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Severe Weather and Collateral Practices*

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Abstract

Physical climate risks significantly influence banks' collateral practices. Drawing on comprehensive loan-level data from Sweden, we find that adverse weather events increase both the likelihood and the amount of collateral required for new loans. For existing loans, banks are less inclined to reappraise collateral following weather shocks; when reappraisals occur, collateral values are typically revised downward. Our analysis also highlights the mitigating role of geographic proximity between borrowers and lenders. Overall, our results indicate that while banks limit potential losses from physical climate risks by tightening collateral requirements, this practice may eventually exacerbate firms' financial constraints.

Keywords: bank lending, collateral, climate risk

JEL Classification Codes: G21, G32

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1 Introduction

Collateral value is a critical determinant of loan security, directly influencing a lender's capacity to recover losses in the event of borrower default. The finance literature has extensively explored the role of collateral and the contractual mechanisms governing its use (Bernanke and Gertler, 1986; Brunnermeier, Eisenbach, and Sannikov, 2012; Kiyotaki and Moore, 1997; Mendoza, 2010). Previous studies emphasize that borrower risk, credit market competition, lender type, and macroeconomic conditions are pivotal factors shaping collateral requirements (Jiménez, Salas, and Saurina, 2006). At the same time, physical climate risks have emerged as an important challenge for banks, as extreme weather events can both disrupt firm cash flows and damage the physical assets that secure loans (Intergovernmental Panel on Climate Change, 2021).

This paper studies how acute physical climate risks affect banks' collateral practices along several distinct dimensions. First, we document how severe weather shocks shape collateral requirements at loan origination (ex ante standards). Second, we study how severe weather shocks affect ex post collateral management, focusing on reappraisal frequencies, timing, and value adjustments for existing loans. Third, we link these ex ante and ex post responses to bank–borrower proximity, thereby providing novel evidence on the role of informational frictions in how climate-related shocks enter collateral policies. Taken together, these three contributions offer the first comprehensive evidence on how acute physical climate risks influence both ex ante collateral standards and ex post collateral reappraisal practices.

To develop our analyses, we exploit severe local weather events as plausibly exogenous shocks to collateral values, following the approach of Brown, Gustafson, and Ivanov (2021). We obtain monthly county-level severe weather data from the Swedish Meteorological and Hydrological Institute (SMHI) for the period 2018–2024.[1] and combine these data with monthly loan-level information from the Swedish credit database (KRITA).

The KRITA dataset offers detailed contract-level information, including extensive data on collateral posted by firms at loan origination and subsequent changes in collateral values over

[1]We use the term *severe weather events* to identify meteorological events such as extreme wind, snow, rain, and temperatures that prompt the Swedish weather agency to issue a warning to the population.

time, and it records the geographic location of both firms and the real-estate assets used as collateral. Additionally, we employ proprietary data on the locations of banks' branches to further sharpen our analyses.

Our empirical strategy proceeds in two stages. First, we focus on firms with a single establishment to examine collateral requirements across all collateral types at loan origination. Second, we expand the sample to include firms with several establishments but hone in on real-estate collateral only, allowing us to study banks' reappraisal decisions for existing loans after severe weather shocks, an aspect that has been largely absent from the prior literature.

Focusing on new corporate loan origination to single establishment firms, we find that in counties experiencing more frequent severe weather events, new loans are significantly more likely to be collateralized. Moreover, loans in these areas exhibit higher collateral-to-loan ratios. Specifically, 2.5 more days with severe weather in a given month (i.e. a one-standard-deviation increase) raises the probability of collateral requirements by 1.75 percentage points for new business loans. Weather events also significantly influence the magnitude of collateral requirements: Two and a half additional days of severe weather correspond to approximately a 10% increase in collateral value. This effect is particularly pronounced in the loan-to-value (LTV) ratio: a one-standard-deviation increase in the number of events leads to a roughly 40 basis points (bp) increase in the collateral-to-loan ratio. These effects persist after controlling for firm characteristics and a large battery of fixed effects, including county-by-bank fixed effects, with more profitable and larger firms generally posting lower collateral amounts, while highly leveraged firms face stricter collateralization requirements.

We next examine the impact of severe weather on the management of existing loan contracts secured by real-estate collateral. We find evidence that banks exhibit increased hesitancy in reappraising collateral in the aftermath of severe weather events. Specifically, 2.5 additional days of severe weather reduces the probability of reappraisal by 35-bp or 5%. However, when banks proceed with reappraisal, they typically do so faster, with the number of days between reappraisals dropping by 10 days following a one-standard-deviation higher number of severe weather days. Moreover, reappraisals are associated with downward adjustments in collateral values, with a standard-deviation increase in weather events leading to an average 19-bp reduction in collateral value. Taken together, these estimates show that banks do not simply revalue collateral more aggressively after damage. Instead, they reappraise less often on average after severe weather, but when they do, they revalue collateral sooner and predominantly downward. This asymmetric response differs from a simple benchmark in which higher climate risk would mechanically trigger more frequent and symmetric updates.

These results highlight key questions about the mechanisms driving banks' responses. Banks may react to new information about borrowers, with effects most pronounced where information asymmetry is high. Alternatively, the saliency of the event alone could prompt behavioral changes—even absent new information—implying strongest effects where banks themselves are directly exposed to severe weather. To test these mechanisms, we exploit bank branch location data to measure bank–borrower proximity. Consistent with the information hypothesis, banks with a branch in the same municipality as their borrowers require less collateral and exhibit weaker responses to severe weather. In contrast, greater distance or recent branch closures are associated with larger collateral increases following adverse events. These patterns indicate that local presence enhances information and monitoring capacity, whereas its absence amplifies credit constraints during climate shocks.

The attenuation of both origination and reappraisal responses when lenders maintain a local branch is difficult to reconcile with a salience- or compliance-based explanation, which would predict uniform adjustments to weather warnings regardless of geographic proximity. Instead, the evidence points to informational frictions as a key channel underlying the observed reappraisal behavior. Likewise, banks specializing in commercial real estate (CRE) lending show markedly weaker changes in collateral practices after severe weather, consistent with relationship lending and soft-information mechanisms.

We also document notable heterogeneity at the firm level: the impact of severe weather on collateralization is greatest for rural firms and those in more exposed sectors such as agriculture, forestry, and fishing. Urban firms exhibit little change in collateral demand after adverse weather. While firms in climate-sensitive industries face higher collateral requirements at origination, banks are not more likely to reappraise collateral for these sectors, perhaps reflecting challenges in rural asset valuation or cyclical agricultural income. When examining the major flood in

Gävleborg county, we find increased collateral requirements for local firms post-disaster, while reappraisal frequencies fall even further, underscoring that banks use reappraisal selectively rather than mechanically. This event-study corroborates the baseline evidence on the ex post collateral management dimension: even after a major flood that visibly damages assets, banks reduce the frequency of reappraisals of existing loans, while tightening collateral standards at origination.

The results so far suggest that lenders respond to weather shocks ex post when there is potential information asymmetry and the loan contract is directly exposed. Increased insurance coverage offers an alternative mechanism to reduce both information asymmetry and the financial impact of weather shocks. Using municipal-level insurance payout data from the Swedish Insurance Association, we find that higher insurance payouts correlate with increased collateral demands at origination, reflecting greater losses. However, insurance does not dampen the baseline effect of severe weather on collateral practices. These findings highlight the limitations of insurance as a substitute for prudent credit risk management and the need for more transparent insurance data.

Our work contributes to several strands of literature. First, we add to research on how collateral mitigates credit frictions and shapes lending practices (Benmelech and Bergman, 2009; Bernanke and Gertler, 1986; Cerqueiro, Ongena, and Roszbach, 2016; Degryse, De Jonghe, Laeven, and Zhao, 2025; Luck and Santos, 2024; Rampini and Viswanathan, 2013). Prior studies highlight borrower risk, credit market conditions, lender type, and macro factors as key determinants of collateral requirements (Jiménez et al., 2006). We show that acute physical climate risks, proxied by severe weather events, affect both *ex ante* collateral standards at origination and banks' *ex post* dynamic reappraisal of existing collateral—a margin that, to our knowledge, has not been measured at the contract level.

Second, we contribute to the literature on climate risk and collateral. Existing work documents how natural disasters erode collateral values, raise bankruptcy costs, and induce debt specialization, with affected firms facing tighter collateral constraints and greater reliance on leases (Francis, Hasan, Jiang, Sharma, and Zhu, 2022; Wang, 2023). Related papers emphasize the role of credit lines and targeted lending in disaster recovery and the pricing of physical climate risk in loan spreads (Brown et al., 2021; Correa, He, Herpfer, and Lel, 2023; Nguyen, Ongena, Qi, and Sila, 2022; Schubert, 2024). We complement this evidence by showing how severe weather shapes collateral requirements and reappraisal policies, and by linking these responses to lender–borrower proximity, thereby connecting to the literature on soft information and the role of local branches in business lending (Agarwal and Hauswald, 2010; Amberg and Becker, 2024).

Finally, we relate to work on banks' broader responses to climate risks, including disaster-response lending and the greening of credit portfolios (Altavilla, Boucinha, Pagano, and Polo, 2023; Álvarez-Román, Mayordomo, Vergara-Alert, and Vives, 2024; Barth, Sun, and Zhang, 2019; Brown et al., 2021; Cortés and Strahan, 2017; De Marco and Limodio, 2023; Giannetti, Jasova, Loumioti, and Mendicino, 2023; Ivanov, Macchiavelli, and Santos, 2022; Koetter, Noth, and Rehbein, 2020; Meisenzahl, 2023; Rehbein and Ongena, 2020; Schubert, 2024; Schüwer, Lambert, and Noth, 2019). This literature highlights how banks both support recovery and adjust exposures, but pays less attention to collateral management itself. Our study fills this gap by focusing on collateral practices from ex ante requirements to ex post reappraisal of existing collateral as a key channel through which banks incorporate acute physical climate risks into lending.

