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Natural Disasters and Credit Risk

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Natural Disasters and Credit Risk*

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Abstract

This paper examines how large wildfires affect firm credit risk, bank behavior, and bank solvency. By matching granular bank-firm credit data to county-level wildfire episodes in Chile, the paper shows that wildfires increase firm delinquency. The effects are concentrated among small firms, firms in the agriculture and forestry sector, and firms with weak relationships with banks. After large wildfires, banks reassess climate risk by raising interest rates and cutting lending in counties with high prior exposure, even in counties not affected by the wildfires. Banks also respond by raising loan-loss provisions. However, projected losses are not large enough to impact solvency because the affected borrowers are small. Counterfactual exercises based on benchmark calibrations show that banking system resilience depends on the distribution of shocks across bank portfolios. Threatening solvency would require substantially greater lending in burned counties and shocks that affect a larger share of loans than observed historically.

Resumen

Este trabajo examina cómo los grandes incendios forestales afectan el riesgo de crédito de las empresas, el comportamiento y la solvencia de los bancos. Combinando datos granulares de crédito banco-empresa con incendios comunales en Chile, el trabajo muestra que estos aumentan la morosidad de las empresas. Los efectos se concentran en empresas pequeñas, del sector agrícola y forestal, y con relaciones bancarias débiles. Tras grandes incendios, los bancos reevalúan el riesgo climático subiendo tasas y reduciendo el crédito en comunas con alta exposición previa, incluso no quemadas. Los bancos también aumentan las provisiones. Sin embargo, las pérdidas proyectadas no afectan la solvencia porque esos deudores son pequeños. Ejercicios contrafactuales con calibraciones de referencia muestran que la resiliencia bancaria depende de la distribución de shocks entre carteras. Amenazar la solvencia requeriría un crédito mucho mayor en comunas quemadas y shocks que afecten una fracción de préstamos mayor a la histórica.

Keywords: bank loans, bank solvency, financial stability, nonperforming loans, wildfires

JEL Codes: G21, Q54

1 Introduction

Natural disasters, sometimes linked to climate change, have become notorious and costly, with significant economic impacts on communities worldwide (World Meteorological Organization, 2021; United Nations Environment Programme, 2022; IPCC, 2023). One particular concern is how such damages can propagate to the banking sector as affected borrowers become unable to service their debt, threatening the stability of individual institutions or the overall financial system (Basel Committee on Banking Supervision, 2021; Pozdyshev et al., 2025). Moreover, sufficiently large events could be transmitted to other parts of the economy that are not directly hit by those natural shocks.

In this paper, we use unique granular firm-bank data from Chile to examine how wildfires, which are highly prevalent in the country and worldwide, affect credit risk and bank behavior.[1] First, we estimate the causal impact of large wildfires on firm-level credit risk, focusing on loan delinquency and debt dynamics. Second, we examine whether banks reassess climate risk, raising rates and cutting lending in counties with high prior exposure, even when those counties are not directly hit. Third, we trace how this deterioration propagates to banks, asking whether the resulting rise in loan-loss provisions is large enough to affect solvency. Lastly, we ask how concentrated bank portfolios would have to be for wildfires to threaten solvency, mapping the rise in provisions to a fall in the capital ratio as a function of the amount lost on each affected loan and the portion of the loan book exposed.

To conduct the analysis, we assemble a rich dataset covering all wildfires in Chile between 2010 and 2024 at the county-month level, including the number of hectares burned in each county during each wildfire episode. We merge this information with a detailed credit dataset covering the universe of firms operating across Chile's counties. For each firm, we observe the debt outstanding with each bank, the new loans obtained over time, and the amount of delinquent debt. We also have detailed information on each firm's industry classification, size, and address.

[1] The literature mentions several natural disasters that can have consequences for financial stability, including earthquakes, floods, hurricanes, and wildfires. We focus on wildfires because they are very prevalent in Chile each year and are likely to affect economic activity. Furthermore, wildfires are a common phenomenon hitting communities worldwide. Some examples include Canada (2016, 2018, 2023, 2026), France (2026), Greece (2023), Portugal (2017, 2025), Spain (2025, 2026), Turkey (2025), the United States (2017, 2018, 2020, 2024, 2025), and Ukraine (2025).

We first examine the extensive margin. Following a wildfire, the probability that a firm's debt becomes delinquent rises steadily over the 12 months after the shock, with an increase of 0.7 percentage points twelve months after the event, equivalent to 8% of the pre-shock mean. Turning to the intensive margin, we find that outstanding delinquent debt increases by 12.7% twelve months after the shock, while the number of days past due increases by 3 days, equivalent to 9.6% of its pre-shock mean. Although all three effects are statistically significant, their magnitudes are modest on average, pointing to a persistent but economically contained deterioration in repayment behavior.

These average effects across firms mask substantial heterogeneity among them. We examine two dimensions highlighted in the literature: firm size and economic sector. Grouping firms by annual sales into small, medium, and large categories, we compare the average impact of wildfires on each category over the following 12 months. The impact is concentrated among small firms, whose delinquency rate rises by 0.5 percentage points on average over the twelve months following a wildfire, equivalent to 5.8% of the pre-shock mean, against the non-statistically significant 0.2 and 0.1 percentage points for medium and large firms, respectively.

We group firms into broad sectoral categories. Wildfires significantly increase delinquency among firms in the agriculture and forestry sector, with smaller but still significant effects in commerce and services, but no statistically significant effect on manufacturing. Moreover, the point estimate for firms in the agriculture and forestry sector is twice that for firms in the manufacturing sector. This pattern is consistent with wildfires directly damaging agricultural and forestry assets and disrupting the local demand that underpins commerce. On the other hand, manufacturing facilities are typically located away from fire-prone areas and are less tied to the local economy.

We also exploit the granularity of our firm-bank data to examine how firm-bank relationships shape delinquency. We consider three measures of relationship strength: a main-bank indicator (the bank providing most of the firm's loans), the bank's share of the firm's debt, and a single-bank indicator. Among small firms, wildfire-induced delinquency is concentrated in weak relationships: the effect is substantially smaller when the firm-bank relationship is strong. Banks with better information and larger stakes in a firm have less incentive to allow temporary difficulties to translate into formal delinquency, while borrowers are less likely to default on their main creditor.

