, we find an additional effect of soft information over and above the one of relationship lending.[6] Banks

[5] A decrease in bank lending after a climate-related disaster could be attributed to several factors, including, but not limited to, a decline of collateral value—due to the damage of corporate real estate assets—and the economic outlook of households and firms in the affected areas (Garmaise and Moskowitz (2009); Hosono et al. (2016); and Gallagher and Hartley (2017)). Banks could also increase lending to secure additional recovery loans for firms within disaster-stricken zones (Chavaz (2016); Cortés and Strahan (2017); and Koetter, Noth, and Rehbein (2020)).

[6] Although *relationship lending* relies on *soft information* to succeed, the two concepts are distinct. Relationship lending refers to the broader process of building trust over time, while soft information consists of qualitative, non-standardized data used in assessing creditworthiness.

may extend credit to existing clients not due to soft information but to avoid increases in non-performing loans (NPLs) and loan loss provisions through loan evergreening. These incentives affect current borrowers, not new ones. However, local banks also lend to affected firms without prior relationships, demonstrating their effective use of soft information. Moreover, to confirm that the effect is not exclusively due to relationship lending, we conduct an additional analysis on firms without prior bank debt with any bank. We find that local banks are more likely to extend credit to fire-affected firms with no existing bank debt (i.e., no soft information through lending relationships, but through alternative channels), particularly those that are not distressed. Furthermore, we find that local banks provide more loans to opaque, affected firms, where soft information plays a critical role in screening and monitoring.[7] In contrast, both local and outsider banks exhibit similar adjustments in credit supply to less opaque firms impacted by the wildfires. Notably, local banks primarily extend credit to opaque but non-distressed firms, suggesting that their lending practices do not result in credit misallocation.

We extend our analysis of the soft information channel by examining banks' ex-post risk-taking through the performance of firm-bank relationships established after a wildfire.[8] We find that although local banks extend more credit to firms affected by fire, their portfolios of new credit generated after the fire perform similarly to those of outsider banks. Importantly, when we consider all credit relationships in affected areas, local banks do not experience adverse financial consequences from their lending practices before the fire. Instead, they successfully expand credit access without increasing risk or compromising financial stability. Finally, we find that employment declines in fire-affected areas; however, this decline is statistically insignificant in regions where local banks are present.

Additionally, we conduct several robustness tests and confirm that the lending practices of local banks are not influenced by alternative factors, including public subsidies, credit collateralization, firms' ownership of collateralizable assets, securitization,[9] the presence of

[7]Screening is a preemptive evaluation process designed to minimize initial credit risk, while monitoring is an ongoing oversight mechanism to manage and mitigate risks throughout the loan period.

[8]We restrict our analysis to this subsample of loans to ensure that loan refinancing or evergreening does not distort our interpretation of the results.

[9]Only 0.6% of outstanding corporate credit was securitized over our sample period.

property insurance,[10] fire predictability,[11] local influence,[12] limited lending opportunities outside the affected area, sectoral or regional specialization patterns, market power, or alternative definitions of fire-affected areas. Finally, we recognize that the banking sector underwent structural transformations during our sample period due to mergers. To ensure the robustness of our findings, we exclude banks that experienced significant organizational changes from our analysis.

Our work contributes to two strands of the literature. First, our work adds to the body of research in banking that examines the impact of asymmetric information on bank credit by incorporating physical climate risk into the lending framework in the presence of asymmetric information with heterogeneity across banks (i.e., local *versus* outsider banks) and firms (i.e., transparent *versus* opaque firms). We build upon the classic idea that when a bank extends a loan to a company, it gains a competitive advantage due to its superior knowledge of the borrower relative to other financial institutions (Hodgman (1961); Kane and Malkiel (1965); Black (1975); Fama (1985); Sharpe (1990); and Holmstrom and Tirole (1997)). Prior research also finds that geographical distance influences banks' ability to collect soft information on firms (Petersen and Rajan (2002); Degryse and Ongena (2005); Agarwal and Hauswald (2010); and Liberti and Petersen (2019)).

Second, we add to the recently growing literature that studies the effects of climate-related shocks on bank lending (Schüwer (2019); Brown (2021); Kacperczyk and Peydró (2022); Nguyen et al. (2022); Reghezza et al. (2022); and Correa (2023)). Our paper is closely related to the work that analyzes the role of small or local banks in sustaining credit supply after natural disasters. Chavaz (2016) documents that local banks hit by the massive hurricanes in 2005 increased mortgage lending more than banks less concentrated in those areas. He shows that local banks use loan sales to finance the mortgages originated in affected areas. Similarly, Cortés and Strahan (2017) find that multi-market small banks respond by increasing mortgage lending in the areas affected by several types of natural disasters and taking credit away from other markets. Koetter, Noth, and Rehbein (2020) document that

[10]To control for the potential effects of insurance, we incorporate firm-time fixed effects in our empirical analyses.

[11]Our results hold even in areas with a low probability of fire occurrence, indicating that neither the classification of firms as affected or non-affected nor our findings are driven by fire predictability.

[12]We find that firms that are not strategically important to the regional economy also receive significantly more credit from local banks, mitigating concerns about preferential treatment.

local banks, which pursue relationship-based strategies, provided corporate recovery lending after the 2013 Elbe river flood. However, unlike our findings, they argue that exposed banks only avoid increased risk-taking when they have access to more geographically diversified banking group networks. Our definition of local banks diverges from that examined in some of these papers. In our paper, local banks are defined as banks whose activities are concentrated in a specific region and, importantly, are not part of banking groups. Consequently, their activity cannot be explained by internal capital markets considerations, and we can isolate the soft information mechanism by which local banks maintain the provision of credit. We contribute to this literature by using loan-firm-bank level data to show that local banks' superior access to soft information enables them to restrict their lending less to firms with stronger relationships and to opaque profitable firms that are affected by a climate disaster[13].

The remainder of the paper is organized as follows. Section 2 presents a conceptual framework from which we derive the main testable hypotheses of the study. Section 3 describes the data and the empirical strategy that we use to test these hypotheses. Section 4 shows the empirical results related to the reduction in corporate credit after climate-driven events (i.e., wildfires), which corresponds to the first hypothesis. Section 5 studies the change in loan amounts lent by local and outsider banks after a fire and provides evidence of the soft information channel (second hypothesis). Section 6 shows that local banks do not take more risk after a climate-driven event (third hypothesis). Section 7 provides the quantification of the effects in the real economy focusing on employment in the affected area (fourth hypothesis). Finally, section 8 concludes.

2 Conceptual Framework

To motivate the empirical analysis, we develop a stylized conceptual framework to illustrate the mechanisms through which unexpected shocks—specifically climate-related shocks—affect credit supply. First, we discuss the main determinants of credit supply and the channels that might drive the effects of climate disasters on credit supply. Second, we set up and analyze a theoretical framework for credit supply under imperfect information and a climate shock.

[13] Although they do not deal with climate-related shocks, Favara and Giannetti (2017), Giannetti and Saidi (2019), Dursun-de Neef (2023), and Izadi and Saadi (2023) show that banking structure plays a key role in banks' lending strategies after economic shocks.

Third, we formulate four testable hypotheses from the equilibrium results of the framework.

2.1 Credit Supply Determinants

The supply of credit is influenced by a variety of factors, including the nature and structure of lending institutions. Outsider and local banks differ significantly in how they respond to economic shocks, particularly those related to climate disasters. The distinction between these types of banks lies not only in their size but also in their approach to portfolio management and information processing. Outsider banks, due to their diversification across regions and industries, may manage risk more effectively through portfolio reallocation. Conversely, local banks' deep knowledge of their communities allows them to leverage soft information, leading to more personalized lending practices. Understanding these dynamics is crucial in analyzing how credit supply is affected in regions facing climate-related risks. This section explores the unique advantages of outsider and local banks in credit allocation, highlighting their respective strengths in portfolio allocation and soft information channels.

2.1.1 The role of outsider banks: Portfolio allocation channel

Outsider banks may be better equipped to absorb the financial shocks associated with climate disasters compared to local banks for several reasons. First, outsider banks are diversified. They have exposure to a broader range of regions and industries, which reduces their vulnerability to localized climate risks, such as wildfires, floods, droughts, or extreme weather events (see Battiston et al. (2017)). Local banks are typically more concentrated in a single geographic region, meaning they are more vulnerable if that region is disproportionately impacted by climate-related events. Second, outsider banks typically have liquidity management that allows them to absorb shocks, such as climate-related shocks, better than smaller local banks (Houston, James, and Marcus (1997) and Cetorelli and Goldberg (2012)). Overall, outsider banks are often better positioned to respond to sudden, unexpected losses arising from climate events or policy changes, due to their more robust balance sheets and diverse revenue streams (De Haas and Van Lelyveld (2006) and De Haas and Van Lelyveld (2010)). Third, outsider banks can use various financial instruments like derivatives to hedge against climate-related risks (Hong, Karolyi, and Scheinkman (2020)). However, outsider banks' better position to absorb climate shocks comes with potential countervailing effects.

Outsider banks may prioritize external investments, reallocating capital away from disaster-stricken areas. This portfolio allocation channel suggests that outsider banks may respond to increased risk by tightening credit conditions in affected areas more severely than local banks, which have fewer alternative investment opportunities.[14]

2.1.2 Potential advantages of local banks: Soft information channel

Soft information is crucial for effective screening and monitoring, helping mitigate the negative impacts of climate events and enhancing corporate profitability. Because of their geographic proximity and personalized relationships with businesses, local banks are in a superior position to gather more soft information than outsider banks (Berger et al. (2005)). This allows them to better assess firms' specific challenges after climate disasters, making them well-positioned to support profitability improvement. Unlike outsider banks, which rely more on hard information due to their hierarchical structure and reliance on advanced technology (Liberti and Petersen (2019)), local banks can leverage their frequent interactions and deep knowledge of the local market to reduce uncertainty about the impact of a shock. This reduction in uncertainty can incentivize lending, particularly for risk-averse local banks, as they possess superior insight into the firm's financial health and resilience. Overall, their enhanced monitoring—driven by relationship lending and deep familiarity with local firms—mitigates risk and uncertainty in lending following climate shocks.

As a result, local banks are often more willing to extend credit than outsider banks, which lack detailed relationship-driven information. Empirical studies confirm that local banks are better equipped to collect and use soft information in credit decisions (Petersen and Rajan (2002), Degryse and Ongena (2005)), giving them a comparative advantage in supporting opaque firms, which often struggle to meet the extensive financial disclosure requirements of outsider banks. This advantage allows local banks to provide more tailored credit solutions, particularly to opaque firms, further differentiating themselves from outsider banks.

[14]The remark after Result 1 of the theoretical model in Appendix A1 shows that if the covariance between the loan returns and the return of the external investments available to the outsider bank is positive, then the climate shock leads to a reduction in the loan amount extended by the outsider bank, while simultaneously increasing the amount of external investments.

2.2 Framework Setup

We set up and study a framework for credit supply under conditions of imperfect information and a (climate-related) shock.[15] The key components of the framework are outlined here, while a formal model is presented in Appendix A1. Consider an economy with banks that provide financing to firms. Some firms might experience a climate shock that will decrease their profitability and affect the performance of their loans.

Firms. There are two types of firms: transparent and opaque. Transparent firms operate with a high level of openness, disclosure, and accountability. These firms maintain clear and accessible communication channels with their stakeholders, including banks. Transparency allows banks to understand how the company operates and make informed decisions based on reliable information. Opaque firms lack transparency and operate with limited disclosure of information. Opaque firms may have restricted communication channels, limited public reporting, and a lack of openness in their operations. This lack of transparency can make it challenging for banks to fully understand the company's operations, assess its performance, and make informed lending decisions.

Banks. Banks have the ability to screen and monitor firms, which depends on the type of bank and the type of firm considered. There are two types of banks: local and outsider. We assume that local banks can better screen and monitor opaque firms because they have better access to soft information about those firms and usually establish and leverage relationship lending practices. We assume that banks are risk-averse portfolio managers (Hart and Jaffee (1974)).[16]

Loan and external investments. Both local and outsider banks can invest in loans to corporations that can be potentially affected by a climate-related shock. The average return of loans to firms affected by a climate shock decreases after the shock. Outsider banks (and only outsider banks) have access to external investments. For example, outsider banks can provide loans to firms in regions outside the area of analysis, which can be correlated with the corporate loans in the affected areas.

Information precision about loans' performance. Both types of banks (local and outsider)

[15] There is an extensive banking literature that studies the bank-firm relationships with heterogeneous banks and firms (Bester (1985); Diamond (1991); Holmstrom and Tirole (1997); Boot and Thakor (2000); Cerasi and Daltung (2000); Freixas and Rochet (2008) Allen, Carletti, and Marquez (2011)).