The remainder of the paper is organized as follows. Section 2 discusses the datasets and descriptive evidence. Section 3 presents the main empirical results. In Section 4, we further analyze geographic and sectoral differences. Section 5 discusses the role of weather shocks in credit risk. We conclude in Section 6.

2 Data and Economic Mechanism

To study the collat eral channel of weather shocks, we leverage several data sources. First, we collect loan-level data from the Swedish Credit database (KRITA) for the period 2019 to 2024. KRITA is a loan performance dataset constructed by Statistics Sweden (SCB) on behalf of Sveriges Riksbank (the Swedish central bank) to collect information on loans to businesses and the public sector.[2] The data are reported monthly by twenty-four monetary financial institutions and cover approximately 95% of all loans to the corporate sector in Sweden.

KRITA provides contract-level information, including inception and settlement dates, loan conditions, loan purpose, and the type of financial instrument. Importantly, the dataset contains detailed information about collateral provided by firms at the time of contract signing and any changes in collateral values over time. Collateral types can be identified and include real-estate, cash and securities, and personal guarantees, among others. In this study, we separately analyze new loan originations and changes to the terms of existing loans. We identify the total amount of new credit granted by a bank in a given month (referred to as credit granted), as well as the amount actually drawn down by the borrower using the unique loan contract identification number. Information about firm locations, firms' balance sheets and accounting measures are obtained from Serrano-Bisnode (Serrano). Firms in KRITA and Serrano can be uniquely identified using their organization number, enabling us to perfectly match the two databases.

Following Anderson and Robinson (2019), we use *monthly weather warnings* issued at the county level by the Swedish Meteorological and Hydrological Institute (SMHI) to identify severe weather events,[3] which are increasingly linked to climate change (Intergovernmental Panel on Climate Change, 2021). These warnings provide timely alerts for risks such as storms, floods, and heatwaves [4] that directly impact infrastructure, operations, and financial performance. They are especially valuable in assessing localized and sector-specific vulnerabilities, such as those faced by agriculture and construction, where extreme weather may cause disruptions or even defaults.

In total, we observe 11,430 severe weather events between 2010 and 2023, with a yearly average of 816.4 events.[5] Figure 1 plots the number of events by county over the entire sample.

[2]KRITA is the Swedish part of the ESCB's pan-European credit register AnaCredit, which it closely follows in terms of data structure and variable definitions.

[3]The SMHI warnings are graded according to the level of risk and potential impact on society: Class 1 indicates some risks and disturbances, Class 2 indicates danger, damage, and larger disturbances, and Class 3 indicates serious danger, serious damage, and major disturbances. Most of the warnings in our data are Class 2 warnings. We aggregate the different warnings at the county-by-month level.

[4]Unfortunately, in our data we cannot distinguish the type of event behind each warning.

[5]About 80% of all warnings issued by SMHI have culminated in *realized severe weather*, ensuring that our proxy sufficiently captures such events.

The figure reveals that the most affected areas are situated in the north and along the border with Norway. These regions tend to be most affected by rain and snowfall, which make up the majority of events.

To ensure accurate identification of a firm's location and operations, we initially restrict our sample to firms with a single registered location and use this sample to study collateral decisions at contract origination. We then expand the dataset to include all firms that employ real-estate as collateral and for which KRITA provides the property's zip code, allowing us to examine reappraisal practices. These zip codes are matched with severe weather data to construct proxies for physical risk exposure. Our main exposure measure, (*SevereWeather*), defined at the firm (or real-estate) level, is the total number of days with severe weather in the county where the firm (or property) is located, divided by the total number of days in the month.

Table 1 reports descriptive statistics for the main variables included in the analyses. Table 1, Panel A, summarizes results at contract origination, while Table 1, Panel B, provides descriptive statistics for the full sample period. Table 1, Panel C, summarizes main firms characteristics. All variables are described in Appendix A, Table A1.

Our final dataset includes approximately 10,000 firms. The average firm in the sample borrows approximately 2.7 million Swedish kronor per month at origination. Consistent with the existing literature, which shows that firms overcome informational asymmetries by pledging collateral (Barro, 1976; Hart and Moore, 1994; Kirschenmann, 2016; Stiglitz and Weiss, 1981), most contracts in our sample are collateralized (approximately 80 percent), and collateral accounts for a large share of the average loan value (65 percent). However, although real-estate is an important source of collateral, only 10 percent of contracts at origination are secured by real-estate.

When defining collateral requirements, banks consider various factors. These include the borrower's financial health, captured through credit history, debt levels, and profitability, along with the type and quality of the collateral, prevailing macroeconomic conditions, loan terms, industry-specific risks, and regulatory requirements. Together, these elements shape the amount and type of collateral a firm must provide to secure financing. Yet, we posit that climate-related physical risks should also play an essential role in determining collateral requirements.

The impacts of extreme weather events, such as floods, storms, and wildfires, are readily observable to both banks and borrowers. The growing frequency and intensity of such events further underscore the importance of incorporating physical climate risks into credit assessments and loan contract design, particularly in regions where these risks are more acute.[6] Consequently, banks should be more likely to adjust collateral requirements and valuations in areas prone to extreme weather events, either in response to realized damages or in anticipation of more frequent and severe future events. This adaptability underscores the role that climate-related physical risks should play in shaping credit terms through the collateral channel. Building on this insight, the next section examines the relationship between weather shocks and the collateral features of credit contracts more directly.

In the next section, we begin by assessing whether recent severe weather events influence collateral requirements at loan origination, and then analyze collateral reappraisals in existing collateralized loans following such shocks. By distinguishing between new originations and adjustments to outstanding loans, we isolate the different mechanisms through which physical climate risks shape collateral dynamics. The section also presents a detailed outline of our empirical strategy and identification approach.

3 Collateral Decisions and Firm Exposure to Weather Shocks

To begin with, we study whether recent severe weather events affect collateral requirements at loan origination. Second, we turn to analyze collateral reappraisals of existing collateralized lending after weather shocks. Finally, we study the role played in this context by the proximity

[6] Recent evidence highlights a growing frequency and intensity of extreme weather events in Sweden, consistent with broader global trends linked to climate change. The European Investment Bank (2024) reports that 64% of Swedes who responded to their survey experienced at least one extreme weather event in the past five years, with 29% facing extreme heat, 22% encountering heavy storms or hail, and 22% dealing with inland floods. These patterns align with findings from the Swedish Meteorological and Hydrological Institute (SMHI), which notes an increase in maximum summer temperatures and the frequency of extreme heatwaves over recent decades, while cold periods during winter have diminished. Although trends for extreme precipitation, wind, and snow remain unclear due to limited data, projections suggest that weather-related events such as floods, storms, and landslides will grow more frequent over the coming century (SMHI, 2024; ClimateChangePost.com).

between lending banks and firms.

3.1 What Collateral is Required? Collateral Standards at Origination

Our first question examines whether greater exposure to severe weather events increases the likelihood of a loan being collateralized. To investigate this relationship, we focus on single establishment firms and employ loan data at the time the contract was originated.

We define new loan originations as contracts with identifiers that do not appear in the dataset in the preceding month. Our analysis focuses exclusively on loans originated during the collection window from 2019 to 2024, excluding any loan originated prior to 2019. This restriction is implemented because information in the credit registry before 2018 is generally less reliable.

Next we identify all single establishment firms in our sample and exclude post box addresses. This is because the operations of single establishment firms are concentrated in the recorded location, making it easier to link collateral exposure to specific severe weather events. This clear geographic connection allows for precise assessment of how weather shocks affect banks' collateral practices. Focusing on single-establishment firms thus improves the accuracy of identifying whether weather event affect collateral requirements. Moreover, since we can precisely locate the firm, we analyze the total amount of collateral posted at loan origination, not just the portion tied to real-estate. This comprehensive approach enables us to capture the broader impact of severe weather events on the borrower's overall credit quality as perceived by lenders at the time the loans are originated. By considering all collateral types, we better account for how severe weather may affect the firm's financial standing and banks' risk assessments beyond just real-estate exposure. The merged dataset, which combines loan-level data with severe weather events, comprises over 100,000 unique observations.

In the analyses, we employ as dependent variable an indicator variable ($\mathrm{P}[Collateral]$) which takes the value of one if the loan is secured by collateral and zero otherwise. The primary explanatory variable of interest is *SevereWeather* calculated as the total number of days with severe weather in the *county where the firm is located*, divided by the total number of days in the month. Thus, it measures the fraction of days with severe weather in a given county-month.

This variable is lagged by one month to mitigate autocorrelation in regression residuals and capture delayed effects and temporal patterns more accurately. We then estimate the following regression:

$$
\begin{aligned}
P[Collateral]_{l(f,b),t} = & \beta SevereWeather_{c,t-1} \\
& + \boldsymbol{\delta'} \boldsymbol{X}_{l,t-1} + \boldsymbol{\gamma'} \boldsymbol{Z}_{f,t-1} + FE + \epsilon_{l(f,b),t},
\end{aligned}
\tag{1}
$$

where $\boldsymbol{X}_{l(f,b),t}$ is a vector of loan characteristics that includes the loan amount and interest rate. $\boldsymbol{Z}_{f,t}$ represents a vector of (lagged) firm-specific characteristics, including leverage, return on assets (RoA), total assets (in logarithmic form), and basic loan attributes such as the total loan amount.