Having established that large wildfires significantly increase firm delinquency, we next examine whether banks update their assessments of climate-related physical risk after these events by changing their lending practice in high-risk areas and their provisioning in the counties hit. We first examine whether banks also reassess the risk of firms that are *ex ante* exposed to wildfires but not directly affected by a given event. We measure wildfire exposure at the county level using historical burned area over the years preceding the start of our sample. We test whether banks reassess wildfire risk by charging higher interest rates and reducing lending amounts to these indirectly exposed firms. We find clear evidence of such reassessment in counties with high historical wildfire exposure. Within three months of a major wildfire event, interest rates rise by 46 basis points, even for firms that are not directly affected but operate in high-risk areas. Lending also declines in those areas.

Then, we study whether the credit deterioration in the affected counties translates into measurable effects on banks' financial condition. We find that wildfires lead to a significant increase in firm-bank provisions, with substantially larger effects for small firms. This pattern mirrors the stronger deterioration in repayment behavior documented above and indicates that banks internalize the higher expected credit risk associated with wildfire exposure through loan-loss provisioning.

Next, we ask whether the rise in provisions is large enough to affect bank solvency. Aggregating progressively across firms and geographic units, we find that provisioning rises significantly for small firms at the bank-county level, but the effect vanishes once all firms within a bank-county are combined, and remains small and insignificant at the bank level. The deterioration is concentrated in borrowers that account for a small share of total bank lending. Wildfires thus propagate into banks' credit risk provisioning, but the magnitudes involved are small relative to overall balance sheets.

Lastly, we ask a counterfactual question: how different would conditions have to be for wildfires to threaten bank solvency? We write the provision shock as severity (how much is lost per affected peso) times composition (the share of the bank's book exposed to affected firms), and map the shock to a fall in the capital ratio. Holding severity fixed, even the most exposed month in our sample (when a third of the system's loan book sat in burned counties) implies a capital hit of only about 2.5 basis points. Reaching a material decline of 100 basis points, roughly one-third of the system's current capital headroom, would require exposure to rise to some forty times its historical maximum. Banks increase provisions as loans deteriorate, so the small aggregate effect does not reflect deferred loss recognition. This confirms the paper's central message: banking resilience to wildfires is a property of how shocks affect bank portfolios. For the entire banking system to break down, future shocks would need to affect a much larger share of bank portfolios than observed historically.

This paper contributes to three related strands of the literature on how natural disasters affect firms and banks. A first strand examines effects on firms' real and financial performance. Natural disasters generate short-run declines in sales growth, production capacity, and productivity by destroying physical capital (Leiter et al., 2009; Barrot and Sauvagnat, 2016; Zhou and Botzen, 2021). As revenues contract, loan delinquency and default risk rise, especially for smaller firms and those with higher leverage or limited financial flexibility (Barbaglia et al., 2023; Aguilar-Gomez et al., 2024; Fatica et al., 2024; Collier et al., 2025; Shao et al., 2025; Chowdhury et al., 2026).[2]

A second strand examines how banks respond to the increase in delinquency. Banks incorporate physical risk premia into loan contracts ex ante (Do et al., 2021; Javadi and Masum, 2021; Barbaglia et al., 2023; Do et al., 2023; de Bandt et al., 2025), and revise their assessment of climate risk after shocks, raising rates in historically exposed areas not directly affected by an event (Correa et al., 2026). They also increase loan-loss provisions on exposed portfolios as realized losses update expected-loss assessments (Dal Maso et al., 2024; Shala and Schumacher, 2024).[3]

A third strand asks whether natural shocks generate threats to financial stability. Natural disasters can raise banks' credit risk and asset repricing (Battiston et al., 2021). They can also materially weaken the financial condition of exposed banks, as reflected in lower z-scores and asset returns, higher default probabilities, and higher non-performing loans (Klomp, 2014; Brei et al., 2019; Noth and Schüwer, 2023; Chabot and Bertrand,

[2]For wildfires, the evidence is confined to aggregate regional GDP and employment (Meier et al., 2023).

[3]In addition, banks adjust lending: some expand credit in affected zones by reallocating from unaffected markets (Cortés and Strahan, 2017; Koetter et al., 2020; Celil et al., 2022), while others reduce credit in high-risk areas or reallocate credit within the same zone (Berg and Schrader, 2012; Aslan et al., 2022; Meisenzahl, 2023; Álvarez-Román et al., 2024).

2023; Walker et al., 2023; Koch et al., 2026). Banking systems generally withstand localized events but become vulnerable when shocks are spatially concentrated or recurrent (Caloia and Jansen, 2021; de Bandt et al., 2025; D'Orazio, 2025).[4]

Our central contribution is to offer a framework to trace, within a single setting, how borrower-level distress aggregates into bank-level outcomes. A wildfire is a local shock, and how far it travels up the financial system is an empirical question. Using highly granular credit registry and loan transaction data, we examine the effects of large wildfires at every level of aggregation: from the firm-bank pair to the bank-county cell, both overall and by firm size, and up to the bank level. The firm-bank effect, positive and significant, attenuates gradually until it vanishes in the aggregate. The mechanism is compositional: affected borrowers suffer but account for a small share of total bank lending. Overall, the localized effects of wildfires on small firms and those in the agriculture and forestry sectors do not appear to threaten bank solvency.

Beyond documenting these micro-macro linkages, the paper contributes to the literature in three additional ways. First, most studies use bank- or country-level data and focus on advanced economies that experience floods, hurricanes, or droughts. By studying wildfires and exploiting granular credit data, the paper helps to identify the effects of natural shocks on delinquency, as wildfires tend to be acute, spatially concentrated, and directly destroy assets. Second, the paper provides novel evidence that the strength of the firm-bank relationship matters. Firms borrowing from their main bank experience smaller increases in delinquency than those borrowing from other banks, consistent with relationship lending mitigating disaster-induced credit impairments. Third, complementing findings for Spain and the U.S., the paper documents reductions in lending to unaffected firms and sharper increases in interest rates, suggesting that credit spillover effects may be stronger in an emerging country like Chile.

The rest of the paper is organized as follows. Section 2 presents the data. Sections 3 and 4 report the results for firms and banks. Section 5 asks how different conditions would have to be for wildfires to threaten bank solvency. Section 6 concludes.

[4]Undercapitalized banks can amplify spillovers with measurable consequences for regional aggregate output (Rehbein and Ongena, 2022; Walker et al., 2023).