[16] For simplicity, in Appendix A1 we assume that banks have a constant absolute risk aversion (CARA) utility function.

have the same information about transparent firms. Moreover, local and outsider banks have the same information about opaque firms before the climate shock. However, after the climate shock, local banks receive a signal about the loan returns of opaque firms affected by the climate shock. Outsider banks do not receive any signal at any time. Therefore, local banks have superior soft information on opaque firms.

Results (from Appendix A1). Two main results arise from this theoretical framework in equilibrium. First, banks reduce the relative amount of loans provided to firms impacted by a climate event (*Result 1*). Second, local banks decrease lending to opaque firms to a lesser extent (in relative terms) compared to outsider banks (*Result 2*).

2.3 Hypotheses Development

Building on the previously established equilibrium results, we formulate four hypotheses for empirical testing. Our first hypothesis builds on the premise that climate-related shocks reduce the expected returns on lending to affected firms while increasing the perceived risk, prompting banks to reduce their credit exposure to these firms (*Result 1*).

Hypothesis 1: *If a firm is affected by a climate event, then its amount of loan debt declines after the climate event.*

Second, we study whether banks' access to soft information affects the loan reduction driven by climate shocks. We specifically analyze the change in loan amounts lent by local banks (i.e., banks that perform good screening and monitoring at the local level) when compared to the change in loan amounts lent by outsider banks (i.e., banks that perform inferior screening and monitoring at the local level) in the event of a climate shock, with direct implications of the firms' opaqueness on the loan reduction. The emphasis is placed on the change in loan amounts lent by local banks to more opaque firms when compared to the change in loan amounts lent by outsider banks. Given their superior screening and monitoring capabilities and access to soft information, local banks maintain more stable lending levels than outsider banks in the face of climate-induced risks (*Result 2*). In addition, if our findings are attributable to superior soft information, local banks are expected to extend more credit to opaque firms. Building on this concept, we derive the following testable hypothesis related to the role of information on the effect of climate shocks on firms' credit.

Hypothesis 2: *Local banks reduce lending to affected firms to a significantly lesser* *extent than outsider banks, particularly in cases where soft information plays a critical role in lending decisions.*

Next, we check that the mechanism that drives these results is not risk-taking. We want to confirm that local banks do not increase their risk by lending significantly more to opaque firms than outsider banks. Hypothesis 3 summarizes this prediction, which has important implications for banking stability (see Blickle (2021); Noth and Schüwer (2023); and Klomp (2014) for studies on the effect of natural disasters on financial stability).

Hypothesis 3: *Local banks do not take more risk after a climate shock.*

This hypothesis posits that while local banks may extend more credit, they do so without significantly increasing their risk exposure, therefore maintaining stability in their loan portfolios.

Finally, we study the impact of local banks in the local economy in the presence of climate shocks.[17] Building upon the fact that there is a lower contraction of credit associated with local banks after a climate event, we expect that employment in areas where local banks are present does not decrease after a climate shock as it does in areas with no presence of local banks. Hypothesis 4 predicts that the presence of local banks mitigates the adverse economic impacts of climate shocks, such as declines in employment, in the real economy due to their ability to sustain credit flows and support local economic recovery.

Hypothesis 4: *Employment in fire-affected areas served by local banks does not decrease significantly after fire.*

This hypothesis is relevant because it demonstrates that local banks play a critical role in mitigating the effects of climate shocks on the real economy.

Overall, this conceptual framework underscores the critical role of information and relationships in the banking sector's response to climate risk, providing a basis for the empirical analysis that follows.

3 Data and Empirical Strategy

In this section, we explain the data that we use in our empirical analysis and define the empirical strategy that we implement to test the hypotheses that we developed in section 2.

[17]Previous research has examined the impact of bank lending frictions on employment using firm-level data from the 2008 Financial Crisis (Chodorow-Reich (2014)).

3.1 Data

We assemble data from multiple sources to create a dataset that contains information on all firms' characteristics, corporate loans, and attributes of all lender banks, as well as all wildfires in Spain for the period 2004-2017. Our complete micro-level approach provides a robust framework for testing the effects of physical climate risk on credit supply using geolocalized matches at the loan- firm-, and bank- levels.

Firms' characteristics. We use the Bank of Spain's Central Balance Sheet Data Office (CBSDO). It contains the balance sheets and profit and loss accounts, as well as other non-financial characteristics such as industry, year of incorporation, and demographic status, among others, for an average of 769,983 non-financial corporations per year with adequate accounting quality based on the Bank of Spain's internal classification criteria.[18] We merge CBSDO with the Iberian Balance Sheet Analysis System (SABI) from which we obtain the geographical coordinates where each firm is located. We exclude from our sample firms that belong to the agriculture, livestock, forestry, and fishing sectors as the location of their economic activity in many cases differs from where the firms are domiciled.[19]

Corporate loan data. We use the Bank of Spain's Central Credit Register (CCR) data. It contains monthly information on all bank-firm relationships over a reporting threshold of €6,000 for credit institutions operating in Spain.[20] As loans to companies are normally larger than the reporting threshold, we can claim that we have the whole population of loans to those firms. We match firm information in CBSDO to all their entities' relationships by using the firm fiscal identifier, which uniquely identifies firms in all datasets.

Loan applications data. We use an additional dataset that contains all the requests for information on the credit situation of potential customers made by banks to the credit registry. They can be considered as loan applications, at least, for the firms without previous lending relationships with a given bank, as banks receive information from the CCR about their current customers on a monthly basis.

[18] We provide the details about the filters that we apply to the data in the Appendix A2.

[19] For example, some companies in our sample that are involved in agriculture have their crops located far away from where the company is registered.

[20] We note that most of the external financing obtained by the firms in our sample is in the form of standard loans. Arce, Mayordomo, and Gimeno (2021) document that only 94 Spanish non-financial companies issued a bond at any time between 2006 and 2015. Moreover, the securitization of corporate loans is very low (on a monthly average basis, around 0.6% of the amount outstanding of corporate credit was securitized by Spanish banks over our sample period).

Firms affected by wildfires. We use detailed Civio data on all fires in Spain with a burned area of at least 1 hectare from 2001 to 2017. This data contains data attributes such as coordinates, burned area, and time to fire extinction.[21] We use the fire data from 2004 since from this year most fires are geolocated with exact precision. Moreover, we limit our sample to fires of at least 500 hectares, the threshold at which a fire is classified as large with significant economic impact[22] Panel A of Table 1 shows the descriptive statistics of fires in our sample. The initial sample consists of 54,032 fires equal to or greater than 1 hectare with a mean size of 24.6 hectares burned. There are 337 fires larger or equal to 500 hectares, which represents 48.7% of the total burned area between 2004 and 2017.

[INSERT TABLE 1 AROUND HERE]

3.2 Empirical Strategy

Our empirical analysis is based on a quasi-experimental design provided by wildfires. We combine the panel of geolocalized database on loans-firms-banks with the database on wildfires to achieve a very precise identification strategy. Recent literature has quantified the effects of climate-driven events by using approaches that employ less granular information such as ZIP codes, counties, or municipalities as an identification method (Ramos and Sanz (2020); Rehbein and Ongena (2022) and Ouazad and Kahn (2022)).

Our framework distinguishes between two types of banks based on their geographic concentration and access to soft information: local and outsider banks. Local banks in province p allocate a substantial portion of their credit to that province, while outsider banks allocate a smaller share of their credit to the same area. We assume that local banks have greater reliance on soft information and possess a superior ability to monitor the risk profiles of firms within their province. This assumption is supported by the fact that local banks are closer to their borrowers than outsider banks, and superior soft information is achieved when there is a shorter distance between the borrower and the lender (Agarwal and Hauswald (2010)). In our sample, the average distance between local banks in our sample—those with more

[21]Civio extracts data from the General Forest Fire Statistics (Estadística General de Incendios Forestales, EGIF) published by the Spanish Ministry for the Ecological Transition and the Demographic Challenge. See `https://datos.civio.es/dataset/todos-los-incendios-forestales/` for more details. EGIF merges the data of all the wildfire reports from all the Spanish regions. These reports contain 150 variables.

[22]For more details on big fires see section 4 in López-Santalla and López-Garcia (2019). The largest fire in our sample occurred in Cortes de Pallás in 2012, burning a total area of 28,879 hectares.

than 90% of their outstanding credit granted within a given province—and their borrowers is significantly lower (2.5 km) than the one between outsider banks, whose credit is less concentrated in a given province, and their borrowers (6.5 km).[23] Panel B of Table 1 provides additional bank descriptive statistics, showing that the 58 local banks included in the sample are smaller in size and maintain higher capital ratios compared to non-local banks.

Local banks rely more heavily on soft information, and their proximity to the borrower joint with their greater reliance on relationship lending would enable them to collect this type of information more efficiently and better buffer the impact of physical climate risk on credit risk than outsider banks. Consequently, the credit contraction for a firm affected by the wildfire event that operates with local banks is expected to be lower than that for firms that do not operate with local banks.

Henceforth, we propose the following empirical specification to estimate the change in corporate loan amounts and disentangle the credit supply provided by local banks from the one provided by outsider banks:

$$\Delta L_{f,b,t+1} = \beta LocalBank_{b,p,t-1} \times Fire_{f,t} + \gamma_{b,p,t} + \gamma_{f,t} + \epsilon_{f,b,t+1}, \tag{1}$$

where the dependent variable, $\Delta L_{f,b,t+1}$, is the logarithm change in the amount of firm f's outstanding loans with bank b between December of year $t-1$ and December of year $t+1$.[24]

The explanatory variable of interest is the interaction between the fraction of bank b's credit balance in province p where firm f is located, as of December of year $t-1$, $LocalBank_{b,p,t-1}$, and the dummy variable $Fire_{f,t}$, which takes the value of 1 if the firm is located within the *affected* area and 0 otherwise. The coefficient β of this interaction term captures the supply of credit to firms affected by fire depending on whether they operate with local banks (i.e., depending on the concentration of credit of the bank in the province where the firm is located). Notably, our identification strategy relies on a quasi-experimental

[23]We calculate the distance between each firm in our sample and the credit institutions with which it has credit relationships after geolocating all branches using their addresses. We do not have information on the branch that granted the credit to each firm but we assume that the credit is extended by its nearest branch in the province where the firm is located.

[24]We adjust credit balances to deal with bank mergers so that we capture the true variation of the credit of a firm with each specific bank. In particular, before calculating the credit variation between a year $t-1$ and a year $t+1$, we aggregate the credit balances of a firm by the entities that will operate –due to bank mergers– as a single entity by the end of year $t+1$. Therefore, the change at the entity level is clean of the effects due to mergers of banks and reflects the real change of credit of a firm with a particular bank.

setting that naturally provides a built-in comparison between treatment and control firms, along with the pre-post wildfire event structure (see Equation 1).

We consider that a firm is affected by fire if it is located within a circle defined by the *affected* or treatment area. We define this area as the region that includes the burn-area (i.e., circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it (see Figure 1).[25] This ring design enables us to account for firms that are not situated physically within the burn area, but are largely suffering the consequences of the wildfire, for example, because of supply-chain disruptions, damaged infrastructure, and utility service interruptions (Bayham et al. (2022)). The *non-affected* or control area is defined as the peripheral ring (i.e., the shaded ring with inner radius $r + 20km$ and outer radius $r + 40km$. We exclude the firms located in the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$ to guarantee that the group of non-affected firms is not contaminated by firms surrounding the affected area whose businesses could be ultimately damaged because of the fire.[26] Panel C of Table 1 shows the number of firms affected and non-affected by fires between 2004 and 2017. Importantly, there are no significant differences between the affected and non-affected firms in terms of size —measured as total assets—, returns —ROA—, and solvency —capital over total assets—. Finally, panel D shows that the distribution across sectors between affected and non-affected firms does not differ significantly. Thus, the effects associated with the climate event should be driven by the fire itself and not by the fact that affected firms are different from non-affected firms.

[INSERT FIGURE 1 AROUND HERE]

Additionally, we use bank-province-time fixed-effects, $\gamma_{b,p,t}$, to account for concurrent bank-specific time-varying factors that affect banks' credit supply around the occurrence of the fire in a specific province p. For instance, each bank might transmit differently shocks to the firms in a given province depending, for instance, on its specialization in lending to firms in that province (Giannetti and Saidi (2019)). The specification also includes firm-time fixed

[25] We use the coordinates of the origin of the wildfire as the center of the circle and its radius, r, is such that the total area of the circle is equal to the number of hectares burned by fire. We assume a circular shape for the area affected by each fire.

[26] Our results are robust to the choice of the radius of these circles (see Table 2 for different choices of radii of the treatment and control groups). Moreover, Appendix A3 provides a further discussion about the choice of 10 kilometers as a distance of large economic influence of a wildfire.

effects, $\gamma_{f,t}$ to deal with any firm specific shock and with the firm's demand for credit. As a result, we can exploit the variation arising from the credit supply of banks with different exposures to the province where a specific firm affected by fire is located relative to firms that are not affected by fire. Finally, $\epsilon_{f,b,t+1}$ in equation (1) denotes the error term.