To account for potential confounding factors, we saturate the regression with various sets of fixed effects. The baseline specification incorporates bank, time, and county fixed effects, which control for bank-invariant lending practices, time-specific shocks, and county-invariant differences, respectively. Given that a significant proportion of firms in the sample have only one loan, our preferred specification excludes firm fixed effects to avoid over-restriction. However, consistent with prior literature (e.g., Degryse, De Jonghe, Jakovljević, Mulier, and Schepens, 2019), we also estimate specifications that include bank-by-county and county-by-industry- fixed effects to further address unobserved heterogeneity. Moreover, we include season fixed effects to control for normal seasonal differences in weather patterns. Our most saturated regression replaces bank-by-county and county-by-industry fixed effects with bank-by-county-by-industry fixed effects. In all regressions, standard errors are clustered by county. Results are summarized in Table 2.

Table 2, column (1) reports the results with firm and contract controls, but without any fixed effects. In columns (2) to (5), we increasingly saturate the regression with fixed effects controlling for the battery of unobservable characteristics. Throughout, standard errors are clustered at the county level.

The point estimates across the four specifications range from 0.10 to 0.16, suggesting that an additional day with severe weather in the month prior to the loan origination increases the probability of posting collateral by 34 to 55 basis points. Given an unconditional probability of collateral posting of 80%, this corresponds to an increase of 0.7%. The standard deviation of the share of severe weather is roughly 2.5 days, suggesting that a standard-deviation increase in the share of severe weather days is associated with a 1.75% higher probability of posting collateral. In line with prior findings (Jiménez et al., 2006), we also observe that larger firms and those with higher profitability are less likely to post collateral, while firms with higher leverage are more likely to be required to do so.

Overall, the results in Table 2 indicate that severe weather events increase the likelihood of a firm being required to post collateral, suggesting that firms in areas most exposed to acute physical climate risk may face greater financial constraints. Following this finding, we examine whether the amount of collateral required is affected in addition to the probability of posting collateral.

Table 3 reports the results of regressions where the dependent variable is the natural logarithm of the total collateral value in the first column, and the collateral value to total loan amount ratio in column (2) respectively. The point estimates for the variable *SevereWeather* is 1.166, significant at the 1% level, after controlling for lagged firms characteristics and the interest rate charged to the borrower (which is reported by the banks in KRITA) and the total borrowed.[7] The economic impact of this result is quite substantial: a one day increase in severe weather days is associated with an approximate 3.9% increase in the posted collateral value.

To complete our analysis, in the second column of Table 3, we regress the collateral-to-value ratio—defined as the total collateral value posted divided by the total amount borrowed —on the share of severe weather events in the past month. The point estimate is 0.047, suggesting that a one-day increase in the number of days with severe weather events is associated with an increase in the collateral to loan ration of 15 basis points. This result provides an indication of the sensitivity of collateral requirements to severe weather events, highlighting that exposure to extreme weather events leads to significant changes in the collateralization of loans.

[7] Consistent with the findings in Table 2, we observe that more profitable and larger firms tend to post lower collateral amounts, while highly leveraged firms are generally required to post more collateral.

In summary, our results provide robust evidence that exposure to severe weather events affects both the extensive and intensive margins of collateralized borrowing. Specifically, at loan origination, firms more frequently exposed to severe weather events are not only more likely to pledge collateral, but also tend to post a greater amount of collateral per unit of borrowing. This finding suggests that firms in areas frequently affected by severe weather events may face greater financial constraints when seeking to secure a bank loan. We now turn to the ex post collateral management for existing loans, where banks can adjust collateral values over time after severe weather shocks

3.2 When is Collateral Re-evaluated? Real-Estate Collateral Management after Origination

Having established that severe weather events significantly increase the likelihood and total amount of collateral required at origination of new loans for single establishment firms, we next examine whether similar climate-related adjustments occur for existing loans. We then analyze collateral reappraisal practices and value changes following severe weather shocks, providing insight into banks' ongoing risk management in a changing physical environment.

To this end, we restrict our sample to loans secured by real-estate collateral, a major portion of bank collateral directly vulnerable to severe weather: Real-estate values can be directly impacted by weather-related damages, making it a primary channel for banks to assess and manage physical risk. Detailed location data for real-estate collateral allows us to precisely measure exposure to local weather events. This eliminates the need for firm address information and enables inclusion of firms with multiple establishments, as the risk assessment centers on the value of real-estate collateral for which exact location is available.

To examine the relationship between weather events and collateral terms, we construct several variables to capture changes in collateral requirements for a given contract. First, we investigate the probability that collateral is re-evaluated following extreme weather events. To this end, we create an indicator variable that takes a value of one if the collateral value is adjusted in a given month, and zero otherwise. Second, we calculate the number of days between reappraisals, a metric that helps address concerns that we may be capturing pre-scheduled reappraisals. Finally, we compute the percentage change in collateral values, which enables us to assess both the magnitude and direction of these adjustments.

To analyze the ex post collateral management, we estimate following regression:

$$
\begin{aligned}
Y_{l(f,b),t} = &\beta SevereWeather_{c,t-1} \\
&+ \boldsymbol{\delta'} \boldsymbol{X}_{l,t-1} + \boldsymbol{\gamma'} \boldsymbol{Z}_{f,t-1} + FE + \epsilon_{l(f,b),t},
\end{aligned} \tag{2}
$$

where $Y_{l(b,f),t}$ is either the probability of reappraisal, denoted by $\mathbb{P}$[Reappraisal], the natural logarithm of the number of days between reappraisal, or the percent change in collateral value, respectively. $\boldsymbol{Z}_{f,t-1}$ and $\boldsymbol{X}_{l,t-1}$ is the same vector of controls as previously (loan amount, size, leverage, and profitability) plus the loan interest rate. As we follow a specific loan contract over time, we can include firm fixed effects in this regression.

The result for the probability of reappraisal is reported in column (1) of Table 4. The point estimates indicate that a increase in the number of severe weather events is associated with a decrease in the probability of collateral reappraisal. Specifically, a one-day increase in the number of severe weather days reduces the likelihood of reappraisal by 13 basis points, which corresponds to a 2% decrease in the probability of reappraisal, given an average reappraisal rate of 7%. Next, column (2) presents the result for the number of days between reappraisals, based on the sample of days with reappraisals. The point estimates suggest that a one-day increase in the number of severe events leads to a 2.9% decrease in the number of days between reappraisals, in other words, a one-day increase in number of severe weather days reduces the time between reevaluation, on average, by 10 days. These findings suggest that, conditional on reappraisal, banks may increase the frequency of collateral reappraisals following weather-related shocks.

We further investigate whether banks reduce the value of collateral for loans issued in areas more affected by severe weather events when they do reappraise. The estimates in column (3) of Table 4 suggest that, indeed, following severe weather events, conditional on reappraisal, the collateral value is adjusted downwards: a one-day increase in the number of severe events reduces the collateral value by 76 basis points.

Together, the findings in Table 4 define a new ex post collateral management effect: banks reduce the overall likelihood of reappraisal after severe weather. However,rather than symmetric adjustments, we document that conditional reappraisals are accelerated and predominantly results in downward adjustments of collateral value. This pattern suggests that banks may prioritize the most obvious or large damages, while smaller or less evident impacts may remain unaccounted for until sufficient information and expertise become available. From a policy perspective, this selectivity implies that some climate-related losses may remain unrecognized for a prolonged period, even if they eventually materialize in collateral values. Although the paper does not quantify the aggregate size of this unrecognized component, the asymmetric pattern suggests a potential build-up of under-appreciated risk on bank balance sheets.

Our analyses so far illustrate that severe weather events significantly influence collateral requirements at loan origination and affect collateral management for existing loans. Firms exposed to frequent severe weather are more likely to be required to post collateral and tend to pledge larger amounts relative to their borrowing, reflecting tighter financial constraints linked to acute climate risk.

For existing loans, we observe lower probabilities of collateral reappraisal overall; however, conditional on reappraisal, more frequent adjustments and downward revisions in collateral values following weather shocks. These results underscore the complex ways physical climate risks reshape credit conditions, with implications for lender risk management and financial stability. To further explore the mechanisms underlying our results, in the following section we examine how geographic proximity between banks and borrowers interacts with the effects of weather shocks on collateral practices.

4 Which Banks Re-evaluate?

The previous section has shown that shocks to firms' creditworthiness and payment abilities affect collateral on two separate margins: first, the shocks affect ex ante collateral requirements leading to an increased collateralization, and second, they affect the ex post collateral management of existing loans. Crucially, the ex post management depends on banks ability to monitor the firm and the collateral after shock. It may also depend on the banks ex ante incentives on screening its borrowers. The banking literature has proposed a number of different bank characteristics affecting lending, such as capitalization, specialization or proximity. Given the current literature and the particularly novel result on ex post collateral management, this raises the question of how banks' characteristics—particularly their geographic proximity to borrowers—shape the likelihood and timing of collateral revaluation or its postponement.