2 Data

2.1 Data Sources

We combine three primary datasets in this paper. The first dataset is obtained from Chile's Financial Market Commission (CMF), the national banking regulator, and comprises confidential monthly bank-to-firm data from January 2010 to December 2024. The data span firms in all sectors of the economy and provide information on both the stock of outstanding bank credit and the flow of newly originated loans for the country's universe of firms. The dataset includes borrower-level information on outstanding credit balances and repayment histories, as well as measures of credit quality such as delinquency status, provisions for expected losses, and write-offs. In addition, it provides high-frequency information on the contractual terms of newly granted commercial loans (including interest rates, amounts, maturities, currency denominations, and collateral) observed at origination or renegotiation from April 2012 to December 2024.

We organize the credit data in two complementary ways. We first construct a firm-level dataset that tracks each firm's outstanding debt with every bank at any point in the sample period. This dataset provides the level of debt, the amount in default, and the number of days in default. This information contains 23,219,668 observations. We next construct a credit dataset in which each observation corresponds to every credit granted when the firm receives the funds, allowing us to study loan pricing and contractual arrangements at origination. This dataset contains 712,157 transaction-level observations for new loan originations.

The second dataset comes from Chile's national forestry agency (CONAF). It provides information on climate shocks at the county-month level. It includes data on the surface area affected by wildfires (in hectares) from January 2002 to December 2024. We define a large wildfire as an event whose affected surface area, measured as the county's hectares burned, exceeds the 90th percentile of the distribution of burned hectares in the sample. The 2002–2009 sub-period is used to construct each county's ex ante exposure; the 2010–2024 sub-period defines wildfire treatment over the credit sample.

We supplement the wildfire data with daily maximum temperatures at the county level from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis version 5 (ERA5-Land) (Muñoz-Sabater, 2019), which provides gridded estimates at 0.1° resolution (∼9 km) from 1980 to 2025. Each county is matched to its nearest grid point. We use these data to construct a heatwave indicator inspired by the definition of the Chilean Meteorological Office (DMC). Specifically, we define a heatwave as three or more consecutive days in which the daily maximum temperature exceeds the county–month 90th percentile of a 1980–2010 baseline, subject to an absolute floor of 25°C. Additionally, following Correa et al. (2026), we define each county's ex ante wildfire risk exposure as the cumulative affected surface area over the pre-sample period from 2002 to 2009. Together, these definitions allow us to identify areas most exposed to wildfire risk and to align the wildfire measures with the time frame of the banking data.

The third dataset comes from Chile's Tax Authority (Servicio de Impuestos Internos). It provides a comprehensive registry of corporate taxpayers and includes information on firms' geographic location (headquarters county), size classification based on annual sales, and industry classification at the detailed 6-digit level, according to the Chilean Standard Industrial Classification (ISIC Rev. 4).[5] Each firm's county and sector are held fixed at the values recorded in its last observation in the registry, so these attributes do not vary within a firm over the sample. Using the last observation adopts the classification criteria in force at the end of the period. 93% of firms keep the same county over the event window, and 86% keep the same activity code. Firm size is instead defined as the largest size category attained by the firm over the sample period. This conservative classification reduces sensitivity to intermittent reporting or occasional misclassification across years, which could otherwise cause a firm to appear temporarily smaller simply because of missing or erroneous annual information. As a result, firms are classified as small only if they are never observed in a larger category during the sample.

The registry covers legal entities. Sole proprietors with a registered business

[5]The sectoral-code criterion changed during our sample. During the 2017 commercial year, the code was derived from the annual income tax filing and did not necessarily reflect the principal activity. From 2018 onward, it is the activity in force during the year, or, for firms with several activities, the one declared as principal.

activity are excluded, so our results reflect the response of incorporated firms. Because sole proprietors are typically smaller and plausibly more exposed to local shocks, their exclusion makes our estimates of deterioration among small borrowers conservative.

For single-establishment firms, the headquarters county coincides with the location of productive activity, but for multi-plant firms, it need not: operations may lie in a county other than the one recorded. Because the mismatch is unrelated to the timing of wildfire events, it introduces measurement error in the treatment indicator, which is expected to attenuate the estimated coefficients toward zero, implying that our estimates represent a lower bound on the effect for firms whose operations are in a burned county. The mismatch is most likely for larger, multi-plant firms and for firms registered in the capital, which motivates the specification excluding Greater Santiago reported in Section 3, where the estimated effects are essentially unchanged.

2.2 Summary Statistics

Table 1 reports summary statistics for the main credit variables. The stock-of-credit variables (outstanding and delinquent debt) are at the firm-bank relationship level (Panel A), whereas the interest-rate and loan-amount variables are drawn from transaction-level origination data (Panel B). Debt variables are right-skewed: mean outstanding debt far exceeds the median, indicating that credit aggregates are driven by a small number of large relationships. Delinquent debt is highly intermittent, with a median of zero, implying that more than half of observations exhibit no delinquency in a typical month. Consistent with this pattern, the delinquency indicator also has a median of zero.

Interest rates and loan amounts vary substantially across loan types. Real (inflation-linked) loans are, on average, larger than nominal loans, while interest rates span a wide range, reflecting differences in risk, maturity, and contractual features. These patterns show that credit and delinquency are concentrated in a relatively small subset of firms and bank relationships at baseline, a feature that shapes how the wildfire effects documented below aggregate.

Panel C describes the composition of bank credit across firms. Small firms account for 69.4% of borrowers but hold only 8.3% of outstanding debt, highlighting the strong concentration of credit among larger firms. This pattern is even more pronounced for small firms in the agriculture and forestry sector, which represent 3.8% of borrowers but only 0.8% of outstanding debt. These differences between borrower-count and debt-weighted shares are important for the analysis below: the firms most vulnerable to wildfire shocks account for a relatively small share of banks' loan portfolios, limiting the extent to which borrower-level credit deterioration translates into bank-level effects.

Figure 1 plots the monthly number of counties experiencing large wildfires. Wildfire activity is highly seasonal, with sharp, recurrent spikes concentrated in the summer months of December through March. The intensity of these episodes varies substantially over time: during peak periods, more than 70 counties are simultaneously affected, whereas in most months, only a few counties are exposed. This strong temporal clustering underscores the episodic nature of wildfire shocks and motivates the use of an event-study framework to trace dynamic responses around each event.