The analysis of the effects of fires on firm credit is motivated by a body of literature that has established the impact of climate-related physical risks on firm performance. Regarding the effect of climate physical risk on firms, previous literature documents that climate shocks affect business sales (Addoum, Ng, and Ortiz-Bobea (2020)), earnings (Addoum, Ng, and Ortiz-Bobea (2023)) and cash-flows (Brown, Gustafson, and Ivanov (2021)). There is also some evidence supporting the adverse effects of wildfires on business activity. For instance, Addoum et al. (2023) study the effect of wildfire smoke on local businesses in areas not directly hit by wildfires and find that they lose approximately 10% of sales on days with elevated wildfire smoke due to the reduction in local consumer demand. We support this evidence based on the evolution of sales in areas directly affected by fire and in those surrounding these areas, as in Addoum et al. (2023). Our estimates point to a drop in sales of firms in those areas relative to their total assets of around 7 pp as compared to similar firms in unaffected areas the year after a fire. Lastly, we verify that the percentage of affected firms with local banks is not significantly different from that of firms in the control group.

4 Change in Credit After a Climate-Driven Event

In this section, we test whether the occurrence of a wildfire is associated with a significant decrease in firms' credit (Hypothesis 1). To this aim, we estimate a modified version of equation (12), where credit growth is measured at the firm level rather than the bank-firm level. Specifically, we exploit the exogenous variation in firms' exposure to economic damage from wildfires each year and run an OLS regression, where the dependent variable is the logarithm change in the firm f's credit balance between December of year $t-1$ and December of year $t+1$, $\Delta L_{f,t+1}$. Firm-level credit growth is regressed on the dummy variable denoting if the firm f is affected by fire at time t, $Fire_{f,t}$, along with a set of additional explanatory variables. These controls include firm characteristics as of December of year $t-1$ to control for its size (logarithm of total assets), profitability (return on assets), and solvency (equity over total assets). In addition, we use industry-municipality-size-time fixed effects.[27] This set of fixed effects enables us to estimate whether the credit growth of two firms with similar characteristics within a given municipality differs between them when one of these firms is affected by fire and the other one is not. Comparing firms within a given municipality is important to deal with political connections at the municipality level or the effectiveness of forestry brigades, among other factors.

The results of this analysis are reported in Table 2. We find that the amount of outstanding credit of firms affected by fire drops by about 6% more than for firms with similar characteristics and located in the same municipality, but not affected by fire (column 1). This result confirms that fires exert a negative effect on firms' access to financing. To check whether this effect is exclusively driven by firms that are closer to the burn area, we split the dummy variable denoting firms affected by fire, $Fire$ $(10km)$, into two groups depending on their proximity to the burn-area: $Fire$ $(5km)$ includes firms located inside the area defined by the burn-area plus a peripheral ring of 5 km outside the burn-area, and $Fire$ $(5km - 10km)$ incorporates the peripheral ring with inner radius $r + 5km$ and outer radius $r + 10km$. Column (2) of Table 2 shows that firms located in both areas suffer a larger drop in their credit growth when compared to the control group.

[INSERT TABLE 2 AROUND HERE]

One potential concern with these results is that banks might have prior information regarding firm exposure to climate events. If this is the case, banks could have incorporated their prior information advantage into their ex-ante screening process and adjusted the credit supply to such firms before the fire occurred at time t. To address this concern, we perform a robustness test in which we re-estimate the specification in (1) of Table 2 but using the change in the logarithm of credit between December of year $t-3$ and December of year $t-1$ as the dependent variable. Column (3) shows that there is no significant difference in the credit growth of a firm before the fire regardless of whether the firm is affected by the fire at time t.[28] This result confirms the absence of differential pre-trends in the access to credit between treatment and control firms before the fire, ensuring that the observed effects are not driven by systematic differences in credit growth trends prior to the event.

[27] Specifically, we consider the interaction of a set of fixed effects that deal with the industry in which the firm operates (1-digit NACE), the municipality where the firm is located, several dummy variables dealing with the firm-size (micro, small, medium-sized, and large corporations) and year dummy variables.

[28] We conduct this analysis using data for the period 2006—2017. We replicate the estimation from column (1) using this shorter period and find a similar effect in sign and magnitude.

A second concern regarding this test is the presence of firms that belong to a business group. Since subsidiaries may be located in a different municipality or province than their headquarters, a fire could affect a subsidiary without impacting the headquarters. These firms could secure financing from the group rather than relying on debt at the subsidiary level. To address this issue, we exclude firms that are part of a group and re-estimate the specification in column (1). The results, reported in Column (4), indicate that the overall findings in Column (1) remain unaffected by this concern.

Additionally, we conduct a robustness check on the period of the dependent variable, $\Delta L_{f,t+1}$, which considers the variation in credit between December of year $t-1$ and December of $t+1$ to evaluate the effects of a fire at time t. We re-estimate our main specification using an alternative dependent variable that measures credit variation between December of year $t-1$ and December of year t. The results, presented in Column (5), indicate that the coefficient of interest is larger in magnitude than our baseline estimate in Column (1).

We also examine whether the decline in credit obtained by firms affected by fire is driven by some of these firms becoming inactive. To address this, we exclude from our sample the firms that became inactive in the year of the fire or the following year.[29] The results of this robustness test are reported in column (6), present the same sign and magnitude as those in column (1), confirming the robustness of our findings.

In column (7), we estimate a model where the dependent variable is a dummy indicating whether a firm applied for credit in either t or $t+1$.[30] This analysis aims to determine if the reduction in credit for affected firms is due to supply constraints or a decreased demand for credit following the fire. Credit demand could rise due to increased liquidity or investment needs post-shock, or decrease if the firm experiences severe financial distress. To measure credit demand, we use information requests made by banks on firms with no prior bank debt, effectively capturing their loan applications. The rationale is that banks with existing credit exposures to firms do not need to check the credit register, as they receive monthly updates directly. Therefore, an information request for a firm with prior bank debt indicates that

[29] We define inactive firms as those that went out of business based on their status in CBSDO during the year of the fire or the year after. A firm is considered active if it was inactive at time t but became active at time $t+1$.

[30] The sample size decreases significantly in this analysis due to the restricted sample of firms. Additionally, we relax the set of fixed effects by using province instead of zip-code for location, and 2-digit NACE instead of 4-digit NACE for industry, to avoid having too many singleton observations.

the requesting bank is a new lender, representing the extensive margin of credit supply. Our findings show no statistically significant difference in credit demand between affected and non-affected firms.

Overall, this first set of empirical results shows that there is a significant drop in the credit supply to firms affected by fire. In the next section, we examine the extent to which local banks influence the restriction or extension of credit to firms impacted by fires.

5 Local Banks, Soft Information and Change in Credit After a Climate-Driven Event

In this section, we empirically test Hypothesis 2. First, we analyze the change in loan amounts lent by local banks when compared to the change in credit supplied by outsider banks in the event of a fire (Section 5.1). Second, we provide evidence that soft information is the main channel that drives the relationship between climate risk and credit supply (Section 5.2).

5.1 Local Banks and Credit Supply with Climate Risk

In this subsection, we test whether local banks reduce lending to firms to a significantly lesser extent than outsider banks (Hypothesis 2; first part). First, we present the baseline results and analysis of this test (subsection 5.1.1). Second, we conduct robustness tests on the role of other bank characteristics that typically define outsider banks (subsection 5.1.2). Third, we examine whether the lending activity of local banks is indeed influenced by the limited lending opportunities outside the fire-affected area (subsection 5.1.3). Fourth, we account for bank specialization—across industries and industries and provinces—, and bank market power (subsection 5.1.4).

5.1.1 Baseline analysis

Column (1) of Table 3 presents the estimated coefficients from equation (1). The positive and significant sign of the interaction term $LocalBank_{b,p,t-1} \times Fire_{f,t}$ shows that a firm affected by fire obtains more credit from local banks (i.e., banks with a larger proportion of its credit outstanding in the province where the firm is located).

[INSERT TABLE 3 AROUND HERE]

The firm-time fixed effects employed in equation (1) prevent us from estimating the coefficient for the variable $Fire_{f,t}$. Thus, in column (2) we propose a more flexible specification, which is saturated with industry-municipality-size-time fixed effects instead of firm-time fixed effects. This specification allows us to control for firm-specific shocks under the assumption that firms in a given industry (1-digit NACE industry), municipality, and size in year t are affected similarly by shocks. This means that we exploit the variation arising from the credit supply of banks with different credit concentrations in a given province to firms affected by fire in a given year that have a similar size, are located in the same municipality, and operate in the same industry. The coefficient associated with the dummy $Fire_{f,t}$ measures the credit supply to firms affected by fire by banks with zero exposure to a given province. This coefficient is negative and significant, which confirms the negative effect of the fires on the credit supply of banks that are not active in the province where the firm is located. However, the higher the fraction of credit in a given province, the lower the cut in credit supply to firms affected by fire in that province. In fact, local banks with a relatively high concentration of credit in a given province could even increase the credit balance of fire-affected firms.

5.1.2 Other bank characteristics that define outsider banks

Furthermore, we investigate whether additional attributes of banks that typically define outsider banks—aside from the proportion of credit allocated within a specific province—lead to a significant effect on credit supply to firms affected by fire. To do so, we include different interaction terms in our baseline specification. Columns (3)—(5) in Table 3 report the results of this analysis. In column (3) we include the interaction of the logarithm of total assets, TA with the dummy $Fire_{f,t}$. The interaction term is not significant and, therefore, we reject the hypothesis that the results in columns (1) and (2) are driven by the fact that the bank's exposure to a given province reflects just the size of the bank. In column (4), we show that our results are not driven by the banks' reporting standards because the interaction between the dummy IRB, which is equal to one if the bank uses internal rating-based (IRB) models and zero otherwise, and the dummy $Fire_{f,t}$ is not statistically significant. The dummy IRB deals with the reporting standards and it can be understood as a variable that measures the quality of risk management in a bank.[31] In column (5), we include all the previous interaction terms as well as the interaction of the bank's capital, Cap, and ROA. These results confirm that the bank characteristic that leads to a statistically significant differential effect is the fraction of credit that the bank has in a specific province.

5.1.3 Banks' lending opportunities and credit reallocation

An alternative explanation for our findings could be that local banks continue lending to affected firms due to their limited ability to reallocate credit outside the affected area. In other words, local banks' credit supply to firms affected by fire could be driven by the local banks' lack of lending opportunities out of the area affected by fire, which forces them to lend to affected firms. To address this concern we compute the lending opportunities (LO) that banks have in a given province p in a given year t as the ratio of the sales of the firms non-affected by fire in that province over the total amount of sales of the firms in the province as in Mayordomo and Rachedi (2022):

$$LO_{p,t} = \frac{\Sigma_{f \epsilon PROV_p}^{Non\text{-}affected} Sales_{f,p,t}}{\Sigma_{f \epsilon PROV_p}^{All} Sales_{f,p,t}} \tag{2}$$

A high value of the variable $LO_{p,t}$ implies that, in a given province, there are relatively more lending opportunities outside the set of firms affected by fire. Therefore, if a bank operates in areas with fewer lending opportunities, then it might be forced to continue lending to affected firms.[32]

To test whether the role of local banks is exclusively explained by the lack of lending opportunities to reallocate credit —instead of the advantages of soft information—, we split the sample of firms into two groups depending on whether the province offers low or high lending opportunities to banks. We assume that a given province offers low opportunities in a given year t when the measure $LO_{p,t}$ is in the bottom quintile of the distribution across

[31] Bank of Spain approved the IRB models for the first time in 2008. We assume that the IRB dummy is always equal to one for the observations linked to those banks that had adopted the IRB model as of the end of our sample period. Fewer than ten banks in our sample adopted the IRB model. Consequently, neither the local banks nor many of the non-local banks implemented the IRB model.

[32] Alternatively, they could reshuffle their loan portfolio away from these provinces but this may be costly. For instance, local banks could be forced to lend outside their local areas and make distant loans when they face fierce competition in their local branch markets (Granja, Leuz, and Rajan (2022)).

provinces and it is not the case when it is above the 20th percentile. The results for the two subsamples of firms are reported in columns (1) and (2) of Table 4. We observe that banks with a higher share in a given province lend significantly more to firms that are affected by fire for the two subsamples. However, the credit supply of local banks to affected firms is higher in provinces with lower lending opportunities. Moreover, we obtain similar results when we use alternative definitions of lending opportunities based on the gross value added (columns 3 and 4), the total assets (columns 5 and 6), and the employment (columns 7 and 8) instead of sales. Overall, this finding is not consistent with the hypothesis that our results are due to the lack of lending opportunities of local banks to reallocate credit.