4.1 Bank Proximity

Banks with stronger local presence may have better information about actual risk conditions and borrower quality, potentially moderating their reliance on collateral re-evaluations as a risk management tool. Conversely, greater local presence might also increase loan officers' attention to weather events, amplifying the collateral response. To test these competing hypotheses, we formally estimate the following regression:

$$\begin{aligned} Y_{l(f,b),t} =& \beta SevereWeatherc, t-1 + \eta SevereWeather_{c,t-1} \times \mathit{Bank\ Presence}_{f,b,t-1} \\ &+ \boldsymbol{\delta}'\boldsymbol{X}_{l,t-1} + \boldsymbol{\gamma}'\boldsymbol{Z}_{f,t-1} + FE + \epsilon_{l(f,b),t}, \end{aligned} \tag{3}$$

where we focus first on measures of ex post collateral management for existing loans. Specifically, $Y_{l(f,b),t}$ is either the probability of reappraising collateral, the number of days in between reappraisal, or the change in the value of collateral after reappraisal. We then show that analogous patterns arise for ex ante collateral requirements at origination when using the same measures of bank presence.

We measure *Bank Presence* in several different ways. Using data on the lending bank branch locations and the location of the firm establishment,[8] we compute an indicator variable, *Has Branch*, that equals one if the lending bank operates at least one branch in the same municipality as the firm. Alternatively, to measure proximity, we compute the driving distance between the *firm address* and the *bank branch*, measured in time.[9] Using this variable, we create a

[8]Data of bank branches and their address have been obtained from Amberg and Becker (2024). The full description of the data can be found in Section 3.1 of their paper.

[9]To measure proximity, we originally computed the driving distance between the *firm address* and the *bank branch* both in time and kilometers. However, since both measures yield the same results, we focus on the

dummy variable (*High Distance*) equal to one if the firm is in the top 25 percent of the distance distribution and zero otherwise. The average driving time for the firms in the 75 percent of the driving distribution is under 15 minutes.

Table 5 focuses on measures of collateral reappraisal and employs all existing loans. In these regressions, $Y_{l(f,b),t}$ is either the probability of changing collateral, the number of days in between reappraisal, or the change in the value of collateral after reappraisal, and the analysis centers on the location of the collateral itself. Currently, we are only able to calculate the distance variable using the full address of a firm and not using the location of the collateral. In fact, KRITA reports only the zip code of the collateral and not its full address. Therefore, when studying reappraisal practices in Table 5, we only show results with the variable *Has Branch*.

The results indicate that the presence of a local branch systematically attenuates the effect of severe weather on ex post collateral management. Banks without a local branch are more likely to reduce the probability of reappraisal after severe weather, and, conditional on reappraisal, to shorten the interval and adjust collateral values downwards, whereas banks with a local presence exhibit a weaker response along all three dimensions. This attenuation is consistent with local presence reducing informational frictions: when loan officers have better access to soft information about borrowers and collateral, they may need fewer drastic adjustments to reported collateral values, while banks operating at a distance rely more heavily on selective, event-triggered revaluations.

4.1.1 Bank Proximity and New Loan Originations

To relate these ex post patterns to ex ante collateral standards, Table 6 turns to loan origination and employs firms with only one establishment for which the *full address* is available. In these specifications, the variable $Y_{l(f,b),t}$ is the probability of posting collateral, the collateral amount, or the collateral ratio. Using the same measures of bank presence as above, we study whether the sensitivity of collateral requirements at origination to severe weather shocks varies with proximity.

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distance measured as the amount of time it takes to drive from the bank branch to the firm.

Focusing on loan origination, Table 6 shows that although severe weather days are generally associated with a higher probability of collateral being posted and larger collateral amounts being required, these effects are noticeably weaker for firms located closer to their lending bank. These findings align with the extensive literature on the importance of banking relationships in alleviating credit frictions. Geographic proximity enables lenders to gather soft information, screen borrowers more effectively, and monitor their performance—often resulting in more favorable borrowing conditions (Granja, Leuz, and Rajan, 2022). Our results further suggest that a local presence enhances banks' ability to evaluate the potential consequences of acute physical climate risks. Specifically, officers at nearby banks, by being more attuned to local events, may be better positioned to assess both the immediate and longer-term implications of severe weather events for their clients.

The evidence on collateral amounts, measured both in absolute terms and relative to loan size, supports this view: collateral requirements increase with greater bank–borrower distance, indicating that arm's-length lending amplifies the impact of climate shocks on collateralization. This conclusion is reinforced when using alternative distance measures, as the effect of severe weather is significantly larger for firms geographically farther from their lending bank branches. Moreover, for existing loans, Table 5 shows that when the lending bank maintains a branch in the same municipality as the firm, the correlation between severe weather intensity and collateral practices is reduced. In other words, the presence of a local branch attenuates the impact of severe weather on both the likelihood and the intensity of collateral adjustments, ex ante and ex post.

Taken together, our findings suggest that local banking relationships can play a stabilizing role in integrating physical climate risks into credit assessments by enhancing lenders' ability to evaluate the consequences of severe weather events. At the same time, they show that the novel ex post margin—how and when existing collateral is re-evaluated—is tightly linked to the same proximity mechanism that governs ex ante collateral standards. However, proximity to clients may also encourage bank officers to place greater emphasis on preserving longstanding relationships, potentially leading to a more gradual adjustment of credit terms in response to climate-related risks.

4.2 Local Presence of Banks

To better understand this nuanced dynamic, we next examine how the relationship between severe weather and collateral practices varies with different indicators of *bank presence*, reflecting the importance of a given municipality within a lending bank's portfolio. We first focus on ex post collateral management for existing loans, and then show that similar patterns arise for ex ante collateral requirements at origination.

First, we measure the relevance of a municipality for a bank by calculating the share of its branches located there.[10] This measure captures the bank's strategic presence, market commitment, and depth of local knowledge and relationships, all of which enhance its capacity to make informed and timely credit decisions within that locality. Second, to evaluate potential declines in local attention, we identify branch closures by each bank in specific municipalities, based on the assumption that such closures diminish the bank's focus and monitoring ability in those areas.

Table 7 reports the estimates for collateral reappraisals of existing loans. In these regressions, the outcome variables capture the probability of changing collateral, the number of days between reappraisals, and the change in collateral values upon re-evaluation. The interaction terms with municipality relevance are generally consistent with the proximity results: a greater strategic presence of banks within a municipality is associated with a weaker sensitivity of re-evaluation behavior to severe weather shocks, while branch closures amplify the response of reappraisal probabilities, timing, and value changes to adverse weather. These patterns suggest that when a municipality is more central to a bank's network, the bank relies less on drastic ex post collateral adjustments after severe weather, whereas diminished local presence heightens the use of selective, and often downward, re-evaluations.

[10] Specifically, we compute *Municipality Relevance* $= \frac{\#branches\ of\ bank\ b\ in\ county\ c}{\#branches\ of\ bank\ b\ in\ Sweden}$.

4.2.1 Bank Presence and New Loan Originations

Table 8 then turns to loan origination and shows that analogous relationships emerge for ex ante collateral requirements. The interaction terms with municipality relevance are predominantly negative, albeit only significantly so in the case of the probability of collateralization. This pattern suggests that a greater strategic presence of banks within a municipality may diminish the sensitivity of collateral requirements to severe weather shocks, arguably due to enhanced local monitoring, superior information acquisition, and more effective borrower screening. Conversely, coefficients associated with branch closures are positive and statistically significant at the 5% level for both collateral probability and collateral amount, indicating that diminished local banking presence intensifies the responsiveness of collateral practices to adverse weather events.

From a policy perspective, our findings underscore the stabilizing role that proximity in banking relationships can play in incorporating physical climate risks into credit assessment frameworks. Banks with a strong local presence appear better equipped to monitor and evaluate both the immediate and longer-term consequences of severe weather events for their clients, enhancing the accuracy of risk assessments and supporting resilience in credit markets amid rising climate-related physical risks. At the same time, proximity and the strategic relevance of certain municipalities may also lead bank officers to prioritize preserving established client relationships, which could result in a more gradual adjustment of credit terms in response to evolving climate risks. Unfortunately, our current analyses are not able to discern between these two contrasting hypotheses. However, this dual effect highlights that relationship lending, while beneficial for localized monitoring, carries the potential to moderate the pace at which climate risks are fully incorporated into credit decision-making. Accordingly, these insights emphasize the critical importance of supervisory guidance and consistent risk management standards. Regulators and supervisors should ensure that relationship lending practices bolster, rather than unintentionally undermine, the financial system's resilience to climate shocks by promoting vigilant local monitoring alongside prudent and timely risk adjustments.

4.3 Specialization in CRE Lending

Building on the evidence that local bank presence mitigates the effects of climate shocks through enhanced information and monitoring, we next consider how banks' lending portfolio specialization contributes to similar informational advantages.

In a similar spirit to the roles of relationship lending and geographic proximity discussed above, banks' specialization may influence how they manage real estate collateral after adverse weather events (Blickle, Parlatore, and Saunders, 2023). Specialization in commercial real estate (CRE) lending typically involves repeated interactions with property developers and investors, fostering long-standing relationships and a nuanced understanding of both client behavior and local market conditions. Through these repeated dealings, lenders accumulate soft information—idiosyncratic knowledge about borrowers, property characteristics, and contextual factors that are difficult to codify or verify externally. This soft information may enables CRE-specialized banks to interpret weather-related disruptions more accurately, distinguishing between transient damage and structural declines in asset value. Consequently, these banks may face less uncertainty regarding collateral quality and may exhibit smaller adjustments in collateral requirements following severe weather, consistent with the informational-friction mechanism highlighted earlier.