To complement Figure 1, we classify counties by the number of large wildfires they experienced during the sample period. Table 2 shows that 115 counties (nearly 33% of the total) experienced no events, while roughly 30% recorded at least five. This distribution highlights two key features of the empirical design. First, identification relies on variation in the timing of wildfire exposure across counties. Second, repeated exposure in a subset of counties raises the possibility of dynamic and cumulative effects, motivating specifications that allow for treatment-effect heterogeneity over time and across exposure intensity.

Lastly, Figure 2 shows the spatial distribution of large wildfire activity across Chilean counties, mapping the cumulative surface area affected from 2010 to 2024. Wildfire activity is highly concentrated in the central-south regions, where Mediterranean climate conditions, plantation forestry, and dry summers make large fires more likely. In contrast, northern desert regions and the far south exhibit minimal exposure, highlighting the strong geographic concentration of wildfire risk.

3 Wildfires and Firm Debt Delinquency

This section studies the effects of large wildfires on firm-bank debt delinquency.

3.1 Methodology

We estimate the impact of wildfires on firm-bank debt outcomes using the Local Projections Difference-in-Differences (LP-DiD) method developed by Dube et al. (2025). We restrict the estimation to clean treated and clean control observations. A unit is a clean-treated observation if it receives treatment in month t and was untreated in the previous 12 months; a clean-control observation remains untreated throughout the event window, from twelve months before t through the end of the horizon. The baseline restriction removes contamination from prior and concurrent control-side events and ensures controls provide a clean counterfactual. It does not exclude subsequent wildfire occurrence along the treated path, so the baseline treated effect allows for the realistic possibility of repeated exposure within the horizon.

This methodology traces the evolution of outcomes before and after the shock, comparing the treatment and control groups over the same period. We conduct the analysis using a firm–bank-time panel that tracks the stock and performance of outstanding bank debt for each firm–bank relationship. Our regression specification is:

$$y_{i,b,t+h} - y_{i,b,t-1} = \alpha_i + \lambda_{b,t} + \beta_h \text{Wildfire}_{i,c,t} + \rho_h y_{i,b,t-1} + \varepsilon_{i,b,t+h}, \tag{1}$$

where $y_{i,b,t}$ denotes the debt delinquency outcome, for firm i borrowing from bank b in month t. The unit of observation is the firm-bank relationship in a given month: a firm can be delinquent with one lender and current with another. h denotes the horizon (in months) of the local projection. The regression includes firm fixed effects (α_i) and bank-time fixed effects ($\lambda_{b,t}$) to absorb firm-specific heterogeneity and time-varying bank-level credit fluctuations. The treatment indicator $\text{Wildfire}_{i,c,t}$ is a dummy equal to one if firm i belonging to county c is exposed to a large wildfire at time t. The specification controls for one lag of the dependent variable. Standard errors are two-way clustered at the county and year-month level to account for spatial and temporal dependence.

The coefficient of interest, β_h, captures the average change in the delinquency outcome h months after a large wildfire, relative to firms not exposed to a wildfire during the relevant comparison window. Because treatment is defined at the county level, and we do not observe which firms within a county are hit, β_h reflects the average effect across all firms in a burned county, only a fraction of which are directly affected by the fire. It is therefore an intent-to-treat effect that understates the impact on firms directly affected. Section 5 exploits this structure, recovering the firm default response by scaling the estimated coefficient by the average within-county share of affected firms.

The estimation window spans six months before and twelve months after each event. Because treated and clean-control observations satisfy the restrictions described above, a firm within its exclusion window is never used as a control for another event, so estimated effects are not driven by comparisons between newly treated firms and firms affected by recent wildfire shocks. For these initial analyses, we present the dynamic LP-DiD estimates in a figure format.

In the subsequent analyses, we report the results in a compact table format to conserve space and facilitate comparisons across specifications. In particular, we use pooled local projection estimates, which summarize the average effect over the full post-treatment window $h = 0, \ldots, H$. Specifically, we estimate a single LP-DiD regression in which the dependent variable is the average of long-differenced outcomes over the post-treatment horizon in relation to the month before the treatment:

$$\Delta^H y_{i,b,t} = \frac{1}{H+1} \sum_{h=0}^{H} \left(y_{i,b,t+h} - y_{i,b,t-1}\right). \tag{2}$$

This specification delivers an average treatment effect of wildfire exposure on delinquency outcomes over the subsequent $H = 12$ months. Then, we estimate the pooled LP-DiD regression:

$$\Delta^H y_{i,b,t} = \alpha_i + \lambda_{b,t} + \beta \text{Wildfire}_{i,c,t} + \rho y_{i,b,t-1} + \varepsilon_{i,b,t}, \tag{3}$$

where $\Delta^H y_{i,b,t}$ is the average long-differenced outcome over horizons $h = 0, \ldots, H$ relative to $t - 1$. The coefficient β therefore summarizes the average local-projection treatment effect over the full post-treatment horizon.

3.2 Main Results

Figure 3 presents the estimated effects of large wildfires on three delinquency outcomes: an indicator equal to one if the firm is delinquent, the (log) outstanding delinquent debt[6], and the number of days past due. Panel A shows the extensive margin. The probability of holding delinquent debt rises steadily after the shock, peaking at 0.7 percentage points after twelve months (8% of the pre-shock mean). Panel B turns to the intensive margin, examining (log) outstanding delinquent debt, which rises by 0.12 twelve months after the shock, representing a 12.7% increase.[7] Panel C shows a similar pattern for days past due, which rises by three days after 12 months (9.6% of the pre-shock mean). All effects are statistically significant but modest in magnitude, pointing to a persistent yet economically contained deterioration in repayment behavior. This gradual buildup reflects both the entry of newly delinquent firms and the tendency of affected firms to remain delinquent once they enter that state.[8]

Importantly, as shown in Figure 3, none of the outcomes display economically meaningful movements in the six months prior to the wildfire, consistent with the parallel-trends assumption. We provide two formal tests. Appendix Table 1 reports pre-treatment LP-DiD coefficients by horizon. The point estimates are uniformly small and not significant (a few leads are pointwise significant at the 10% level, but the magnitudes are negligible relative to the post-treatment effects). Appendix Table 2 further supports identification by providing a fixed-sample randomization inference test. Holding the estimation sample fixed, treatment is randomly reassigned across county-month cells within each month and within strata of predetermined ex ante wildfire exposure, so that placebo treatment is assigned only among counties comparable in fire risk. The placebo distributions are centered at zero, and no placebo estimate matches the actual baseline coefficient estimated across 500 permutations, ruling out the possibility that the estimated effects reflect seasonal or cyclical patterns specific to fire-prone counties.