[INSERT TABLE 4 AROUND HERE]

5.1.4 Bank specialization and bank market share

Our identification relies on the assumption that changes in credit supply do not vary systematically across firms. This assumption is challenged by the presence of firm- and sector-specific patterns in credit supply due to bank specialization (De Jonghe et al. (2020) and Paravisini, Rappoport, and Schnabl (2023)). Although the use of bank-province-time fixed-effects enables us to identify the credit supply of local banks to firms affected by fire over and above any pattern of bank specialization at the province level, we expand our analysis in equation (1) with bank-industry-time and bank-industry-province-time fixed effects to account for bank specialization across industries and industries and provinces, respectively. This approach allows us to obtain an identification strategy that isolates the effect of fires on the credit supply of local banks over and above any pattern of specialization at the sector level and province level or the sector-province level. These results are reported in columns (2) and (3) of Table 5 and confirm that our results are not affected by any type of bank specialization. Column (1) is identical to column (1) of Table 3 and is included to ensure comparability.

[INSERT TABLE 5 AROUND HERE]

The set of fixed effects in column (1) enables us to account for any effect that occurs at the bank-province-time level, including the consequences of market power. Nevertheless, in column (4) we show that the information advantage is not driven by the market share but by the bank's credit concentration in a given location. To do so, we interact the market share of each bank in each province in a given year, $BankMarketShare$, with the dummy variable $Fire$. We obtain results of the same sign and magnitude as the baseline ones in column (1). Importantly, this new interaction term is not statistically significant and as a consequence, we discard that our results are driven by banks' market power.

5.1.5 Robustness tests

We conduct robustness tests using alternative samples to address potential concerns about our baseline results regarding the role of local banks in providing credit to affected firms.[33] First, we address potential biases from the staggered occurrence of fires by excluding firms once affected and considering only their first appearance in the dataset.[34] Second, we run a robustness test on the definition of fire-affected areas and the exclusion of firms located in a ring between the treatment and control groups. Third, we address the concern that banks could be aware of firms' abilities to receive subsidies and find that subsidies do not drive local banks' credit allocation. Fourth, we examine the role of tangible assets and guarantees, finding that local banks provide credit regardless of tangible asset ratios, and credit without guarantees remains consistent with the baseline results. Fifth, our conclusions are not affected by the consolidation process that occurred in Spain over our sample period given that our results persist when we remove banks from the sample the year in which the bank consolidation or absorption process occurred, as well as the preceding and following year, so that credit variation is not affected by the merger. Finally, we investigate credit supply across areas with varying fire risks and firms of strategic importance within a province. We find that local banks extend more credit to both fire-affected firms in high- and low-risk areas and to strategically significant firms compared to outsider banks. Importantly, even firms that are not strategically significant for the local economy receive significantly more credit from local banks during the fires. Overall, the results from these analyses confirm robustness against all these concerns.

[33] Appendix A4 provides all the details and results of these robustness tests.

[34] Our results are also robust to the exclusion of the region of Galicia from the sample, where numerous wildfires occur due to its challenging terrain, rural depopulation, and seasonal droughts. Results are available upon request.

5.2 Soft Information and the Relationship Between Climate Risk and Credit Supply by Local Banks

In this subsection, we test whether local banks reduce lending to a significantly lesser extent than outsider banks when soft information becomes crucial for lending decisions (Hypothesis 2; second part). This premise indicates that soft information plays a major role as a driver of the link between climate-driven events and credit supply.

We begin by examining relationship lending as a mechanism through which banks gain a competitive advantage by leveraging superior borrower knowledge compared to other financial institutions. To this end, we re-estimate our baseline specification in equation (1) using alternative samples of bank-firm pairs, categorized by their degree of relationship lending. We measure the strength of the relationship between firm f and bank b immediately before the fire as the share of firm f's total credit provided by bank b at time $t-1$. A firm-bank relationship is classified as strong if this share at $t-1$ is equal to or above the median of the distribution across all bank-firm pairs. Table 6 shows that the interaction term $LocalBank \times Fire$ is not significant for the subsample of firms with weak relationship lending (column 2), but becomes significant for the subsample of firm-bank pairs with stronger relationship lending (column 3). These findings indicate that local banks more engaged in relationship lending with a firm extend more credit to that firm after a wildfire, extensively leveraging soft information. This result aligns with the empirical literature on relationship lending.[35]

Next, we study whether banks are more likely to extend credit to their existing clients when they are affected by fire because they might have incentives to engage in loan evergreening to avoid an increase in their non-performing loans (NPLs) and loan loss provisions. These incentives exclusively impact loans already in place and do not apply to new credit arrangements. Therefore, to support our soft information channel, we should observe that local banks also lend to firms without previous relationships. To confirm if this is indeed true, we conduct a robustness analysis in which the dependent variable is a dummy that takes the value 1 if the firm had a positive balance of credit (draw and undrawn) with the bank before the fire. We restrict the sample to firms with a positive variation of credit to

[35] For further empirical evidence on the link between relationship lending and bank credit, see Petersen and Rajan (1994), Boot (2000), Elsas (2005), Bolton et al. (2016), Sette and Gobbi (2015), Kysucky and Norden (2016), López-Espinosa, Mayordomo, and Moreno (2017), and Banerjee (2021).

understand whether it is more likely that local banks establish new relationships when they are affected by fire. Results are reported in column (4) of Table 6 and show that local banks are more likely to establish new credit relationships, which might be consistent with their superior use of soft information.

[INSERT TABLE 6 AROUND HERE]

If the supply of business loans by local banks is driven by their superior ability to extract and use soft information, then local banks should extend more credit to those affected firms that are more opaque. To test this hypothesis, we split the sample according to the level of the firm's opacity, which is measured as the fraction of a firm's inflows and outflows of cash that cannot be predicted accurately.[36] Following Leuz, Nanda, and Wysocki (2003), we measure opacity as the ratio of the accruals over the net cash flows from operating activities. The accruals are measured as the absolute value of the difference between the change of non-cash current assets and non-cash current liabilities minus depreciation and amortization. The net cash flows from operating activities are defined as the absolute value of the difference between the net operating income and our proxy for accruals. Thus, the higher the ratio, the higher a firm's opacity is. Columns (1)-(3) of Table 7 shows the results of this test.

[INSERT TABLE 7 AROUND HERE]

The specification in column (1) of Table 7 is equivalent to the one in column (1) of Table 3, but includes only firms with information on their accruals. Columns (2) and (3) report the results for the samples of the most opaque and the least opaque firms, respectively. The most and the least opaque firms are those whose levels of accruals are in the top and bottom quintiles of the distribution of accruals of the firms in our sample, respectively.

Consistent with our theoretical framework, we find that both local and outsider banks adjust their credit supply to transparent firms affected by a fire in a similar manner. However, local banks provide more credit to opaque, fire-affected firms due to their superior access to

[36]Earnings can be split into cash flows and accruals. Earnings quality is a concept related to earnings persistence (the ability to predict future earnings based on the information of current earnings). Sloan (1996) shows that the persistence of accruals is much lower than that of cash flows. So, firms with extremely positive and negative accruals are considered to have poor earnings quality (Bhattacharya, Desai, and Venkataraman (2013)) that, as a consequence, damage the information that lenders can infer from the earnings.

soft information, which enables more accurate credit risk assessment.[37] Conversely, banks that primarily rely on hard information may find it suboptimal to conduct thorough credit risk assessments for fire-affected borrowers.[38]

Column (4) is equivalent to column (1), but includes only firms with information on their questionnaires. In columns (5) and (6) of Table 7 we consider an alternative measure of firms' opaqueness which is defined depending on the type of questionnaire that firms report to the Bank of Spain. More opaque firms are those that report the reduced questionnaire, whereas less opaque (i.e., more transparent) firms are those that report the normal questionnaire.[39] Consistent with the outcomes in columns (2) and (3), we observe a significant increase in the supply of credit from local banks to more opaque firms, but we do not observe significant differences for more transparent firms.

Nevertheless, if local banks extend more credit to opaque and distressed firms, these outcomes may result in the misallocation of credit. To understand whether this is the case, we estimate equation (1) for two subsamples of firms: (i) opaque firms with negative equity (i.e., distressed firms); and (ii) opaque firms with positive equity (i.e., non-distressed firms).[40] Results are reported in columns (2) and (3) of Table 8, respectively. Column (1) contains the results for the whole sample of opaque firms for comparability. The classification of firms depending on their level of opacity is based on accruals, as in columns (2) and (3) of Table 7. The results indicate that local banks' credit supply flows to more opaque but non-distressed firms, suggesting that their lending practices do not result in credit misallocation. We obtain

[37]Our analysis does not account for differences in the organizational structures of local and outsider banks, which may affect information production and the allocation of credit. Skrastins and Vig (2019) find that increased hierarchization within bank induces credit rationing, reduces loan performance, and leads to greater standardization in loan contracts. The authors relate hierarchization (a characteristic of large, diversified banks) to the loss of soft information.

[38]For a more direct comparison of the estimated effects, the last row of Table 7 reports the relative economic impact, computed as the product of the coefficient and the average concentration of credit at the province level, scaled by the standard deviation of the dependent variable. We observe that the effect of a bank's credit concentration in a given province on credit supply to affected opaque firms (2.4%) is substantially higher than for affected but transparent firms (1.5%).

[39]Specifically, CBSDO has two questionnaires —normal and reduced—, which are sent to collaborating companies. The firms in our sample are allowed to report in reduced format during our sample period if they meet two out of three of the following criteria at the end of the fiscal year: (i) Total assets $\leq$ €2,850,000 (€4,000,000 from 2013), (ii) net turnover $\leq$ €5,700,000 (€8,000,000 from 2013), and (iii) average number of employees during the financial year $\leq$ 50. The fundamental difference between the two questionnaires lies in the amount of data requested.

[40]Bonfim et al. (2023) define zombie firms as those with negative equity.

similar results when defining opaque firms as those that submit the reduced questionnaire to the CBSDO (see columns 4–6). This finding aligns with Bolton et al. (2016), which demonstrates that banks acquiring soft information on firms extend loans to profitable firms during periods of crisis.

[INSERT TABLE 8 AROUND HERE]

A set of firms for which soft information is particularly relevant are those without any existing bank debt. Blanco et al. (2024) demonstrate that non-bank-debt firms face challenges in obtaining new credit due to their lack of credit history, leading to information asymmetries between loan applicants and potential lenders. This issue becomes especially pronounced during periods of high uncertainty. As information asymmetries intensify, banks tend to prioritize extending credit to their existing customers.

To investigate this further, we focus on firms without outstanding bank debt. Specifically, we examine whether local banks are more likely to extend more credit to non-bank-debt fire-affected firms once their loan applications are accepted (the "intensive margin"). To identify this effect, we do not employ firm-time fixed effects, as non-bank-debt firms typically obtain new credit from a single bank. Instead, we use industry-municipality-size-time fixed effects. Results, reported in column (1) of Table 9, indicate that local banks extend more credit to non-bank-debt fire-affected firms, consistent with the findings for other categories of opaque firms. Importantly, this effect is observed exclusively among fire-affected but non-distressed firms, as shown in columns (2) and (3). This result highlights the importance of soft information in credit allocation decisions and provides evidence against credit misallocation.

[INSERT TABLE 9 AROUND HERE]

The impact of fires on credit supply may not stem from local banks' access to soft information but rather from the fire's effect on their financing sources. Deposits are the primary funding source for euro area and Spanish banks, accounting for more than 80% of their financing (see Mayordomo and Roibás (2023)). Therefore, if a fire significantly impacts a particular area and some banks experience more deposit withdrawals than others, their ability to intermediate would be affected. Although we lack bank-province-level deposit data, we analyze aggregate data. We compare the evolution of deposits in local banks (those with over 90% of their credit concentrated in a single province) in the year following a fire in that province with the evolution of deposits in non-local banks lending in the same province. We find no significant differences between the two types of banks, suggesting that the ability to supply credit is not driven by differences in the fire's impact on their funding sources.

6 Soft Information and Lenders' Risk-Taking with Climate Risk

This subsection confirms the soft information channel further by testing that local banks do not take more risk after a climate-driven event, which corresponds to Hypothesis 3. We have already shown that local banks extend more credit to firms affected by a wildfire —especially if they are more opaque— given that they rely on their superior ability to incorporate soft information into their lending decisions. However, although local banks' lending practices do not point to credit misallocation *ex-ante*, the quality of local banks' loan portfolios could deteriorate after lending to firms affected by fire. In other words, local banks could be increasing *ex-post* risk-taking when increasing their exposure to affected firms. Our empirical analysis shows that this is not the case. We formally test that local banks do not take more risk after a climate shock (Hypothesis 3). To test this hypothesis, we compare the *ex-post* fraction of non-performing loans (NPL) held by local and outsider banks in affected areas.