To test whether this informational advantage translates into distinct re-evaluation patterns, we identify CRE-intensive banks as those in the top quartile of the distribution of CRE lending shares—measured as total loans to CRE firms relative to total corporate lending in the credit registry. The estimates reported in Table9 indicate that, consistent with this interpretation, the behavior of CRE-specialized banks is less responsive to severe weather shocks. The decline in the likelihood of collateral reappraisal is noticeably weaker for these banks, and conditional on reappraisal, the interaction term shows little evidence of timing adjustments. Moreover, CRE-exposed lenders implement smaller downward revisions to collateral values. Together, these findings reinforce the view that accumulated soft information mitigates uncertainty and helps stabilize credit relationships in the wake of adverse weather shocks.

Having established the role of banks' informational capacity in shaping their responses to adverse weather, we now turn to the borrower side and examine how firm heterogeneity influences the way severe weather events are reflected in collateral management.

5 Which Borrowers are Re-evaluated?

Our baseline results indicate that severe weather exerts a statistically significant influence on banks' collateral requirements and that proximity between the lending bank and the firm significantly reduces the effect. Nonetheless, the magnitude of this effect is likely context-dependent and shaped by firm-specific characteristics. To capture this heterogeneity, we next analyze how geographical location and industry-level exposure influence the effect of severe weather, employing interaction terms with measures that reflect these dimensions. We also study a particularly devastating event, the flood in Gävleborg in August 2021, and try to assess the role played by insurance. Results are summarized in in Table 11 and Table 10.

The analyses in Table 11 focus on loans origination and employ the location of the one-establishment firms to study the probability of posting collateral. Instead, in Table 10, we study the probability that real-estate collateral is reappraised. In this latter Table, we employ all existing loans and match directly on the zip code of the real-estate collateral posted by the firms in our sample (both single and multiple establishments firms).

5.1 Weather Sensitivity of Rural and Urban Municipalities

We start by analyzing how the impact of severe weather on collateral practices is affected by the geographic location of the firms.

Column (1) of Table 11 analyzes the potentially different effects depending on whether a firm is located in a rural or densely urban municipality. The coefficient on $SevereWeather$ by itself captures the effect for the omitted category representing mixed municipalities that are not entirely rural, but outside the main cities. The results suggest that the effects of severe weather do not affect the probability of posting collateral for firms located in major cities. Results in column (1) of Table 10 shows that for existing loans, collateralized by real-estate located in main urban or rural areas, the effect on the probability of collateral to be reappraised is very similar to the main effect captured in column (1) of Table 4 which indicate that banks most likely tend to reassess collateral only after events that cause substantial or immediately visible damage.

Overall, these results highlight that the effect of physical climate risks on collateral requirements and their subsequent management is much more pronounced outside city centers. From a policy standpoint, this underscores the importance of targeted supervisory attention on credit markets outside major urban areas, ensuring banks employ robust risk assessment practices tailored to the greater vulnerabilities present there—while also avoiding unnecessary interventions in more resilient urban loan portfolios.

5.2 Weather-Exposed Sectors: Agriculture, Forestry, and Fishing

We next turn to study how industry heterogeneity affects our results. Therefore, in Column (2) of Table 11 and Table 10 we interact our main variable of interest $SevereWeather$ with an indicator variable equal to one if the firm operates within the agriculture, forestry, or fishing sectors.

These industries are particularly significant in Sweden and are frequently exposed to adverse weather conditions, as reflected in the positive and significant coefficient on the interaction term in column (2) of Table 11. Firms in these sectors are more likely to be required to post collateral following severe weather events compared to firms in other industries. Notably, adding this interaction term leaves the baseline effect of the $SevereWeather$ variable largely unchanged, suggesting that both general and industry-specific weather risks influence collateral practices.

However, evidence from Column (2) of Table 10 reveals that, when it comes to existing loans backed by real-estate, agricultural, forestry, and fishing firms are not more likely than firms in other sectors to have their collateral reappraised after adverse weather. This may point to a certain reluctance among banks to frequently adjust collateral values for these sectors, possibly due to the challenges associated with rural land valuation or the episodic nature of agricultural income.

Taken together, these results highlight the complexity of managing climate risk in sectors with direct exposure to weather shocks. From a policy perspective, they suggest that while more stringent collateral requirements for at-risk industries may be warranted, careful consideration should be given to ensuring these measures do not unduly limit credit access. Encouraging nuanced, sector-sensitive approaches to collateral management could help balance the goals of financial stability and continued support for industries particularly exposed to climate risks.

5.3 Limits of Insurance for Risk Mitigation

Insurance can provide important financial protection for firms exposed to climate hazards and may influence how banks adjust collateral requirements. To investigate this, we incorporate insurance payout data and examine whether insurance moderates the relationship between severe weather events and collateral practices.

While business insurance is not legally mandatory for all firms in Sweden, its role in mitigating financial risks makes it a critical component of corporate risk management and bank-firm relationships. Banks may require borrowers to carry specific types of insurance—particularly when loans are secured by physical assets—as these requirements serve to protect both lenders and borrowers against adverse events that could impair repayment capacity. The presence of adequate insurance can reduce the perceived risk associated with physical assets used as collateral, potentially allowing firms to access more favorable loan terms, including lower collateral-to-loan ratios. These dynamics align with previous findings that real-estate and other immovable assets are widely preferred as collateral due to their stable value and ease of recovery in case of default (Benmelech and Bergman, 2009; Calomiris, Larrain, Liberti, and Sturgess, 2015). However, climate risks pose a growing challenge to these assumptions, as properties in vulnerable areas are increasingly subject to devaluation and liquidity concerns (Sastry, 2022; Sastry, Sen, and Tenekedjieva, 2024).

To examine the role of insurance in the relationship between climate events and collateral provision, we incorporate disaster-related insurance payout data from Insurance Sweden, which reports damages covered by Swedish insurers between 2015 and 2023.

Column (4) of Table 11 reports the results for existing loans, when specifically controlling for insurance claim payouts separately and interacted with the measure of severe weather. The estimates on severe weather and insurance payouts separately are positive and significant, while the coefficient on the interaction term is indistinguishable from zero. The results suggest that higher insurance payouts are likely related to larger events. As the baseline effect on severe weather persists, it also provides evidence that insurance, most likely, does not cover all the damages.

Column (4) of Table 10 reports the same regression but for the likelihood or reappraisal. The baseline estimate on severe weather remains unchanged when we additionally control for insurance payouts. The coefficient on the insurance payout and the interaction terms are however, insignificant, and their magnitudes are close to zero. Together, these results indicate that while insurance availability and payouts are associated with tighter collateral requirements—likely reflecting residual risk or compensation limitations—they do not meaningfully reduce the sensitivity of collateral practices to acute climate events.

Economically, these findings point to the limits of insurance as a financial buffer in the face of escalating climate risk: although it can temper some lending constraints, it does not fully shield banks (or firms) from the need to adjust collateral terms after severe events. This underscores the critical importance of improving the collection and transparency of detailed data on insurance coverage, claims, and payouts to better understand the interaction between insurance and credit risk management under climate stress. Enhanced data availability would also support more effective risk pricing and regulatory oversight.

For policymakers, these insights highlight the need to strengthen both the insurance sector's resilience to climate losses and the integration of insurance considerations into prudential frameworks, while recognizing that insurance alone cannot eliminate the necessity for banks to actively manage and reassess credit risk amid increasing physical climate hazards.

5.4 Strategic Re-evaluation: Evidence from the Gävleborg Flood

Next, we zoom in on one of the major floods that occurred in Sweden during our sample. In August 2021, in the county of Gävleborg, over 100mm of rain fell in just two hours, costing over SEK 1,800 million to Swedish insurance companies (Svensk Försäkring, 2024). In Column (3) Table 11 and Table 10, we test whether our baseline results are driven by that episode by including an interaction term between an indicator variable that equals one if the firm is located in the county of Gävleborg and a *Post* variable that equals one in the months after the flood.

In line with our analysis, Column (3) Table 11 shows that the coefficient on the interaction term is positive and significant when studying the probability of posting collateral at loan origination. This result suggests that firms in Gävleborg have been required to provide more collateral since the flood. Moreover, the baseline effect of $SevereWeather$ is not eliminated by the additional control, implying that the observed relationship between weather shocks and collateral requirements is not solely attributable to this single episode.

For existing loans secured by real-estate, reported in Table 10, we find that collateral for firms in Gävleborg has been even less likely to be reappraised after the flood compared to the average firm in the sample. This may reflect a cautious approach by banks, who might be balancing the need to update collateral values with concerns about stability for both borrowers and their own balance sheets in the wake of a major event.

Taken together, the proximity and heterogeneity results point to informational frictions as a central mechanism. Banks operating closer to borrowers appear less reliant on collateral tightening and selective reappraisals after severe weather shocks, consistent with better soft information and closer monitoring. In contrast, distant lenders and those with weaker local presence exhibit stronger collateral responses to the same events, which is harder to reconcile with a purely mechanical or regulation-driven adjustment and more consistent with climate shocks interacting with pre-existing information gaps.

6 Conclusion

This paper investigates how banks incorporate physical climate risks into their credit risk assessments, with a particular focus on the role of collateral. While much of the existing literature emphasizes loan pricing as the main channel through which climate risks manifest, our study highlights collateral requirements as a distinct and critical mechanism and underscores the importance of soft information production in the relationship between lenders and borrowers.

Collateral is a cornerstone of lending contracts, and its valuation plays a key role in determining firms' access to external financing (Rajan and Zingales, 1995; Rampini and Viswanathan, 2013). Given that real-estate—one of the most significant collateral types—is highly vulnerable to physical climate risks, understanding how banks adjust collateral practices in response to climate-related shocks is essential for both academics and policy makers.