3.3 Heterogeneous Effects

The average effects mask substantial heterogeneity across firms. We explore two key dimensions highlighted in the literature: firm size and sector. To examine heterogeneity

[6] Delinquent debt is right-skewed with a mass at zero, so we apply a $\log(1 + y)$ transformation to retain zero-valued observations. The resulting coefficients are approximate percent changes, computed as $100 \times (\exp(\beta) - 1)$, which is accurate for the small effects we estimate.

[7] Because this outcome is defined over the full panel, it combines movements into delinquency with changes in balances among already-delinquent firms.

[8] Extending the horizon and the clean condition to 18 months suggests that the effects begin to revert after 14 months (Appendix Figure 1).

by firm size, we group firms by annual sales into small, medium, and large categories.[9] For the sectoral analysis, we classify firms into five broad categories by sector: (i) agriculture and forestry, (ii) manufacturing, (iii) utilities and construction, (iv) commerce, transportation, and tourism, and (v) services.[10] The agricultural sector is important to distinguish, given that heatwaves tend to affect it directly (Aguilar-Gomez et al., 2024).

For reference, Table 3, Panel A reports the pooled local projection estimates for all firms, providing a compact-form counterpart to the dynamic estimates in Figure 3 and a benchmark for the heterogeneity analysis that follows. All three delinquency outcomes increase over the post-event window for treated firms, with statistically significant effects. The delinquency rate increases by an average of 0.4 percentage points after a wildfire, equivalent to 4.5% of the pre-shock mean. The log of delinquent debt increases by an average of 0.061, representing 6.3% of the pre-shock level. Days past due increase by an average of one day, equivalent to 6.9% of the pre-shock mean.

We estimate heterogeneity by running this regression separately on each subsample. Table 3, Panels B–D report the pooled local projection estimates by size. It shows that the impact of wildfires on delinquency is concentrated among small firms, whose delinquency rate increases by 0.5 percentage points following a wildfire, equivalent to 5.8% of the pre-shock mean. In contrast, we find no statistically significant effects for medium or large firms. The point estimate for small firms is more than twice that for medium firms and about five times that for large firms.

Table 4 reports the results by sector. It shows that wildfires significantly increase the probability of delinquency across firms in the agriculture and forestry sector and in the commerce and services sector. On the other hand, the effects on industrial firms are small and statistically insignificant. The point estimate for the agriculture and forestry sector is twice that for the manufacturing sector. This pattern is consistent with wildfires directly damaging agricultural and forestry assets and disrupting local

[9] Size definitions follow the Chilean Tax Authority criteria based on annual sales. We classify firms into three categories: small (sales $<$25,000 UF, approx. $<$1.11M USD), medium (25,000–100,000 UF, 1.11–4.44M USD), and large ($>$100,000 UF, $>$4.44M USD). UF (*Unidad de Fomento*) is the unit of account used in Chile to measure values in constant Chilean pesos.

[10] Fishing and mining originally belong to the primary sector, together with agriculture and forestry. We exclude them from the analysis because their exposure to wildfires operates through channels different from those of agriculture and forestry, whose assets are directly damaged by fire.

demand that supports commerce, transportation, and tourism. On the other hand, manufacturing activity is typically less exposed, both geographically and in terms of its weaker dependence on local conditions.

3.4 Role of Firm-Bank Relationships

We next examine whether the strength of firm-bank relationships shapes the transmission of wildfire shocks to delinquency. Following the relationship-lending literature (Degryse et al., 2009; Dass and Massa, 2011; Srinivasan, 2014; Kysucky and Norden, 2016), we construct three complementary measures. The first is a main-bank indicator equal to one when the bank holds the largest share of the firm's total borrowing in a given month. The second is the bank's share of the firm's outstanding debt, a continuous measure of relationship concentration. The third is a single-bank indicator equal to one for firms borrowing from only one bank, capturing the exclusivity of the lending relationship. Each specification includes wildfire treatment, the relationship measure, and their interaction.[11]

Table 5 reports the results for small firms, the group most affected by wildfires and the most bank-dependent. Across all three measures, the interaction terms are negative and significant for every outcome, indicating that stronger relationships systematically attenuate the wildfire-induced rise in delinquency. Panel A shows that, for non-main bank relationships, wildfires raise the delinquency indicator by 1 percentage point, delinquent debt by 19%, and days past due by 2.06 days. The main-bank interaction offsets roughly 60% of these effects across all three outcomes. Panel B confirms this pattern using the continuous share measure, with the interaction offsetting 75 to 90% of the baseline effect. Panel C shows that single-bank firms also exhibit attenuated responses, with the interaction significant at the 1% level for days past due and marginally significant for the other outcomes.

These patterns are consistent with stronger firm-bank relationships being associated with lower delinquency following wildfire shocks. Banks with greater informational advantages may be more willing to renegotiate loans or grant forbearance. The design identifies a conditional heterogeneity pattern, so we cannot fully rule out alternative

[11]The coefficient reported as treated is therefore the effect of a wildfire when the relationship measure equals zero, and the interaction term reports the differential effect associated with the relationship measure.

readings, such as how distressed borrowers allocate limited repayment capacity across lenders or selection into deeper relationships, but the consistency of the attenuation across all three relationship measures points to an insurance role.

Appendix Table 3 reports the corresponding estimates for medium and large firms. Both the baseline treated effects and the relationship interactions tend to be small and statistically insignificant across specifications. These results are consistent with medium and large firms being less affected by wildfires overall and less dependent on any single banking relationship.

Having shown that stronger relationships attenuate wildfire-induced delinquency, we ask through which channel this protection might operate. Appendix Table 4 relates main-bank status to loan reprogramming and contractual terms for small firms. Main-bank relationships are associated with more loan reprogramming and larger loan amounts, while the interest-rate difference is insignificant. The pattern is consistent with main banks supporting small borrowers by renegotiating existing obligations rather than by pricing credit more cheaply. Because this is a cross-sectional association rather than a shock-induced effect, we read it as suggestive of the insurance channel.

3.5 Robustness Tests

Our main results are robust to a broad set of sensitivity tests. First, we assess whether repeated wildfire exposure compounds the effect on delinquency, as a cumulative deterioration would imply. Appendix Table 5 splits the treatment into wildfires in counties with and without a prior wildfire in the preceding 13 to 24 months, keeping the clean-control specification. The effect is concentrated in counties with no prior exposure. Estimates for counties with a recent wildfire are smaller and generally not significant across all three outcomes, though delinquent debt remains marginally significant. We thus find no evidence that prior exposure amplifies the response; if anything, the marginal effect is larger when no wildfire has occurred recently.