First, we consider only the firm-bank pairs featuring no credit relationship before the fire. We do this because we cannot identify the specific loan facility that turns out to be non-performing in the post-fire period. If we were to consider the firms with a relationship with a bank before the fire, some NPLs reported afterward might be associated with lending that originated before the climate event. The main advantage of this approach is that loan refinancing or evergreening cannot impair the interpretation of our findings. We first calculate the euro amount of NPLs (i.e., doubtful, non-performing, and default loans) for all new firm-bank relationships as of December of year $t+2$, that is, in December of year 2 after the event. Then, we define $NPL_{b,m,i,t+2}$ as the ratio of the total amount of NPLs of each bank b associated to firms affected by fire that are domiciled in a given municipality m and operate in industry i in December of year $t+2$ relative to the total outstanding credit that comes from new bank-firm relationships involving firms affected by fire in that municipality and industry. We use a 2-year window because the maturity of more than 90% of the new credit granted during our sample period is lower than one year. Therefore, a 2-year time window enables us to deal with the performance of the credit granted after fire until their maturity. We use $NPL_{b,m,i,t+2}$ as the dependent variable in the following specification:

$$NPL_{b,m,i,t+2} = \beta LocalBank_{b,p,t-1} + \delta X_{b,m,i,t-1} + \gamma_{i,m,t} + \gamma_{b,t} + \epsilon_{b,m,i,t+2}, \tag{3}$$

where the variable of interest is the fraction of bank b's credit balance in province p, which encompass the municipality m where its borrowers are located, as of December of year $t-1$, $LocalBank_{b,p,t-1}$. The vector $X_{b,m,i,t-1}$ contains the average characteristics (i.e., size, profitability, and solvency) of firms that had a positive credit exposure to bank b as of December of year $t-1$ in municipality m and industry i. We aim to control for the characteristics of bank b portfolio of existing borrowers that could affect bank future lending policies. $\gamma_{i,m,t}$ and $\gamma_{b,t}$ denote the use of fixed effects at the industry-municipality-time and bank-time levels.[41]

Column (1) of Table 10 shows the results obtained from equation (3). We show that there is no significantly different performance of the new credits granted after fire between local and outsider banks. In other words, although local banks extend more credit to firms affected by fire, their portfolios of credit perform similarly to outsider banks' portfolios. Similar results are obtained when we estimate the most saturated specification in equation (3) as shown in column (2).

Furthermore, we extend our analysis to include all bank-firm pairs in fire-affected areas, regardless of their prior credit relationship before the climate event. The results of this analysis are reported in columns (3)–(4), which present findings consistent with those in columns (1)–(2). We also find that the profitability and solvency of local banks are not adversely affected, relative to outsider banks, as a result of these lending practices (untabulated). Our findings highlight the capacity of local banks to increase credit provision without compromising the performance of their overall loan portfolio and without affecting their stability. The ability of local banks to extend more credit to both existing clients and new clients affected by fire, without any deterioration in the quality of their credit portfolios, demonstrates their efficient use of soft information for monitoring and screening firms.

[INSERT TABLE 10 AROUND HERE]

[41]Note that we cannot use bank-province-time fixed effects as in previous specifications because it would prevent us from estimating the coefficient associated to the variable of interest.

7 Effects in the Real Economy

We have documented that there is a significant decrease in firms' credit after fire. We have also shown that local banks reduce lending to a lesser extent than outsider banks. In this subsection, we study the effect of these results on the real economy. Specifically, we test whether employment in fire-affected areas served by local banks does not decrease significantly (Hypothesis 4).

A key channel through which increased credit supply may influence employment is firms' ability to maintain operational liquidity and finance short-term expenses, including wages and supplier payments. While our dataset does not allow us to directly observe the use of funds, prior literature suggests that credit-constrained firms are more likely to reduce employment following negative shocks. To estimate how local banks contribute to mitigating the negative consequences on firm real outcomes, we propose the following specification:

$$\Delta Employm_{f,t+2} = \beta Fire_{f,t} + \delta X_{f,t-1} + \gamma_{i,m,s,t} + \epsilon_{f,t+2}, \tag{4}$$

where $\Delta Employm_{f,t+2}$ denotes the growth of the average number of employees at the firm level between $t-1$ and year $t+2$ and $Fire_{f,t}$ is a dummy variable that indicates whether the firm is affected by fire at time t. Let $X_{f,t-1}$ and $\gamma_{i,m,s,t}$ denote control for firm characteristics (solvency, size, and profitability) and fixed effects at the industry-municipality-size-time level, respectively. $\epsilon_{f,t+2}$ represents the error term.

Next, we divide the sample into two groups based on whether local banks operate in the municipality where the company is situated. We consider that a municipality has active local banks if any firm in the municipality has a positive credit exposure to a bank with 90% or more of its credit balance in the province where the firm is located. This split enables us to exploit the exogenous variation in the existence (or not) of local banks operating in a specific municipality. Results are reported in Table 11. Column (1) reports the results obtained for the whole sample of firms and shows that the occurrence of a fire in year t is associated with a drop in the employment of the firms in areas affected by fire two years later. Columns (2) and (3) show the results obtained for the subsample of firms in municipalities with and without local banks, respectively. Importantly, the drop in employment after fire is specific to municipalities where local banks are not active lenders. On the contrary, the employment of firms affected by fire in municipalities with local banks does not decrease as compared to the employment of non-affected firms. Columns (4) and (5) show similar results when we use a stricter definition of local banks.

[INSERT TABLE 11 AROUND HERE]

8 Conclusions

This paper shows that local banks are better positioned than outsider banks to support borrowers affected by physical climate risks. We use a simple framework of bank lending under climate shocks with asymmetric access to information and test its main predictions using data on all wildfires and bank-firm credit relationships in Spain from 2004 to 2017.

We find that climate-related events lead to a significant decline in corporate loans in the affected areas. This reduction is driven by outsider banks, which drastically contract lending in the affected areas. In contrast, access to and superior use of soft information enable local banks to be more accurate in their lending practices. Interestingly, local banks lend more to opaque firms and to those with stronger credit relationships than outsider banks without incurring a greater risk exposure. Finally, the paper documents that the ability of local banks to extend credit after climate-related disasters benefits the economy. Specifically, employment in fire-affected areas served by local banks does not decrease significantly after a fire, while employment decreases in fire-affected areas without local banks.

The findings of this paper provide relevant policy implications. Our results suggest that local banks play a critical role in mitigating the effects of climate shocks on the real economy, mainly because they can use soft information to provide recovery lending to firms that have been impacted by climate disasters. However, it is important to note that banking systems worldwide have been undergoing significant consolidation over the past few decades, with fewer and larger banks dominating the market. In Spain, for instance, the number of banks has sharply decreased since 2004. According to data from the Bank of Spain, the number of active credit institutions in Spain dropped from 512 in 2004 to just 345 by 2014[42], reflecting a broader trend of bank mergers and acquisitions. Similarly, in the United States, the number of commercial banks has also seen a substantial decline, falling from approximately 7,628 in 2004 to 4,036 in 2023, according to the Federal Deposit Insurance Corporation (FDIC).[43]

[42]Source: Bank of Spain. Nota de Prensa, 21 de enero de 2014.
[43]Source: FDIC. BankFind Suite: Find Annual Historical Bank Data.

This trend raises concerns about the future of local banking systems, which could limit the capacity of banks to offer crucial soft information-based lending to mitigate the effects of climate shocks. As larger banks continue to dominate, it becomes vital for policymakers to consider the potential trade-offs between banking consolidation and the local support needed during periods of climate distress.

Figures and Tables

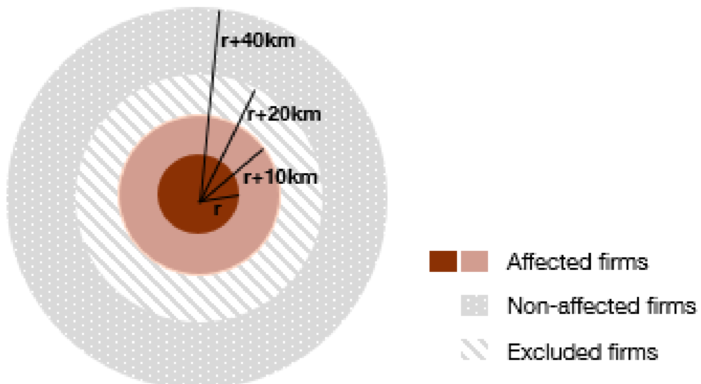

Figure 1: **Definition of affected and non-affected firms by wildfires.** This figure shows a sketch of the areas where firms have been affected and those that remain unaffected by wildfires. We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r + 20km$ and outer radius $r + 40km$. We exclude the firms located in the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$.

Size (hectares)	Number of fires	Mean	Median	Std. Dev.	p5	p95	Mean time to extinguish (hours)
>= 1	54,032	24.6	3	276	1	59.8	12.3
>= 500	337	1,923.7	1,009.0	2,896.5	533.6	7,161.0	165.8

Panel A: Descriptive statistics of fires (2004-2017)

	Total number in sample	Log (total assets)	ROA (%)	Capital ratio (%)	Mean credit share in province (%)
All banks	290	14.6	0.42	8.1	6.4
Non-local banks	232	15.5	0.41	7.4	4.9
Local banks	58	12.2	0.45	9.7	95.8

Panel B: Descriptive statistics of banks (2004-2017)

	Affected firms		Non affected firms	
	Obs.	Mean	Obs.	Mean
Log (total assets)	54,317	5.8	423,342	5.9
ROA (%)	54,317	-1.4	423,342	-1.5
Capital over total assets (%)	54,317	14.7	423,342	14.4

Panel C: Descriptive statistics of firms affected and non-affected by fires (2004-2017)

	Affected firms		Non affected firms	
	Obs.	Percentage	Obs.	Percentage
Industrial	8,627	15.9	72,934	17.2
Retail	15,726	29.0	115,722	27.3
Services	18,469	34.0	153,191	36.2
Construction	11,495	21.2	81,495	19.3

Panel D: Sector distribution of firms affected and non-affected by fires (2004-2017)

Table 1: **Descriptive statistics.** Panel A of this table reports the number of fires in each group according to their size and their summary statistics. The last column shows the mean of the number of hours employed to extinguish fires. Panel B shows characteristics of local and non-local banks in the sample, where local banks are defined as those that in a year have 90% or more of their credit concentrated in a single province. Non-local banks have never been defined as local in the sample. Mean credit share in province represents the average share of its total credit that a bank has in the provinces where it operates. Panel C shows the number of observations and the mean of several firm characteristics: size as Log(total assets), profitability as ROA, and solvency as capital over total assets depending on whether they are affected by fire or not. Panel D displays the distribution of firms across sectors depending on whether they are affected by fire or not. We only consider fires greater or equal to 500ha. We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r + 20km$ and outer radius $r + 40km$. We exclude the firms located in the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$.

Dep. Var.: $\Delta L_{f,t+1}$	(1) All firms [t-1, t+1]	(2) All firms [t-1, t+1]	(3) All firms [t-3, t-1]	(4) No groups [t-1, t+1]	(5) All firms [t-1, t]	(6) Active firms [t-1, t+1]	(7) Dummy loan applic. (t, t+1)
Fire (10km)	-0.059*		-0.005	-0.054*	-0.079***	-0.057*	-0.007
	(0.032)		(0.035)	(0.032)	(0.025)	(0.032)	(0.008)
Fire (5km)		-0.065*					
		(0.038)					
Fire (5km-10km)		-0.057*					
		(0.033)					
Observations	444,772	444,772	356,621	437,454	428,961	440,743	43,983
R-squared	0.126	0.126	0.126	0.124	0.111	0.127	0.496
Firm controls	YES	YES	YES	YES	YES	YES	YES
Ind.-Municipality-Size-Time FE	YES	YES	YES	YES	YES	YES	YES