Our findings show that local severe weather events, serving as proxies for acute physical climate risk, is associated with banks increasing collateral requirements and reducing collateral reappraisals, reflecting efforts to mitigate short-term risks to climate-exposed assets. This tightening of collateral constraints may restrict financing access precisely when firms need support for recovery. Notably, proximity between the lending bank and the firms (or real-estate assets employed as collateral), as well as lending specialization, mitigate these effects, highlighting the stabilizing role soft information production.

We also document meaningful heterogeneity: collateral adjustments are more pronounced for rural firms and those in environmentally sensitive sectors, while urban firms exhibit little response. Insurance payouts correlate with higher collateral but do not meaningfully temper banks' sensitivity to climate shocks, signaling limits to insurance as a risk buffer.

Overall, our results suggest that banks mitigate potential losses from physical climate risks through stricter collateral requirements. However, this practice may heighten firms' financial constraints, with potential adverse effects on local and aggregate economic activity. While studying these real effects lies beyond this paper's scope, they represent a promising avenue for future research.

In this context, integrating comprehensive policy-level insurance data, strengthening local monitoring, and developing targeted stress tests that capture physical risk heterogeneity and institutional capacity should be key priorities for financial authorities. Advancing these measures will be critical to enhancing the resilience of the financial system and mitigating widespread losses in economic activity as climate-related physical risks intensify.

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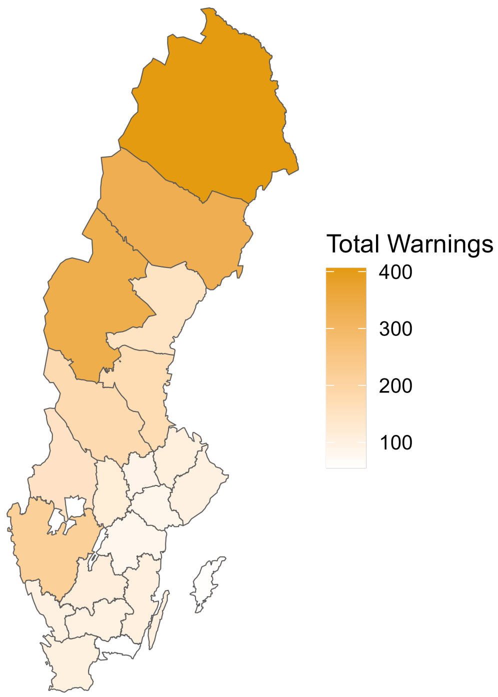

Figure 1: Extreme weather warnings in Sweden from SMHI.

Table 1: Summary Statistics

This table presents summary statistics on loan origination variables (Panel A) and loan performance variables (Panel B) for the sample periods from 2019 to 2024. The data combine information from the Swedish Credit Registry, balance sheet data from Serrano, and weather warnings from the Swedish Meteorological Institute (SMHI) at the monthly frequency. *Default Prob. (UC)* is obtained from the Swedish Credit Bureau, UC, and is available for a large subsample of firms.

	Number of Obs.	Mean	p5	Q1	Median	Q3	p95	Max	Standard Deviation
Panel A: Loan Origination									
Prob(Collateral)	151,496	0.81	0	1	1	1	1	1	0.40
log(Collateral Amount)	109,148	13.99	11.38	12.83	13.89	15.07	17.30	23.76	2.01
log(Loan Amount)	150,808	13.90	11.51	12.69	13.71	14.87	17.14	23.02	1.72
Collateral-to-Loan	150,013	0.69	0	0	1.00	1.00	1.18	2.34	0.47
Interest Rate	146,947	0.04	0.01	0.02	0.04	0.06	0.08	0.35	0.02
SevereWeather	115,964	0.07	0	0	0.03	0.10	0.23	0.58	0.08
Panel B: Loan Performance									
log(Collateral Amount)	5,967,999	16.53	13.96	15.50	16.65	17.80	19.12	25.24	2.11
P(Reappraisal)	5,988,211	0.07	0	0	0	0	1	1	0.25
Change in Collateral Value	5,857,050	0.39	0	0	0	0	0	75.82	5.22
Nb. Days Between Reappraisals	316,227	138.66	30	31	61	214	366	366	134.19
log(Loan Amount)	5,772,048	15.91	12.24	14.74	16.00	17.32	19.55	23.22	2.38
Interest Rate	5,977,387	0.03	0.01	0.01	0.02	0.04	0.06	0.38	0.02
SevereWeather	3,811,811	0.07	0	0	0.03	0.10	0.23	0.58	0.08
Panel C: Firm Characteristics									
log(Total Assets)	97,272	8.97	6.27	7.88	8.98	10.06	11.58	15.59	1.61
Leverage	70,797	0.81	0.24	0.56	0.78	0.98	1.61	19.44	0.39
RoA	70,787	0.11	-0.09	0.02	0.06	0.15	0.49	1.52	0.18
Driving Distance (Km)	62,233	17.24	0.62	2.19	7.38	21.90	58.55	759.89	30.76
Driving Time (Min)	62,233	18.29	1.55	4.41	10.29	23.64	54.99	682.78	26.71

Table 2: Severe weather days and other determinants of collateral

The sample is constructed at loan origination using data from the credit registry, Serrano, and UC. We perform the following regression:

$$\mathbb{P}[Collateral]_{l(f,b),t} = \beta SevereWeather_{cf,t-1} + \boldsymbol{\delta}' \boldsymbol{X}_{l,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{b,t-1} + FE + \epsilon_{f,b,t},$$

where $\mathbb{P}[Collateral]_{l(f,b),t}$ is the probability that a loan is collateralized or not; The variable takes either value 1 or 0. *SevereWeather* captures a firm's exposure to severe weather and is defined as the number of days with severe weather warnings in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. The regressions include an increasing number of fixed effects, up to county-by-industry-bank, season, and year FE, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Collateral)					
	(1)	(2)	(3)	(4)	(5)	(6)
SevereWeather	0.162***	0.159***	0.104***	0.107***	0.101***	0.103*
	(5.661)	(5.795)	(2.906)	(3.003)	(2.918)	(1.905)
Interest Rate	-2.916***	-0.909***	-0.802***	-0.862***	-0.867***	-0.838**
	(-6.692)	(-4.039)	(-4.214)	(-4.431)	(-4.987)	(-2.132)
log(Total Loan)	0.021***	0.001	0.002	0.003	0.005*	0.006***
	(3.676)	(0.392)	(0.593)	(1.103)	(2.068)	(3.696)
RoA	-0.129***	-0.017	-0.019*	-0.022**	-0.026***	0.050
	(-10.941)	(-1.549)	(-2.007)	(-2.295)	(-2.976)	(1.299)
Leverage	0.105***	0.072***	0.053***	0.050***	0.044***	-0.002
	(7.500)	(7.683)	(6.760)	(6.226)	(7.052)	(-0.106)
log(Total Assets)	0.011***	0.009***	0.008***	0.008***	0.008***	-0.017**
	(3.670)	(4.514)	(3.453)	(4.117)	(4.433)	(-2.254)
Observations	106,782	106,782	106,782	106,782	106,782	106,782
R^2	0.065	0.200	0.216	0.229	0.290	0.726
Fixed Effects:						
County		✓				
Bank		✓				
Year		✓	✓	✓	✓	✓
County-Bank			✓	✓		
Season			✓	✓	✓	✓
Industry			✓			
County-Industry				✓		
County-Bank-Industry					✓	✓
Firm						✓

Table 3: Collateral amounts and severe weather days

The sample is constructed at loan origination using data from the credit registry, Serrano, and UC. We perform the following regression:

$$Y_{l(f,b),t} = \beta SevereWeather_{c,t-1} + \boldsymbol{\delta}'\boldsymbol{X}_{l,t} + \boldsymbol{\gamma}'\boldsymbol{Z}_{b,t-1} + FE + \epsilon_{f,b,t},$$

where Y is either the natural logarithm of the total collateral value posted or the collateral value to loan ratio. *SevereWeather* captures a firm's exposure to severe weather and is defined as the number of days with severe weather warnings in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. The regression includes county-by-bank, county-by-industry, season, and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	log(Collateral Value)	Collateral-To-Loan Ratio
	(1)	(2)
SevereWeather	1.166***	0.047*
	(3.033)	(1.947)
Interest Rate	-6.722***	-0.634***
	(-3.133)	(-3.115)
log(Total Loan)	0.973***	0.019***
	(9.417)	(3.946)
RoA	0.280	-0.003
	(0.844)	(-0.158)
Leverage	0.728***	0.045***
	(6.909)	(5.506)
log(Total Assets)	0.002	0.000
	(0.029)	(0.006)
Observations	106,782	106,782
R^2	0.354	0.281
Fixed Effects:		
County-Bank	✓	✓
Year	✓	✓
Season	✓	✓
County-Industry	✓	✓