We also disentangle wildfire effects from broader temperature shocks. While heatwaves can weaken firms' debt-repayment capacity (Aguilar-Gomez et al., 2024), our results indicate that the increase in delinquency is primarily driven by wildfire exposure rather than heat stress. Appendix Table 6, Panel A, shows that wildfires and heatwaves overlap only partially. Of 1,408 county-months with a large wildfire, 592

(42%) coincide with a heatwave under our baseline definition and 324 (23%) under the stricter 30°C threshold. Panel B shows that under the 90th percentile definition, contemporaneous and lagged heatwaves significantly predict wildfires, although the magnitudes are small. Under the 30°C definition, the pattern is mixed. Overall, we find limited evidence that heatwaves systematically forecast county-level wildfires on a monthly basis.

In Appendix Table 7, we explicitly control for heatwave indicators in the baseline specification. The wildfire coefficient remains virtually unchanged. Moreover, the estimated effects of heatwaves are much smaller in magnitude and not statistically significant. This evidence suggests that our baseline results do not capture general temperature-related stress but rather the direct impact of wildfire exposure on firms' repayment capacity.

Lastly, our results remain largely unchanged when wildfire exposure is redefined using alternative burned-area thresholds (75th and 95th percentiles), the county-normalized burned-area share (hectares burned relative to county area), red alert episodes, or the log of affected surface area as a continuous measure of intensity (Appendix Table 8). Estimates are also stable when: (i) dropping high ex ante exposure county-months from the control group that are not contemporaneously burned, (ii) excluding firms in Greater Santiago, dropping the lagged dependent variable, (iii) enriching the fixed effects with sector-time, region-time, and firm size-time interactions, and (iv) adding county-month fixed effects that absorb seasonal credit cycles specific to a county (Appendix Table 9).[12] The dynamic responses persist under stricter clean sample definitions: extending the horizon to 18 months (Appendix Figure 1) and requiring both treated and control observations to be free of large wildfire exposure over the relevant windows (Appendix Figure 2).[13]

[12]Excluding Greater Santiago addresses the location measurement issue discussed in Section 2. The sectoral patterns documented above hold for this restricted sample, and the contrast between agriculture and forestry and manufacturing is somewhat sharper (Appendix Table 10). Furthermore, adding county-month fixed effects modestly attenuates the estimated effects but leaves them positive and highly significant, indicating the baseline is not an artifact of spillover contamination of the control group. Unreported results also show that using bank and time fixed effects, rather than bank-time fixed effects, does not alter the conclusions.

[13]Estimates at these longer horizons are based on progressively fewer observations satisfying the clean-sample restrictions, so the apparent reversion should be interpreted with caution.

4 Wildfires and Bank Behavior

The previous section shows that large wildfires significantly increase firm-bank delinquency, particularly among small firms and firms in the agriculture and forestry sector. In this section, we examine whether this deterioration in borrower performance translates into measurable effects on bank behavior.

4.1 Reassessment of Wildfire Credit Risk

We start by analyzing how banks reassess climate-related credit risk after the events, following Correa et al. (2026). We examine whether banks adjust both the price and quantity of new loans to firms located in wildfire-prone areas following a large wildfire, even when those firms are not directly affected by the event.

We measure wildfire exposure using historical burned area prior to the sample period and estimate the following loan-level specification:

$$y_{i,b,c,t} = \beta^k \left(\text{Wildfire}_t^k \times \text{HighExposure}_c\right) + \delta X_{i,b,t} + \alpha_i + \lambda_{b,t} + \varepsilon_{i,b,c,t}, \tag{4}$$

where $y_{i,b,c,t}$ denotes either the interest rate or loan amount granted to firm i by bank b in county c at time t; Wildfire_t^k, with $k \in \{0\text{–}3, 4\text{–}6\}$, indicates the occurrence of a large wildfire anywhere in the country within the previous 0–3 or 4–6 months, respectively; and HighExposure_c equals one if county c's cumulative affected surface area over 2002–2009 is above the 75th, 80th, or 90th percentile of the distribution across counties, depending on the specification. The vector $X_{i,b,t}$ collects loan-level controls, and α_i and $\lambda_{b,t}$ denote firm and bank-time fixed effects. We exclude counties directly affected by wildfires during the event window, so that β_k captures the repricing of wildfire risk in exposed but not affected counties rather than the pricing of realized physical damage.[14]

Table 6 shows significant evidence of wildfire risk reassessment. In counties above the 75th percentile of historical wildfire exposure, interest rates rise by about 37 basis points in the first three months after a wildfire (Panel A), while loan amounts decline significantly (Panel B). The effects increase with greater historical exposure, reaching

[14] As discussed in Correa et al. (2026), the direct effects on the counties hit are more difficult to measure because the treatment occurs for the whole county, without knowledge of which firms are specifically affected by the event. An analysis of the direct effects could conflate changes in the types of firms that receive new loans after the event with the reprogramming of existing loans. Instead, the analysis of the indirect effect provides a clearer test of the impact of external events on firms in counties with different levels of exposure.

roughly 46 basis points in the most exposed counties (4.8% of the pre-shock mean). These results indicate that banks respond to realized wildfire shocks by both increasing loan pricing and reducing loan amounts originated in riskier areas. The increases in interest rates in Chile far exceed the 8-basis-point adjustment in the U.S.

Because interest rates and amounts are observed only for granted loans, our baseline estimates describe changes in the equilibrium terms of originated loans and could be affected by selection bias if wildfires alter the composition of firms that obtain credit. However, Appendix Table 11 shows that the adjustment in loan terms does not reflect the exclusion of vulnerable borrowers from credit markets.[15] Moreover, the composition of borrowers by size and sector is unchanged at both the bank-county and county level.