Table 2: **Corporate credit growth after fire.** Column (1) of this table reports the effect of a firm being affected by fire in year t on the change in the logarithm of credit (plus one to deal with zeros) between December of year $t-1$ and December of year $t+1$. We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. The estimation period in all columns is 2004-2017, unless otherwise specified. In column (2) we split the dummy variable denoting firms affected by fire into two groups depending on whether the firm is located within the circle comprising the radius plus 5 km or between the border of this circle and the radius plus 10 km. In column (3) the dependent variable is the change in the logarithm of credit (plus one to deal with zeros) between December of year t-3 and December of year $t-1$ (i.e., before the fire) over the period 2006-2017. In column (4) we remove firms that are part of a business group (e.g., subsidiaries). Column (5) is analogous to column (1) but the dependent variable is the change in the logarithm corporate credit between December of year $t-1$ and December of year t. Column (6) is analogous to column (1) but we exclude from the sample firms that were inactive and had gone out of business based on their status in CBSDO at time t or $t+1$. We consider a firm as active if it was inactive at time t but became active at time $t+1$. In column (7) the dependent variable is a dummy denoting whether the firm applied for bank credit in either t or *t+1*. In this column the sample is limited to applications from firms with no bank credit relationships. All specifications in columns (1) - (6) include firm controls and industry-municipality-size-time fixed effects, where the industry is measured at a 1-digit level and size refers to the four categories considered by the EC: micro, small, medium-sized, and large corporations. In column (7) we employ the same structure of fixed-effects but use province instead of municipality to avoid loosing too many observations. Standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1)	(2)	(3)	(4)	(5)
LocalBank × Fire	0.324***	0.219***	0.290**	0.328***	0.306**
	(0.069)	(0.081)	(0.110)	(0.091)	(0.118)
Fire		-0.082**			
		(0.031)			
TA × Fire			-0.007		-0.006
			(0.013)		(0.023)
IRB × Fire				0.003	0.015
				(0.052)	(0.072)
Cap × Fire					0.437
					(0.621)
ROA × Fire					-3.578
					(8.245)
Observations	664,960	892,942	664,960	664,960	664,960
R-squared	0.441	0.146	0.441	0.441	0.441
Firm-Time FE	YES	NO	YES	YES	YES
Ind.-Municipality-Size-Time FE	NO	YES	NO	NO	NO
Bank-Province-Time FE	YES	YES	YES	YES	YES

Table 3: **Credit supply by local banks after fire.** Column (1) of this table reports the results obtained from the estimation of equation (1) in which the dependent variable is the log-change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest, $LocalBank \times Fire$, is the interaction of the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$) and a dummy variable that is equal to one if the firm was affected by fire in year t ($Fire$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. The regression analysis includes firm-time and bank-province-time fixed effects. In column (2) we propose a less demanding specification of equation (1) which is saturated with industry-municipality-size-time fixed effects, instead of firm-time fixed effects. Industry is measured at a 1-digit level and size refers to the four categories considered by the European Commission: micro, small, medium-sized, and large corporations. These sets of fixed effects allow for the use of the dummy variable that denotes if the firm has been affected by fire as an additional variable of interest. Columns (3)—(5) are similar to column (1) but we included additional interaction terms where the dummy $Fire$ is interacted with the logarithm of total assets —column (3)—, a dummy that denotes if the bank uses IRB models —column (4)—, and the two previous variables plus the interactions with banks' capital and ROA —column (5). The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1) Sales Low LO	(2) Sales High LO	(3) GVA Low LO	(4) GVA High LO	(5) Assets Low LO	(6) Assets High Low	(7) Employment Low LO	(8) Employment High LO
LocalBank × Fire	0.468***	0.226**	0.467***	0.227**	0.359***	0.304***	0.421***	0.246**
	(0.084)	(0.087)	(0.084)	(0.087)	(0.072)	(0.100)	(0.078)	(0.099)
Observations	119,854	545,092	116,442	548,506	122,723	542,225	130,525	534,423
R-squared	0.429	0.443	0.429	0.443	0.428	0.443	0.427	0.444
Firm-Time FE	YES	YES	YES	YES	YES	YES	YES	YES
Bank-Prov-Time FE	YES	YES	YES	YES	YES	YES	YES	YES

Table 4: **Credit supply by local banks after fire depending on banks' lending opportunities.** This table reports the results obtained from the estimation of equation (1) for alternative samples of firms depending on the lending opportunities (LO) that exist in the province where they are located. The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest is the interaction of a dummy variable that is equal to one if the firm was affected by fire in year t and the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. We consider that lending opportunities in a specific province in a given year are low when the ratio of the total sales of the firms non-affected by fire relative to the total amount of sales of firms within a given province (see equation 2) is in the bottom quintile of the distribution across provinces (Low LO) and it is not the case when it is above the 20th percentile (High LO). Column (1) reports the results for this subsample of firms in low lending opportunities provinces whereas column (2) contains the results for the subsample of firms located in provinces where the lack of lending opportunities is not an issue according to the total amount of sales of non-affected firms. We use alternative definitions of lending opportunities based on the gross value added —columns (3) and (4)—, total assets —columns (5) and (6)—, and employment —columns (7) and (8)— instead of sales. The regression analysis includes firm-time and bank-province-time fixed effects. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank levels. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1)	(2)	(3)	(4)
LocalBank × Fire	0.324***	0.358***	0.349***	0.308***
	(0.069)	(0.071)	(0.073)	(0.066)
Bank Market Share × Fire				0.210
				(0.188)
Observations	664,960	663,481	653,201	664,960
R-squared	0.441	0.449	0.465	0.441
Firm-Time FE	YES	YES	YES	YES
Bank-Province-Time FE	YES	YES	NO	YES
Bank-Industry-Time FE	NO	YES	NO	NO
Bank-Industry-Province-Time FE	NO	NO	YES	NO

Table 5: **Credit supply after fire with bank specialization and market power.** This table reports the results obtained for alternative specifications of equation (1). The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest, $LocalBank \times Fire$, is the interaction of the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$) and a dummy variable that is equal to one if the firm was affected by fire in year t ($Fire$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r + 20km$ and outer radius $r + 40km$. We exclude the firms located in the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$. We consider fires with an area burned equal to or larger than 500 ha. Column (1) is identical to column (1) of Table 3 and is included for comparability reasons. Columns (2)-(3) include bank-industry-time and bank-industry-province-time fixed effects, respectively. Column (4) includes the interaction of the market share of bank b in December of year $t1$ in the province where the firm is located with a dummy variable that is equal to one if the firm was affected by fire in year t. The market share of bank b is calculated as the total credit (drawn and undrawn) of the bank in a province over the total credit in the province. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.:	$\Delta L_{f,b,t+1}$			Dummy $L_{f,b,t-1}$ >0
	(1)	(2)	(3)	(4)
	All	Low rel. lending	High rel. lending	All
LocalBank × Fire	0.324***	0.136	0.214**	-0.033**
	(0.069)	(0.101)	(0.088)	(0.016)
Observations	664,960	288,031	181,891	208,577
R-squared	0.441	0.509	0.608	0.502
Firm-Time FE	YES	YES	YES	YES
Bank-Province-Time FE	YES	YES	YES	YES

Table 6: **Credit supply to firms and relationship lending.** This table reports in columns (1)-(3) the results obtained from the estimation of equation (1) for alternative samples of bank-firm pairs depending on their level of relationship lending. The dependent variable in columns (1)-(3) is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. Column (1) is identical to column (1) of Table 3 and is included for comparability reasons. We split the sample of firms in columns (2) and (3) based on the following measure of relationship lending: Share of the total firm's credit (drawn and undrawn) that a bank has of each firm at $t-1$. More specifically, we classify the intensity of the relationship between a firm and a bank as high when the share at $t-1$ is equal to or above the median of the distribution of bank-firm pairs. Column (2) reports the results for the subsample of firms with low relationship lending with the bank, while column (3) shows the results for the subsample of firms with high relationship lending with the bank. In column (4) the dependent variable is a dummy that takes the value 1 if the firm had a positive balance of credit (drawn and undrawn credit) with the bank at $t-1$ and the sample is restricted to the firms with positive variation of credit between $t-1$ and $t+1$. The explanatory variable of interest in all columns, $LocalBank \times Fire$, is the interaction of the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$) and a dummy variable that is equal to one if the firm was affected by fire in year t ($Fire$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. The regression analysis includes firm-time and bank-province-time fixed effects. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank levels. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1) All	(2) More opaque	(3) Less opaque	(4) All	(5) Reduced questionaire	(6) Normal questionaire
LocalBank × Fire	0.301***	0.382**	0.247	0.324***	0.332***	0.371
	(0.077)	(0.163)	(0.196)	(0.069)	(0.064)	(0.284)
Observations	590,683	114,001	117,853	664,960	608,003	55,445
R-squared	0.427	0.453	0.470	0.441	0.451	0.412
Firm-Time FE	YES	YES	YES	YES	YES	YES
Bank-Province-Time FE	YES	YES	YES	YES	YES	YES
Relative Economic Effect	0.019	0.024	0.015	0.020	0.021	0.015

Table 7: **Soft information and credit supply by local banks after fire.** The results in this table are analogous to those in column (1) of Table 3 but the firms are split depending on the firm opacity. The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest is the interaction of a dummy variable that is equal to one if the firm was affected by fire in year t and the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r + 20km$ and outer radius $r + 40km$. We exclude the firms located in the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$. We consider fires with an area burned equal to or larger than 500 ha. Column (1) is the same as in Table 3 but it is estimated just for firms with information on their accruals and is included for comparability reasons. Column (2) reports the results for the sample of more opaque firms whereas column (3) includes the results for the least opaque corporations. Firms used in the estimation of column (2) are those whose levels of accruals are in the top quintile of the distribution of accruals of the firms in our sample whereas those in column (3) correspond to the sample of the least opaque firms whose levels of accruals are in the first quintile of the distribution of accruals. Columns (4) – (6) are analogous to columns (1) – (3) but opaque firms are those that send the reduced questionnaire to the CBSDO. The last row reports the relative economic impact of each variable that is obtained as the product of the coefficient times the average of the share of credit of banks across provinces relative to the standard deviation of the dependent variable. Standard errors in parenthesis are clustered at the province and bank levels. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1) Opaque All	(2) Opaque Distressed	(3) Opaque Non-distr.	(4) Red. quest. All	(5) Red. quest. Distressed	(6) Red. quest. Non-distr.
LocalBank × Fire	0.382**	0.152	0.424***	0.332***	0.317	0.334***
	(0.163)	(0.313)	(0.157)	(0.064)	(0.243)	(0.081)
Observations	114,001	12,351	100,316	608,003	62,856	543,307
R-squared	0.453	0.584	0.447	0.451	0.561	0.442
Firm-Time FE	YES	YES	YES	YES	YES	YES
Bank-Prov.-Time FE	YES	YES	YES	YES	YES	YES

Table 8: **Soft information and credit supply to distressed firms after fire.** This table focuses on opaque firms divided into distressed and non-distressed firms. We consider that a firm is in financial distress if it has negative equity. The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest, $LocalBank \times Fire$, is the interaction of the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$) and a dummy variable that is equal to one if the firm was affected by fire in year t ($Fire$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. In columns (1) - (3) we report the results obtained for the sample of firms that are classified as opaque because their levels of accruals are in the top quintile of the distribution of accruals of the firms in our sample. Column (1) reports the results for the whole sample of opaque firms and it is equivalent to column (2) in Table 7 whereas columns (2) and (3) report the results for the sample of opaque firms that are distressed and non-distressed, respectively. Columns (4) - (6) report the results obtained for those firms that are classified as opaque because they sent the reduced questionnaire to the CBSDO. Column (4) reports the results for the whole sample of opaque firms based on this criteria and it is equivalent to column (5) in Table 7 whereas columns (5) and (6) report the results for the sample of opaque firms that are distressed and non-distressed, respectively. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank levels. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1) All	(2) Distressed	(3) Non-distr.
LocalBank $\times$ Fire	0.220**	-0.439	0.227**
	(0.092)	(0.454)	(0.113)
Observations	55,950	3,389	49,904
R-squared	0.361	0.464	0.367
Ind.-Municipality-Size-Time FE	YES	YES	YES
Bank-Province-Time FE	YES	YES	YES

Table 9: **Credit supply to firms with no previous bank debt after fire.** The explanatory variable of interest, $LocalBank \times Fire$, is the interaction of the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located ($LocalBank$) and a dummy variable that is equal to one if the firm was affected by fire in year t ($Fire$). We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. We consider only firms that had no bank debt in year $t-1$ and that applied for it in either year t or $t+1$. Column (1) includes all firms in our sample that had no bank debt in year $t-1$ and that applied for it in either year t or $t+1$. Columns (2) and (3) report the results for the sample of these firms that are distressed and non-distressed, respectively. The regression analysis includes industry-municipality-size-time and bank-province-time fixed effects. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $NPL_{b,m,i,t+2}$	New credit relationships		All credit relationships	
	(1)	(2)	(3)	(4)
LocalBank	-0.022	-0.049	-0.033	-0.158
	(0.052)	(0.515)	(0.027)	(0.123)
Observations	5,459	5,304	20,523	20,261
R-squared	0.397	0.449	0.529	0.553
Avg Firm controls	YES	YES	YES	YES
Ind-Municipality-Time FE	YES	YES	YES	YES
Bank-Time FE	YES	YES	YES	YES
Bank-Province FE	NO	YES	NO	YES