Table 4: Severe weather days and timing of collateral appraisal

The sample is the sample of outstanding loans in every month and is constructed using data from the credit registry, Serrano, and SMHI. We perform the following regression:

$$
\begin{aligned}
Y_{l(f,b),t} = & \beta SevereWeather_{c,t-1} \\
& + \boldsymbol{\delta}' \boldsymbol{X}_{l,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{b,t-1} + FE + \epsilon_{f,b,t},
\end{aligned}
$$

where Y is either $\mathbb{P}[Reappraisal]_{l(f,b),t}$, the probability that a the collateral value changes from one month to the other —The variable takes value 1 or 0; $log(Nb.\, Days\, Between\, Change)$, which is the total number of days from an observed change in collateral value to the next observed change; and the percent change in collateral value defined as $(Collateral\, Value_{l,t} - Collateral\, Value_{l,t-1})/Collateral\, Value_{l,t-1}$. $SevereWeather$ captures a firm's exposure to severe weather and is defined as the number of days in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. The regression includes firm, county-by-bank, county-by-industry, season and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Reappraisal)	log(Nb. Days Between Reappraisals)	log(Change in Collateral Value)
	(1)	(2)	(3)
SevereWeather	-0.037***	-0.859***	-0.226**
	(-8.019)	(-11.475)	(-2.080)
log(Loan Amount)	-0.002***	0.032***	0.049***
	(-4.320)	(3.258)	(2.583)
Interest Rate	0.088	-2.777***	2.624***
	(1.404)	(-6.653)	(3.099)
log(Total Assets)	0.001	-0.011	0.029
	(0.314)	(-0.668)	(1.197)
Leverage	-0.002	0.047	-0.125
	(-0.418)	(1.029)	(-1.415)
RoA	-0.009*	0.038	-0.043
	(-1.795)	(0.942)	(-0.598)
Observations	2,156,826	106,096	107,695
R^2	0.233	0.706	0.767
Fixed Effects:			
County-Bank	✓	✓	✓
Year	✓	✓	✓
Season	✓	✓	✓
Firm	✓	✓	✓
County-Industry	✓	✓	✓

Table 5: Collateral Appraisal and Bank Proximity

The sample is the sample of outstanding loans in every month and is constructed using data from the credit registry, Serrano and SMHI. We perform the following regression:

$$Y_{l(f,b),t} = \beta Severe\,Weather_{c,t-1} + \eta Severe\,Weather_{c,t-1} \times Has\ Branch_{f,t} + \boldsymbol{\delta}' \boldsymbol{X}_{l,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{b,t-1} + FE + \epsilon_{f,b,t},$$

where Y is either $\mathbb{P}[Reappraisal]_{l(f,b),t}$, the probability that a the collateral value changes from one month to the other —The variable takes value 1 or 0; $log(Nb.\,Days\,Between\,Change)$, which is the total number of days from an observed change in collateral value to the next observed change; and the percent change in collateral value defined as $(Collateral\,Value_{l,t} - Collateral\,Value_{l,t-1})/Collateral\,Value_{l,t-1}$. $Severe\,Weather$ captures a firm's exposure to severe weather and is defined as the number of days in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. $Has\,Branch$ equals one if the bank operates a branch in the same municipality as the borrower. The regression includes firm, county-by-bank, county-by-industry, season, and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Reappraisal)	log(Nb. Days Between Reappraisals)	log(Change in Collateral Value)
	(1)	(2)	(3)
SevereWeather	-0.121***	-1.350***	-0.500
	(-3.677)	(-3.705)	(-1.031)
SevereWeather × Has Branch	0.112***	0.651**	0.404
	(5.068)	(2.199)	(1.676)
Observations	2,123,747	121,289	105,622
R^2	0.237	0.725	0.760
Fixed Effects:			
County-Bank	✓	✓	✓
Year	✓	✓	✓
Season	✓	✓	✓
Firm	✓	✓	✓
County-Industry	✓	✓	✓

Table 6: Collateral and Bank Proximity

The sample is constructed at loan origination using data from the credit registry, Serrano, and UC. We perform the following regression:

$$Y_{l(f,b),t} = \beta \, Severe\,Weather_{c,t-1} + \eta \, Severe\,Weather_{c,t-1} \times Bank\ Presence_{f,t} + \boldsymbol{\delta}' \boldsymbol{X}_{l,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{b,t-1} + FE + \epsilon_{f,b,t},$$

where Y is either the natural logarithm of the total collateral value posted or the collateral value to loan ratio. *Severe Weather* captures a firm's exposure to severe weather and is defined as the number of days with severe weather warnings in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. *Bank Proximity* captures the lending banks' proximity to the borrowing firm's municipality. The measures are either *Has Branch*, an indicator variable that equals one if the lending bank has an active branch in the firm's municipality, or *High Distance (Time)*, the distance between the firm and the bank measured in minutes. The regression includes county-by-bank, county-by-industry, season, and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Collateral)		log(Collateral Value)		Collateral-To-Loan Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
SevereWeather	0.175***	0.002	2.183**	0.157	0.136**	-0.031
	(3.009)	(0.053)	(2.792)	(0.351)	(2.259)	(-0.845)
SevereWeather × Has Branch	-0.112*		-1.637**		-0.138**	
	(-2.085)		(-2.147)		(-2.282)	
SevereWeather × High Distance (Time)		0.099**		1.209**		0.101*
		(2.451)		(2.266)		(2.044)
Observations	106,782	54,032	106,782	54,032	106,782	54,032
R^2	0.292	0.198	0.426	0.297	0.364	0.251
Fixed Effects:						
County-Bank-Industry	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Season	✓	✓	✓	✓	✓	✓

Table 7: Collateral Appraisal and Bank Relevance

The sample is the sample of outstanding loans in every month and is constructed using data from the credit registry, Serrano, and SMHI. We perform the following regression:

$$Y_{l(f,b),t} = \beta Severe\,Weather_{c,t-1} + \eta Severe\,Weather_{c,t-1} \times Bank\ Relevance_{f,b,t-1} + \boldsymbol{\delta}'\boldsymbol{X}_{l,t} + \boldsymbol{\gamma}'\boldsymbol{Z}_{f,t-1} + FE + \epsilon_{l(f,b),t}$$

where Y is either $\mathbb{P}[Reappraisal]_{l(f,b),t}$, the probability that a the collateral value changes from one month to the other —The variable takes value 1 or 0; $log(Nb.\,Days\,Between\,Change)$, which is the total number of days from an observed change in collateral value to the next observed change; and the percent change in collateral value defined as $(Collateral\,Value_{l,t} - Collateral\,Value_{l,t-1})/Collateral\,Value_{l,t-1}$. $Severe Weather$ captures a firm's exposure to severe weather and is defined as the number of days in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. $Bank\,Relevance$ captures the importance of a municipality to the lending bank. The measures are either $High\,Municipality\,Relevance$, the share of loans the lending bank issues in the firm's municipality or $Branch\,Closure$ that equals one if the lending bank has closed at least one branch in the municipality. The regression includes firm, county-by-bank, county-by-industry, season, and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Reappraisal)		log(Nb. Days Between Reappraisals)		log(Change in Collateral Value)	
	(1)	(2)	(3)	(4)	(5)	(6)
SevereWeather	-0.052**	-0.036*	-1.043***	-0.965***	-0.371	-0.350
	(-2.452)	(-2.069)	(-4.478)	(-5.296)	(-0.831)	(-0.774)
SevereWeather × High Municipality Relevance	0.044***		0.466*		0.542**	
	(2.866)		(2.067)		(2.637)	
SevereWeather × Branch Closure		-0.015		0.240		1.048*
		(-1.215)		(0.918)		(1.991)
Observations	2,123,747	2,123,747	121,289	121,289	105,622	105,622
R^2	0.237	0.237	0.725	0.725	0.760	0.760
Fixed Effects:						
County-Bank	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Season	✓	✓	✓	✓	✓	✓
Firm	✓	✓	✓	✓	✓	✓
County-Industry	✓	✓	✓	✓	✓	✓

Table 8: Collateral and Bank Relevance

The sample is constructed at loan origination using data from the credit registry, Serrano, and UC. We perform the following regression:

$$\begin{aligned} Y_{l(f,b),t} =& \beta Severe\,Weather_{c,t-1} + \eta Severe\,Weather_{c,t-1} \times Bank\ Relevance_{f,b,t-1} \\ &+ \boldsymbol{\delta'} \boldsymbol{X}_{l,t} + \boldsymbol{\gamma'} \boldsymbol{Z}_{f,t-1} + FE + \epsilon_{l(f,b),t} \end{aligned}$$

where Y is either the natural logarithm of the total collateral value posted or the collateral value to loan ratio. $Severe\,Weather$ captures a firm's exposure to severe weather and is defined as the number of days with severe weather in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. $Bank\,Relevance$ captures the importance of a municipality to the lending bank. The measures is either $High\,Municipality\,Relevance$, the share of loans the lending bank issues in the firm's municipality or $Branch\,Closure$ that equals one if the lending bank has closed at least one branch in the municipality The regression includes county-by-bank, county-by-industry, season and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Collateral)		log(Collateral Value)		Collateral-To-Loan Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
SevereWeather	0.043	0.010	0.516*	0.127	0.016	-0.017
	(1.345)	(0.363)	(1.790)	(0.519)	(0.640)	(-0.820)
SevereWeather × High Municipality Relevance	-0.071**		-0.068		-0.051	
	(-2.358)		(-0.130)		(-1.215)	
SevereWeather × Branch Closure		0.084**		1.943***		0.086
		(2.553)		(3.289)		(1.204)
Observations	87,775	87,775	87,775	87,775	87,775	87,775
R^2	0.210	0.210	0.345	0.345	0.288	0.288
Fixed Effects:						
County-Bank-Industry	✓	✓	✓	✓	✓	✓
Year	✓	✓	✓	✓	✓	✓
Season	✓	✓	✓	✓	✓	✓