Because our estimates reflect the joint outcome of bank supply and borrower demand among originated loans, they do not necessarily isolate a belief update. As a robustness check, we add a two-step Heckman term. The first-stage probit models loan-market participation as a function of local ex ante wildfire exposure, prior-year borrowing status, bank identifiers, sector and firm-size controls, and the number of banks operating in the county. We use the number of banks in the county as an exclusion restriction, which remains fixed over our sample period. The rationale is that greater local bank presence increases firms' access to bank credit by expanding the set of potential lenders, and therefore affects the probability that a firm obtains a loan. At the same time, conditional on firm fixed effects, bank-time fixed effects, and loan-level characteristics, we assume that the presence of local banks does not directly affect the contractual terms of a loan once it is originated. We use the first-stage estimates to recover the inverse Mills ratio, which captures the non-random component of credit-market participation, and include it as an additional control in the lending and interest-rate regressions (Appendix Table 12). The estimates are quantitatively and statistically similar to the baseline. This addresses selection among observed borrowers but not discouraged or rejected applicants, who are unobserved; we therefore read the estimates as equilibrium terms conditional on origination.

[15] In fact, following a large wildfire, the probability that a firm holds bank credit rises by about 5 percentage points, similarly for small firms and for agriculture and forestry firms, the segments where delinquency concentrates.

We also test whether the repricing reflects banks learning about individual borrowers rather than reassessing local wildfire risk. If borrower-specific information were important, the response should be stronger for newer firm-bank relationships, where banks have less private information. Appendix Table 13 shows that this is not the case: the interaction with relationship length is economically negligible. This suggests that banks are primarily reassessing local wildfire risk rather than responding to borrower-specific information gaps.

Lastly, we examine whether the reassessment reflects wildfires specifically, rather than the heat stress that often accompanies them. Appendix Table 14 re-estimates specification (4) using heatwave episodes instead of wildfires. The positive reassessment pattern observed for wildfires is absent across all exposure cutoffs. Heatwaves are associated with lower interest rates in the most narrowly defined exposed counties (90th percentile), while estimates at the 75th and 80th percentiles are insignificant. Thus, results are consistent with banks reassessing wildfire risk specifically, rather than temperature risk more broadly.

4.2 Loan-Loss Provisions at the Firm-Bank Level

Next, we examine whether banks adjust their expected credit loss assessments for borrowers in wildfire-affected counties. Banks are required to update provisions as borrower risk evolves, so the deterioration in repayment performance documented in Section 3 should translate into higher expected losses on the loans exposed. A second channel operates on borrowers that remain current: banks may revise upward the probability of default or the loss given default assigned to exposed firms, for instance, because collateral has been damaged.

We estimate the same firm-bank LP-DiD specification as in Section 3, but replace the dependent variable with three alternative provisioning outcomes for firm i borrowing from bank b in month t: the provisioning ratio, defined as total loan-loss provisions over outstanding debt, (log) total loan-loss provisions[16], and loan-loss provisions on delinquent debt.

Table 7 reports the pooled estimates over the twelve-month post-treatment

[16]The logged provisioning outcomes use the same $\log(1 + y)$ transformation as delinquent debt to retain zero-valued observations.

horizon. Wildfires raise the provisioning ratio and provisions on delinquent loans, both of which are positive and statistically significant, while (log) total provisions remain unchanged. The delinquent-provisions effect implies an increase of about 5.9% in delinquent loan-loss provisions relative to their pre-shock level for all firms (Panel A). The effects are substantially larger for small firms (Panel B) than for medium or large firms (Panels C and D), consistent with the stronger deterioration in repayment behavior documented in the previous section. Overall, the results indicate that banks internalize the higher expected credit risk associated with wildfire exposure through higher loan loss provisioning.

The pooled estimates do not reveal when this recognition occurs. Provisions depend on expected-loss models, collateral valuation, and decisions on renegotiation and write-offs, so they could lag the deterioration in delinquent debt or track it less than proportionally. To assess this, Appendix Figure 3 plots the dynamic responses of delinquent provisions and delinquent debt, both in log points. The two series move almost one-to-one, with provisions rising in tandem as delinquent debt accumulates. Loss recognition is thus timely and proportional to the underlying deterioration, allowing us to map the increase in delinquent debt into provisions and bank capital in Section 5.

4.3 Bank-Level Solvency

Higher provisions can weaken banks' financial health because they are recorded as an expense, reducing current net income and, through lower retained earnings, regulatory capital. By solvency, we mean the bank's regulatory capital ratio, Common Equity Tier 1 (CET1) capital over risk-weighted assets, and the margin by which it exceeds the regulatory minimum. The relevant question is whether the increase in provisions resulting from wildfires is large enough to materially affect bank solvency. A wildfire is a local shock, so how far it reaches is an empirical question. We therefore raise the level of aggregation step by step, from the firm-bank pair to the bank-county cell and then to the bank, and ask at which level the shock is no longer visible.

The first step is the bank-county cell, the level at which the wildfire is defined. Table 8 reports pooled LP-DiD estimates at this level, for all firms and separately by firm size. Panel A shows no significant effect on provisions when all firms are pooled. In contrast, wildfire exposure raises provisions on delinquent loans and total provisions among small firms, indicating that banks recognize higher expected losses for these borrowers, while the provisioning ratio remains unchanged (Panel B). For medium and large firms, the effects are mostly modest and insignificant, with one exception: delinquent provisions for medium firms decline, with a coefficient that is only marginally significant (Panels C and D). Because bank-county cells for medium firms contain few borrowers, we interpret this as an imprecise estimate rather than evidence of lower provisioning. Overall, these results point to a compositional effect: the borrowers most affected by wildfires account for a relatively small share of bank lending, so the increase in provisions for them is diluted when all borrowers are pooled.

We next aggregate to the bank level. Because banks lend across multiple counties, wildfire treatment can no longer be defined by a single county-level indicator. Instead, we construct a bank-level variable, which we call *Exposure*, measuring the share of each bank's lending in counties experiencing a large wildfire. Table 9 examines whether banks with greater exposure experience larger changes in delinquent debt and provisions. Although delinquent debt and the share of delinquent firms rise modestly with exposure (Panel A), the provisioning ratio remains small and statistically insignificant (Panel B). Delinquent provisions also increase with exposure (Panel B). Thus, while wildfire-induced borrower distress raises provisions, its limited weight in banks' overall portfolios prevents it from materially affecting bank-level provisioning ratios, suggesting limited pressure on bank solvency.

We also ask whether the limited bank-level effects mask greater pressure on smaller banks, which hold less diversified portfolios. Appendix Table 15 re-estimates the bank-level specification for banks below the median size and in the lower quartile. Among banks in the lower quartile, delinquent debt rises significantly with wildfire exposure. However, the provisioning ratio remains small and statistically insignificant for both groups, so higher realized delinquency does not translate into capital-relevant increases in provisioning. Thus, wildfire shocks leave a detectable imprint on smaller banks' delinquency without generating detectable pressure on their solvency.