Table 10: **Quality deterioration of loans granted by local banks after fire.** This table reports the results obtained from the estimation on equation (3) in which the dependent variable is the ratio of the total amount of NPLs of each bank b associated to firms affected by fire that are domiciled in a given municipality m and operate in industry i in December of year $t+2$ relative to the total outstanding credit involving firms affected by fire in that municipality and industry. In columns (1) and (2) we define this ratio using only the firm-bank pairs featuring no credit relationship before the fire. The variable of interest is the fraction of bank b's credit balance in province p, which encompass the municipality m where its borrowers are located, as of December of year $t-1$ ($LocalBank$). Column (2) also includes bank-province fixed effects. Columns (3) - (4) are analogous to columns (1) - (2) but the dependent variable considers all firm-bank pairs and not only those featuring no credit relationship before the fire. All specifications include the average characteristics (size, profitability, and solvency) of the firms to which each bank had a positive credit exposure as of December of year $t-1$ in municipality m and industry i to control for the characteristics of the bank's portfolio of existing borrowers and industry-municipality-time and bank-time fixed-effects. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the bank level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta Employm_{f,t+2}$	(1) All	(2) Local banks $\geq$ 90%	(3) Outsider banks $\geq$ 90%	(4) Local banks $\geq$ 95%	(5) Outsider banks $\geq$ 95%
Fire	-0.013*	-0.006	-0.018*	-0.003	-0.019**
	(0.007)	(0.012)	(0.010)	(0.012)	(0.009)
Observations	466,455	206,297	260,158	176,260	290,195
R-squared	0.136	0.119	0.150	0.110	0.152
Firm controls	YES	YES	YES	YES	YES
Ind.-Municipality-Size-Time FE	YES	YES	YES	YES	YES

Table 11: **Local banks' contribution to mitigate the negative consequences of fires on firms' employment.** This table reports the effect of a firm being *affected* by fire in year t on the growth of the average number of employees between December of year $t-1$ and December of year $t+2$. We consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. We consider fires with an area burned equal to or larger than 500 ha. Column (1) reports the results for the whole sample whereas columns (2) and (4) report the results for those municipalities with active local banks whereas columns (3) and (5) contain the results obtained from municipalities without active local banks. In columns (2) and (3) we consider that a municipality has active local banks if any firm in the municipality has a positive credit exposure to a bank with 90% or more of its credit balance in the province where the firm is located whereas this threshold is set at 95% in columns (4) and (5). All specifications include firm controls and industry—municipality—size-time fixed effects, where the industry is measured at a 1-digit level and size refers to four categories: micro, small, medium-sized, and large corporations. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the firm level. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

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Appendix

A1. Model

This Appendix provides a stylized model of bank lending with soft information, banks' screening and monitoring of opaque and transparent firms, risk aversion under uncertainty in the form of a climate shock to rationalize the main empirical results that we observe in the data.

A1.1. Model Setup

Consider a 2-period economy with banks that provide loans to firms. Let $L_t^{b,f}$ denote the loan amount provided by bank b to firm f at time t. Some firms experience an unexpected climate shock between times $t = 0$ and $t = 1$ that will decrease their profitability and affect the performance of their loans.

Firms. There are two types of firms f: transparent (tr) and opaque (op), with $f = \{tr, op\}$. Transparent firms are companies that operate with a high level of openness, disclosure, and accountability. Opaque firms are companies that lack transparency and operate with limited disclosure of information. This lack of transparency can make it challenging for banks to fully understand the company's operations, assess its performance and make informed lending decisions.

Banks. Banks have the ability to screen and monitor firms, which depends on the type of bank and the type of firm considered. There are two types of banks b: local (loc) and outsider (out), with $b = \{loc, out\}$. Local banks can better screen and monitor opaque firms because they have better access to soft information than outsider banks. We assume that banks are risk averse portfolio managers Hart and Jaffee (1974). For simplicity, we assume that banks' have a constant absolute risk aversion (CARA) utility function with risk tolerance parameter γ.[44]

Loans. Both local and outsider banks can invest in loans to corporations that can be potentially affected by a climate-related shock. The return of these loans, R_t, is $R_0 \sim N(\mu_0, \sigma^2)$ before the climate shock ($t = 0$) and $R_1 \sim N(\mu_1, \sigma^2)$ after the shock ($t = 1$), with

[44]Implicitly, we assume that banks' risk aversion does not change with changes in their wealth. This assumption is irrelevant in our empirical analysis because we use bank-fixed effects, accounting for differences in bank size and, consequently, in their wealth.

$\mu_1 < \mu_0$. Let $\tau = 1/\sigma^2$. The opportunity cost of granting a loan for local and outsider banks is the interbank rate r, where $r < \mu_1$. For simplicity we also assume that the operational costs of giving loans is zero.

External investments. Outsider banks (and only outsider banks) have access to investments outside of the local market. For example, outsider banks can provide loans to firms in regions outside the area of analysis. Assume that the return of these loans is $R_{ext} \sim N(\mu_{ext}, \sigma^2_{ext})$ at any time. The returns of these external investments, R_{ext} and the returns of loans, R_t, present a covariance cov.

Information precision about loans' performance. Both types of banks (local and outsider) have the same information about transparent firms. Moreover, local and outsider banks have the same information about opaque firms before the climate shock. However, after the climate shock, the local bank receives a signal s about the loan returns of the opaque firm affected by the climate shock, R_1, such that $s = R_1 + \epsilon$, with $\epsilon \sim N(0, \sigma^2_\epsilon)$. We assume that ϵ is independent from the returns R_t and R_{ext}. Let $\tau_\epsilon = 1/\sigma^2_\epsilon$. The outsider bank does not receive any signal at any time.

A1.2. Loan Amounts in Equilibrium

i. Local bank's loan amount

The loan amount given by the local bank to firm f, $L_t^{loc,f}$, is:

- Before the climate shock: $L_0^{loc,f} = \gamma\tau[E(R) - r]$. Hence, $E(L_0^{loc,f}) = \gamma\tau(\mu_0 - r)$.
- After the climate shock: For transparent firms, $L_1^{loc,tr} = \gamma\tau(\mu_1 - r)$. For opaque firms, $L_1^{loc,op} = \gamma(\tau + \tau_\epsilon)[E(R_1|s) - r]$. After observing the signal s, the local bank updates its beliefs about the opaque firm loan's returns. Hence, $E(L_1^{loc,op}) = \gamma(\tau + \tau_\epsilon)\mu_1 - r)$.

The relative change in the investment amount (change in loan size) after versus before the climate shock for local banks' loans given to firm $f = op$ is $\Delta L_{loc,op} = \frac{E(L_1^{loc,op}) - E(L_0^{loc,op})}{E(L_0^{loc,op})} = \frac{\mu_1 - \mu_0}{\mu_0 - r} + \frac{\tau_\epsilon(\mu_1 - r)}{\tau(\mu_0 - r)}$, and for $f = tr$ is $\Delta L_{loc,tr} = \frac{E(L_1^{loc,tr}) - E(L_0^{loc,tr})}{E(L_0^{loc,tr})} = \frac{\mu_1 - \mu_0}{\mu_0 - r}$.

ii. Outsider bank's loan amount

Let Σ be the variance-covariance matrix for the variables R_t and R_{ext}. Therefore, the determinant of the variance-covariance matrix is $det(\Sigma) = \sigma^2\sigma^2_{ext} - cov^2$. Let $\tau^{out} = \frac{1}{det(\Sigma)}$.

The loan amount to firm f given by the outsider bank, $L_t^{out,f}$, and the amount invested in the external investment, $L_t^{out,ext}$, are as follows:

- Before the climate shock:

$$E(L_0^{out,f}) = \gamma\tau^{out} \cdot [(\mu_0 - r)\sigma_{ext}^2 - (\mu_{ext} - r)cov]$$

$$E(L_0^{out,ext}) = \gamma\tau^{out} \cdot [(\mu_{ext} - r)\sigma^2 - (\mu_0 - r)cov].$$

- After the climate shock: If we include the banks' screening and monitoring ability, then

$$E(L_1^{out,f}) = \gamma\tau^{out} \cdot [(\mu_1 - r)\sigma_{ext}^2 - (\mu_{ext} - r)cov]$$
$$E(L_1^{out,ext}) = \gamma\tau^{out} \cdot [(\mu_{ext} - r)\sigma^2 - (\mu_1 - r)cov].$$

The relative change in the investment amount of loans to firms (change in loan size) after versus before the climate shock for outsider banks is: $\Delta L_{out,f} = \frac{E(L_1^{out,f}) - E(L_0^{out,f})}{E(L_0^{out,f})}$, therefore,

$$\Delta L_{out,f} = \frac{(\mu_1 - \mu_0)\sigma_{ext}^2}{(\mu_0 - r)\sigma_{ext}^2 - (\mu_{ext} - r)cov}.$$

A1.3. Main Results

Our first result (Result 1) shows that both types of banks reduce lending to firms impacted by climate shocks, reflecting a response to increased risk.

- **Result 1**: Banks reduce the relative amount of loans provided to firms impacted by a climate event: $\Delta L_{b,f} < 0$ for any bank b and firm f (provided that $\tau_\epsilon < \tau \ \frac{\mu_0 - \mu_1}{\mu_1} - r$ for opaque firms).

  Proof: For local banks, $\Delta L_{loc,op} = \frac{\mu_1 - \mu_0}{\mu_0 - r} + \frac{\tau_\epsilon(\mu_1 - r)}{\tau(\mu_0 - r)} < 0$ given that $\mu_0 > \mu_1 > r$ and $\tau_\epsilon < \tau \ \frac{\mu_0 - \mu_1}{\mu_1 - r}$; and $\Delta L_{loc,tr} = \frac{\mu_1 - \mu_0}{\mu_0 - r} < 0$ given that $\mu_0 > \mu_1 > r$. For outsider banks, $\Delta L_{out,f} = \frac{(\mu_1 - \mu_0)\sigma_{ext}^2}{(\mu_0 - r)\sigma_{ext}^2 - (\mu_{ext} - r)cov} < \frac{\mu_1 - \mu_0}{\mu_0 - r} < 0$ because $\mu_0 > \mu_1 > r$.

Our theoretical framework incorporates the fact that outsider banks can shift investments in loans from the area affected by a climate disaster to external investments. After a climate shock, outsider banks shift investments from loans to firms in the affected area to external investments:

- **Remark**: If $cov > 0$, then the climate shock leads to a reduction in the loan amount extended by the outsider bank to firm f, while simultaneously increasing the amount of external investments: $E(L_1^{out,f}) - E(L_0^{out,f}) < 0$ and $E(L_1^{out,ext}) - E(L_0^{out,ext}) > 0$.

  Proof: First, $E(L_1^{out,f}) - E(L_0^{out,f}) = \gamma\tau^{out}(\mu_1 - \mu_0)\sigma_{ext}^2 < 0$ because $\mu_0 > \mu_1 = \mu_1$. Second, $E(L_1^{out,ext}) - E(L_0^{out,ext}) = \gamma\tau^{out}(\mu_0 - \mu_1)cov$ because $\mu_0 > \mu_1$.

However, local banks show a more modest reduction in lending to opaque firms, because of stronger ties and a better understanding of local risk (Result 2). This difference in behavior between outsider and local banks towards transparent and opaque firms, cannot be explained by portfolio considerations but from differences in information.

- **Result 2**: Local banks decrease lending to opaque firms to a lesser extent (in relative terms) compared to outsider banks: $\Delta L_{loc,op} > \Delta L_{out,op}$.

  Proof: $\Delta L_{loc,op} = \frac{\mu_1-\mu_0}{\mu_0-r} + \frac{\tau_\epsilon(\mu_1-r)}{\tau(\mu_0-r)} > \frac{(\mu_1-\mu_0)\sigma_{ext}^2}{(\mu_0-r)\sigma_{ext}^2-(\mu_{ext}-r)cov} = \Delta L_{out,op}$ because: (1) the term $\frac{\tau_\epsilon(\mu_1-r)}{\tau(\mu_0-r)}$ is strictly positive since $\mu_1 > r$, and (2) $\mu_1 - \mu_0 < 0$.

A2. Data Filters

This Appendix describes extra details related to the construction of our database and, specifically, the filters that we apply. We apply several filters to the CBSDO data to define our final sample.

First, we exclude firms with financial ratios that may not be comparable with those of the rest of the firms, as their goal is not profit maximization such as state-owned companies, local corporations, non-profit organizations, membership organizations, associations, foundations, and religious congregations.

Second, we also remove holding companies because their financial results may not be comparable with those of the rest of the firms. Our sample does not include foreign companies and permanent establishments of entities that do not reside in the country.

Third, financial firms and companies that do not belong to the market economy are also excluded according to the NACE industry classification. This set of firms includes financial service activities, except insurance and pension funding (64); insurance, reinsurance, and pension funding, except compulsory social security (65); activities auxiliary to financial services and insurance activities (66); public administration and defense, as well as compulsory social security (84); activities of membership organizations (94); activities of households as employers of domestic personnel (97); undifferentiated goods- and services-producing activities of private households for own use (98); and activities of extraterritorial organizations and bodies (99).

Fourth, we also remove firms that according to the CBSDO have balance sheets with (i) non-reliable monetary units or (ii) errors regarding positive/negative values. We replace the employment with missings when it is classified as non-consistent in the CBSDO.