Table 9: CRE-specialization and Collateral Reappraisal

The sample is the sample of outstanding loans in every month and is constructed using data from the credit registry, Serrano, and SMHI. We perform the following regression:

$$
\begin{aligned}
Y_{l(f,b),t} =& \beta \mathit{SevereWeather}_{c,t-1} + \eta \mathit{SevereWeather}_{c,t-1} \times \mathit{High\ CRE\ Share}_{f,b,t-1} \\
&+ \boldsymbol{\delta}' \boldsymbol{X}_{l,t} + \boldsymbol{\gamma}' \boldsymbol{Z}_{f,t-1} + FE \epsilon_{l(f,b),t}
\end{aligned}
$$

where Y is either $\mathbb{P}[Reappraisal]_{l(f,b),t}$, the probability that a the collateral value changes from one month to the other; $log(Nb.\,Days\,Between\,Change)$, which is the total number of days from an observed change in collateral value to the next observed change; and the percent change in collateral value defined as $(Collateral\,Value_{l,t} - Collateral\,Value_{l,t-1})/Collateral\,Value_{l,t-1}$. *SevereWeather* captures a firm's exposure to severe weather and is defined as the number of days in a given county and given month divided by the number of days in the month. *High CRE Share* is an indicator variables that equals 1 if the bank's CRE lending share is above the sector's median. X is a vector of loan characteristics and Z a vector of firm characteristics. The regression includes Bank-Year, Firm and County fixed effects, denoted by FE. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Reappraisal)	log(Nb. Days Between Reappraisals)	log(Change in Collateral Value)
	(1)	(2)	(3)
SevereWeather	-0.202***	-1.105***	-0.918***
	(-26.686)	(-13.192)	(-8.113)
SevereWeather × High CRE Share	0.169***	0.756***	0.782***
	(17.897)	(5.714)	(4.634)
Observations	1,898,926	118,280	101,609
R^2	0.243	0.732	0.773
Fixed Effects:			
Bank-Year	✓	✓	✓
Firm	✓	✓	✓
County	✓	✓	✓

Table 10: Heterogeneous Effects on the Probability of Reappraisal

The sample is constructed at loan origination using data from the credit registry, Serrano, and UC. We perform the following regression:

$$\mathbb{P}[Reappraisal]_{l(f,b),t} = \beta SevereWeather_{cf,t-1} + \eta SevereWeather_{cf,t-1} \times Firm\ Characteristics_{f,t}$$
$$e + \boldsymbol{\delta}'\boldsymbol{X}_{l,t} + \boldsymbol{\gamma}'\boldsymbol{Z}_{b,t-1} + FE + \epsilon_{f,b,t},$$

where $\mathbb{P}[Change]_{l(f,b),t}$ is the probability that real estate collateral is reappraised; The variable takes either value 1 or 0. *SevereWeather* captures a firm's exposure to severe weather and is defined as the number of days with severe weather warnings in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. *Firm Location* is either *Rural* and *Cities*, two indicators variables that equal one if the firm is located in a rural municipality or a city, respectively and the omitted category are mixed municipalities (i.e. agglomeration), $Farming\, and\, Forestry$, the firms' industry classification or $Covid$, an indicator that equals one for the period of the pandemic (between March 2020 and May 2023). *Gävleborg* is an indicator that equals one if the firm is located in the Gävleborg county. $Post-Flood$ equals one in the period after August 2021, the date of the important flood in Gävleborg. $High\, Insurance\, Payout$ equals one if insurance payout in a given county has been in the top quartile of payouts, and zero otherwise. The regressions include an increasing number of fixed effects, up to county-by-industry-bank, season, and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Reappraisal)			
	(1)	(2)	(3)	(4)
SevereWeather	0.005	-0.038**	-0.036**	-0.037**
	(0.353)	(-2.124)	(-2.136)	(-2.151)
SevereWeather × Rural	-0.039***			
	(-4.675)			
SevereWeather × Urban	-0.045***			
	(-3.178)			
SevereWeather × Farming and Forestry		-0.016		
		(-0.501)		
Gävleborg × Post-Flood			-0.019***	
			(-6.000)	
SevereWeather × High Insurance Payout				-0.002
				(-0.048)
High Insurance Payout				0.000
				(0.163)
Observations	1,818,857	2,174,467	2,174,467	2,174,467
R^2	0.240	0.234	0.235	0.234
Fixed Effects:				
County-Bank	✓	✓	✓	✓
Year	✓	✓	✓	✓
Season	✓	✓	✓	✓
Firm	✓	✓	✓	✓
County-Industry	✓	✓	✓	✓

Table 11: Heterogeneous Effects on Probability of Collateral

The sample is constructed at loan origination using data from the credit registry, Serrano, and UC. We perform the following regression:

$$\begin{aligned} Y_{l(f,b),t} = & \beta \mathit{SevereWeather}_{c,t-1} + \eta \mathit{SevereWeather}_{c,t-1} \times \mathit{Firm\ Characteristics}_{f,t} \\ & + \boldsymbol{\delta'} \boldsymbol{X}_{l,t} + \boldsymbol{\gamma'} \boldsymbol{Z}_{f,t-1} + FE + \epsilon_{l(f,b),t} \end{aligned}$$

where $\mathbb{P}[Collateral]_{l(f,b),t}$ is the probability that a loan is collateralized or not; The variable takes either value 1 or 0. *SevereWeather* captures a firm's exposure to severe weather and is defined as the number of days with severe weather warnings in a given county and given month divided by the number of days in the month. X is a vector of loan characteristics and Z a vector of firm characteristics. *Firm Characteristics* is either *Rural* and *Cities*, two indicators variables that equal one if the firm is located in a rural municipality or a city, respectively and the omitted category are mixed municipalities (i.e. agglomeration), $Farming\, and\, Forestry$, the firms' industry classification or $Covid$, an indicator that equals one for the period of the pandemic (between March 2020 and May 2023). *Gävleborg* is an indicator that equals one if the firm is located in the Gävleborg county. $Post - Flood$ equals one in the period after August 2021, the date of the important flood in Gävleborg. $High\, Insurance\, Payout$ equals one if insurance payout in a given county has been in the top quartile of payouts, and zero otherwise. The regressions include an increasing number of fixed effects, up to county-by-industry-bank, season, and year fixed effects, denoted by FE. Standard errors are clustered at the county level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

	P(Collateral)			
	(1)	(2)	(3)	(4)
SevereWeather	0.096**	0.089**	0.119***	0.111***
	(2.396)	(2.651)	(3.389)	(3.415)
SevereWeather × Rural	0.012			
	(0.203)			
SevereWeather × Cities	-0.081**			
	(-2.267)			
SevereWeather × Farming and Forestry		0.199***		
		(3.491)		
Gävleborg × Post-Flood			0.045**	
			(2.189)	
SevereWeather × High Insurance Payout				-0.002
				(-0.028)
High Insurance Payout				0.042***
				(4.844)
Observations	88,536	106,782	106,782	106,782
R^2	0.182	0.230	0.232	0.231
Fixed Effects:				
County-Bank	✓	✓	✓	✓
Year	✓	✓	✓	✓
Season	✓	✓	✓	✓
County-Industry	✓	✓	✓	✓

A Appendix

Table A1: Variable Definitions and Data Source

Variable	Description	Source
County and weather variables		
SevereWeather	The number of days with severe weather warnings in a given county and given month divided by the number of days in the month.	SMHI
High Insurance Payout	Indicator variable that takes the value of one if the the natural logarithm of insurance claim payouts in county c in a given month is above the median payout, and zero otherwise.	Swedish Insurance Association
Loan variables at loan inception		
Collateral Value	Value of the collateral pledged by the firm	KRITA
P(Collateral)	Indicator variables that equals one if the loan is collateralized by any type of collateral, and zero otherwise.	KRITA
Collateral-to-Loan	Total value of posted collateral divided by total loan, winsorized at the industry-year at the 5% level, in decimal points	KRITA
P(Reappraisal)	Indicator variable that takes value 1 if collateral value is adjusted in a given month, and zero otherwise	KRITA
Nb. Days Between Reappraisals	Number of days from an observed change in collateral value to the next observed change	KRITA
Change in Collateral Value	Percentage change in collateral values, calculated as (Collateral Value$_t$ - Collateral Value$_{t-1}$)/Collateral Value$_{t-1}$	KRITA
Loan Amount	Sum of On balance and Off balanace	
Total Commitment	Loan commitment amount at inception	KRITA
Interest Rate	Interest rate on the loan, in decimal points	KRITA
Firm variables		

log(Total Assets)	Log of Total Assets, winsorized by industry-year at the 5% level	Serrano
RoA	Return on assets computed as EBITDA over total assets, winsorized at the industry-year at the 5% level	Serrano
Leverage	Leverage computed as total debt over total assets, winsorized at the industry-year at the 5% level	Serrano
Rural	Indicator variable that equals one if firm is located in a rural municipality, and zero otherwise	Statistics Sweden
Cities	Indicator variable that equals one if firm is located in a major city, and zero otherwise	Statistics Sweden
Farming and Forestry	Indicator variable that equals one if the firm operates in the agriculture, forestry, or fishing sectors, and zero otherwise	Serrano
Bank-Firm variables		
Has Branch	Indicator variable that equals one if the lending bank operates at least one branch in the same municipality as the firm, and zero otherwise	
High Distance (Time)	Dummy variable equal to one if the firm is in the top 25% of the driving time distribution from bank branch to firm, and zero otherwise	
Driving Distance (Km)	Distance between firm address and nearest bank branch in kilometers	
Driving Time (Min)	Driving time between firm address and nearest bank branch in minutes	
High Municipality Relevance	Indicator variable that equals one if the share of branches the lending bank has in the firm's municipality is above median, and zero otherwise	
Municipality Relevance	Share of branches the lending bank has in the firm's municipality relative to total branches in Sweden	
Branch Closure	Indicator variable that equals one if the lending bank has closed at least one branch in the municipality, and zero otherwise	

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