Fifth, we remove observations that violate basic accounting rules or have impossible values (e.g. negative age).

A3. Distance of Large Economic Impact Outside the Wildfire

In this Appendix, we present a comprehensive collection of academic papers that validate the statement that businesses located within a 10-kilometer radius from the periphery of a wildfire experience adverse consequences attributable to the fire. In general, it is important to define firms' losses to understand which firms can be considered affected by a natural disaster event and what impact that event had on their businesses. The literature has extensively discussed how to account for the losses caused by natural disasters and the effect that they have on business performance (Lindell and Prater (2003); Cochrane (2004) and Rose (2004)). As a broad explanation, losses can be distinguished between direct losses and indirect losses. Direct losses are the immediate consequences of the disaster's physical phenomenon and are suffered by businesses directly affected by the event. Destruction of a warehouse by fire or damage in a retail store by a water inundation are examples of direct losses.

Otherwise, indirect losses include all losses not caused by the natural disaster, but by its consequences and affect not only the business in the extension of the event but also business in a larger spatial scale. As defined by Okuyama and Chang (2004) indirect effects or high-order losses are "all flow losses beyond those associated with the curtailment of output as a result of hazard-induced property damage in the producing facility itself". In other words, businesses not affected but near the event might be unable to produce at pre-event levels.

Some of the causes could be explained by supply-chain disruption, damaged transportation infrastructure, utility service disruption, or damaged infrastructure (Gordon, Richardson, and Davis (1998); Hallegatte (2015) and Carvalho et al. (2021)). The main origin of underperformance is caused through the collateral constraint channel as loss of asset value by the depreciation of prices in the closest reduces the company debt and investment capacity (Chaney, Sraer, and Thesmar (2012); Kiel and Matheson (2018) and Wang (2023)).

The literature supports the idea that a first ring embodying all firms in a 10 km radius from the edge of the wildfire is a good approximation for those companies only suffering indirect effects, especially for a devaluation on collateral assets such as properties. Stetler, Venn, and Calkin (2010) studies how prices of non-burned houses change when a big wildfire occurs near them. They show that house prices drop by -13.7% and -7.6% if they were within 5 km of the fire or between 5 km and 10km, respectively. However, they do not find significant effects beyond a 10 km distance. Other papers found similar results on prices of properties nearby (Loomis (2004);Henriet, Hallegatte, and Tabourier (2012)).

To determine whether a firm has been affected by fire we calculate the distance in kilometers from the location of the firm to the coordinates of the fire. For this purpose, we use the Stata module geodist, which calculates geographical distances by measuring the length of the shortest path between two points along the surface of a mathematical model of the Earth. We drop fires with impossible coordinates or coordinates outside the geographical limits of Spain. Also, we drop the fire-firm observations where the fire took place previous to the existence of the firm.

Firms not affected by fire are those located in the peripheral ring with inner radius $r + 20km$ and outer radius $r + 40km$. Note that we exclude from our sample those firms situated in the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$. This is to guarantee that the unaffected group of firms remains untainted by businesses in the vicinity of the affected area, which might potentially suffer damage due to the wildfire. We subject this assumption to a series of robustness tests and find that our results remain resilient in the face of the definition of the control area.

A4. Robustness tests

In this appendix, we present robustness tests to assess the impact of climate risk on the credit supply of local banks, using alternative samples. Firstly, we address the concern that wildfires might happen in a staggered way, that is, fires might occur in different locations during different periods. If locations were close enough, firms subject to wildfires early in our data could appear later as controls. However, we assess the robustness of our findings by conducting an analysis that excludes from the sample firms once they are affected by fire (column 2 in Table A1) and that considers only firms the first year that they appear in the sample (column 3). They show that our results are robust to the concerns regarding the potential staggered nature of wildfires.

Secondly, one could question the exclusion of firms geographically located in a ring between the treatment and control groups from the sample (see Figure 1). To address this issue, we restrict our sample to firms located within the ring of $r + 20km$ (i.e., radius of the fire area plus 20km) surrounding the edge of the burn-area, such that the *non-affected* or control area of this alternative sample is defined as the peripheral ring with inner radius $r + 10km$ and outer radius $r + 20km$.[45] Results are reported in column (4). We confirm that there are significant differences between the treatment and this alternative control group but consistent with the idea that the activity of firms in this new non-affected area might be contaminated, we observe that the estimated coefficient is lower than in column (1).

[INSERT TABLE A1 AROUND HERE]

Thirdly, we respond to the concern that local banks could be aware of the firms' abilities to receive subsidies. To abstract from the effect of public subsidies or aids on credit supply, we remove from our sample those firms that have received any aid or subsidy according to the information available in the CBSDO. Results are reported in column (5) of Table A1 and confirm that subsidies do not drive local banks' credit supply.

Although we find that the credit supply of local banks is also channeled through loans without guarantees, banks may extend more credit to firms with more tangible assets just because in case of liquidation, the recovery rate would be higher (Davydenko and Franks (2008)). Alternatively, firms with more tangible assets could suffer more losses in case they

[45] Note that these firms were not considered in previous analyses to avoid including areas that are not directly affected by fire but their activity might suffer from externalities of the fire.

are affected by fire. To understand, which of the two effects dominates, we split the sample into two parts depending on whether their ratio of tangible assets over total assets is below or above the median of the distribution in each year. We find that local banks extend new credit similarly to firms no matter their ratio of tangible assets (see columns (6) and (7) in Table A1).

Another factor that might contribute to explaining credit supply by local banks to firms affected by a fire is the requirement of guarantees. Collateral contributes to mitigating not only asymmetric information but also the potential losses the bank faces in case of a firm default. Therefore, we re-estimate the equation (1) using only the evolution of credit without guarantees. Suppose a more extensive use of guarantees drives the activity of a local bank. In that case, we should expect no differences between the credit supply of local and outsider banks to firms affected by fire. However, the results in column (9) of Table A1 fully support those obtained in the baseline analysis (column 8).

To account for potential distortions caused by changes in bank structures, in column (10) of Table A1 we exclude all banks involved in a merger process. Specifically, we remove banks from the sample the year in which the bank consolidation or absorption process occurred, as well as the preceding and following year, so that credit variation is not affected by the merger. While our main results already control for bank mergers, as detailed in footnote 24, we take this additional step to ensure the robustness of our findings by entirely removing banks undergoing significant organizational transitions from the analysis. This approach minimizes the potential influence of bank merger-related changes on the results.

To address the unavailability of potentially relevant data at the firm level such as corporate insurance data, we use firm-time fixed effects to compare the credit supply of two banks to the same firm depending on their specialization in the province where the firm is located. This approach enables us to abstract from the role of property insurance of a firm and the coverage of such insurance. In addition, we find similar results independently on the tangible assets of each firm[46]. We now go one step forward and examine different areas based on their ex-ante probability of experiencing a fire. Specifically, we classify these areas into two categories of fire risk within a given municipality using information from Sociedad de Tasación: (i) those with a low likelihood of fire occurrence and (ii) risky regions with a well-established fire risk. Our prior is that fires in the first type of areas are often unex-

[46]Firms with more tangible assets are more likely to purchase property insurance (Zou and Adams (2008)).

pected, and firms may not prioritize insurance coverage. However, in the risky areas, firms are acutely aware of this danger and may actively optimize their risk management through insurance strategies. Based on this prior, we hypothesize that credit supply dynamics will differ across these two types of areas. If insurance significantly influences credit allocation, we should observe divergent results. Columns (11) and (12) of Table A1 reveal that local banks extend more credit to fire-affected firms both in areas with a low probability of fire occurrence and in areas with a high probability. This suggests that factors beyond insurance play a pivotal role in credit allocation during fire-related crises. Importantly, the fact that the results remain in areas with a low probability of fire occurrence means that both the classification of firms as affected or non-affected and the results are not driven by fire predictability.

Finally, the support of local banks to firms affected by a fire could be driven by firms that exert a strategic role within a given province because these banks could be particularly inclined to aid these firms. We classify a firm as strategically significant for the local economy if it employs a substantial number of workers within a given province, as they act as vital contributors to the regional workforce and economic fabric. Local banks could face pressures from different instances to support lending to these strategic firms such that they could ultimately affect their allocation of credit. To explore whether our results are driven by the role of strategic firms, we split our sample into two groups of firms: (i) strategic firms, defined as those where the ratio of workers employed by a single firm relative to the total number of employees in the province falls within the top quintile of the distribution, and (ii) non-strategic firms, which are all other firms that do not meet the criteria to be classified as strategic. Our empirical analysis, presented in columns (13) and (14) of Table A1 for the subsamples of strategic and non-strategic firms, respectively, reveals that local banks indeed extend more credit to strategic firms when they are affected by fire incidents, compared to outsider banks. Importantly, even firms that are not strategically significant for the local economy receive significantly more credit from local banks during such challenging times.

Dep. Var.: $\Delta L_{f,b,t+1}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LocalBank × Fire	0.324***	0.333***	0.368***	0.204**	0.357***	0.351***	0.280**
	(0.069)	(0.079)	(0.085)	(0.093)	(0.077)	(0.100)	(0.133)
Observations	664,960	602,081	386,420	249,815	584,866	447,554	215,373
R-squared	0.441	0.437	0.452	0.449	0.450	0.428	0.494
Firm-Time FE	YES	YES	YES	YES	YES	YES	YES
Bank-Province-Time FE	YES	YES	YES	YES	YES	YES	YES

Table A1: **Credit supply by local banks after fire. Alternative samples.** This table reports the results obtained for alternative samples in equation (1). Column (1) is identical to column (1) of Table 3 and is included for comparability reasons. The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest is the interaction of a dummy variable that is equal to one if the firm was affected by fire in year t and the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located (*LocalBank*). We consider fires with an area burned equal to or larger than 500 ha. Columns (1) - (5) are analogous to column (1) of Table 3 but with different samples of firms. In column (2) we restrict the group of *affected* firms to first-time fire-damaged firms. Similarly, in column (3) we only consider firms the first year that they appear in the sample (independently of whether they were affected by fire or not). In columns (1) - (3) and (5) – (7) we consider the *affected* or treatment area as the region that includes the burn area (i.e., a circle with radius r) plus a 10-kilometer ($10km$) peripheral ring around it. The *non-affected* or control area is defined as the peripheral ring with inner radius $r+20km$ and outer radius $r+40km$. We exclude the firms located in the peripheral ring with inner radius $r+10km$ and outer radius $r+20km$. However, in column (4) we restrict our sample to those firms located less than $r+20km$ from the centroid of the fire, such that *non-affected* firms are those beyond the threshold of $r+10km$ and they are not considered in columns (1) - (3). In column (5) we restrict our sample to firms that have not received subsidies in years t and $t+1$. Column (6) only considers firms with a ratio of tangible assets over total assets equal to or below the median ratio each year. In column (7) only those firms with a ratio of tangible assets over total assets greater than the median in each year are included in the sample. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank levels. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Dep. Var.: $\Delta L_{f,b,t+1}$	(8)	(9)	(10)	(11)	(12)	(13)	(14)
LocalBank × Fire	0.324***	0.320***	0.358***	0.213***	0.423***	0.284***	0.486***
	(0.069)	(0.113)	(0.124)	(0.078)	(0.139)	(0.061)	(0.109)
Observations	664,960	472,517	270,215	343,486	315,683	462,978	149,405
R-squared	0.441	0.465	0.471	0.434	0.457	0.471	0.389
Firm-Time FE	YES	YES	YES	YES	YES	YES	YES
Bank-Province-Time FE	YES	YES	YES	YES	YES	YES	YES

Table A1: **(cont.) Credit supply by local banks after fire. Alternative samples.** This table reports the results obtained for alternative samples in equation (1). Column (8) is identical to column (1) of Table 3 and is included for comparability reasons. The dependent variable is the log change in credit (plus one to deal with zeros) extended by bank b to firm f between December of year $t-1$ and December of year $t+1$. The explanatory variable of interest is the interaction of a dummy variable that is equal to one if the firm was affected by fire in year t and the fraction of credit of bank b in December of year $t-1$ in the province where the firm is located (*LocalBank*). We consider fires with an area burned equal to or larger than 500 ha. In column (9) we remove firms that had credit with any type of guarantee either the year before or after fire. In column (10) we exclude from the sample all bank entities that were involved in a bank merger during that year and the preceding and following year. In column (11) we include firms located in municipalities with low probability of wildfires. Conversely, in column (12) we include firms located in municipalities with higher probability of wildfires. In columns (13)-(14) we gauge the strategic importance of firms by measuring their employment relative to total employment in the province. Column (13) includes the less strategic firms, representing those in the bottom quintile of the distribution of this measure within a province and year, whereas column (14) considers more strategic firms, identified as those in the 20th percentile of a province and year. The estimation period is 2004-2017. Standard errors in parenthesis are clustered at the province and bank levels. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.