5 When Could Wildfires Threaten Bank Solvency?

The previous section shows that wildfire-induced provisions generated limited pressure on bank solvency. How different would conditions need to be to materially threaten solvency? We answer this question by expressing the provision shock as severity times exposure, mapping it into the capital ratio, and asking how much larger exposure would need to be to materially affect bank solvency.

5.1 From Provisions to Bank Capital

A large wildfire affects some counties, but only a subset of firms within those counties is directly affected. For an affected firm, the probability of a loan default (or delinquency in our estimates above) increases, and the banks that lent to the firm must make additional loan-loss provisions, increasing the reserves they set aside for expected loan losses. The size of this provision shock depends on three things: (1) how much more likely an affected firm is to default on its loan obligation; (2) how much of each loan the bank fails to recover when a firm defaults; and (3) how large a share of the bank's loan book is exposed to affected firms. The provision shock is the product of these three:

$$\frac{\Delta P}{S} = (d^a - d^u)(1 - \tau)\omega^a,$$

where ΔP is the rise in loan-loss provisions (in pesos) and $\Delta P/S$ is that rise as a share of the loan book; d^a and d^u are the probabilities of default of an affected and an unaffected firm, so $d^a - d^u$ is the increase in default probability caused by the fire; $(1-\tau)$ is the loss given default, the fraction of a loan not recovered when a firm defaults (so τ is the recovery rate); and ω^a is the share of the bank's total loans extended to affected firms.

The exposure share ω^a decomposes across counties. Index counties by c and let $\mathcal{W}$ represent the set of counties affected by a wildfire. Let S_c be the total loans the bank has in county c, and S_c^a the loans in county c held by affected firms, both in pesos. By definition, the bank-wide exposure share is the sum of county exposures over the book,

$$\omega^a = \frac{\sum_{c\in\mathcal{W}} S_c^a}{S}.$$

Multiplying and dividing each term by S_c gives

$$\omega^a = \sum_{c \in \mathcal{W}} \frac{S_c}{S} \underbrace{\frac{S_c^a}{S_c}}_{\omega_c^a},$$

where $\omega_c^a = S_c^a / S_c$ is the within-county exposure share, the fraction of county c's loans held by affected firms. Thus, ω^a is a weighted sum of the within-county exposure shares, with weights given by each county's share of the bank's loan book.

For an order-of-magnitude calculation, we approximate the affected share within each wildfire county by its cross-county average, $\omega_c^a \approx \mathbb{E}[\omega_c^a]$. It follows that

$$\omega^a \approx \mathbb{E}[\omega_c^a] \underbrace{\sum_{c \in \mathcal{W}} \frac{S_c}{S}}_{\omega^W} = \omega^W \mathbb{E}[\omega_c^a],$$

where ω^W is the share of the bank's loans located in wildfire-affected counties, and $\mathbb{E}[\omega_c^a]$ is the average share of lending within those counties accounted for by affected firms. Their product is therefore the share of the bank's entire loan portfolio exposed to affected firms.

It is useful to group the primitives into two economic blocks:

$$\frac{\Delta P}{S} = \underbrace{(d^a - d^u)(1 - \tau)}_{\text{Severity}} \times \underbrace{\omega^a}_{\text{Composition}}.$$

"Severity" is how much is lost on each affected peso: it depends on how much more likely an affected firm is to default, $(d^a - d^u)$, times the fraction lost if it does, $(1 - \tau)$. "Composition" is how much of the bank's book is exposed, $\omega^a = \omega^W \mathbb{E}[\omega_c^a]$. The provision shock is therefore the product of how hard each exposed peso is hit and how many pesos are exposed.

Provisions are an expense for banks: a rise in ΔP reduces net profits and, keeping dividend distributions constant, also reduces retained earnings and, hence, capital. Expressed as a change in the capital ratio,

$$\frac{\Delta K}{RWA} = -\frac{\Delta P}{S} \cdot \frac{S}{RWA},$$

where K is bank capital and RWA are risk-weighted assets. We benchmark the size of this fall against a target capital decline deemed material (for example, 100 bps):

$$\frac{\Delta P}{S} \cdot \frac{S}{RWA} \geq \text{target}.$$

Substituting for $\Delta P / S$ and expanding composition as $\omega^a = \omega^W \mathbb{E}[\omega_c^a]$ gives

$$(d^a - d^u)(1 - \tau)\omega^W \mathbb{E}[\omega_c^a] \cdot \frac{S}{RWA} \geq \text{target}.$$

We measure the shock against the system's capital headroom. As of February 2026, the banking system's CET1 capital headroom over the regulatory requirement was about 320 bps (Central Bank of Chile, 2026). A 100 bps fall in K/RWA is therefore roughly one-third of that headroom. The exercise is one of buffer erosion, not insolvency: a 100 bps reduction is material but non-extreme.[17]

5.2 Calibration

We conduct counterfactuals by moving the composition factors ω^W and $\mathbb{E}[\omega_c^a]$, holding severity fixed, and read off the resulting capital hit against the headroom benchmark. The baseline values come from four sources: (i) observed in the data, (ii) estimated as a regression coefficient, (iii) imposed on economic grounds, or (iv) recovered by inverting an identity. Appendix Table 16 records each value, its status, and the computation.

To map the estimated delinquency effect into bank capital, we need to distinguish between the number of firms affected by a wildfire and the amount of credit they represent. We therefore construct two measures from the credit registry. Let ϕ_c^a denote the share of firms by count in wildfire-affected county c that are affected, and ω_c^a the share of credit in that county accounted for by affected firms. The count share, $\mathbb{E}[\phi_c^a] = 0.067$, is used to recover the increase in default probability among affected firms from the LP-DiD coefficient. The credit share, $\mathbb{E}[\omega_c^a] = 0.025$, is used to translate this firm-level default response into losses on the bank's loan portfolio. For purposes of the calibration, affected firms are defined as those current before the fire that default within twelve months.

Because the LP-DiD coefficient averages the delinquency response across all firms in treated counties, we use the count share to recover the implied default response among affected firms. Specifically, under the calibration, the delinquency coefficient identifies the product:

$$\widehat{\beta}_\delta = \mathbb{E}[\phi_c^a](d^a - d^u),$$

so:

$$d^a - d^u = \frac{\widehat{\beta}_\delta}{\mathbb{E}[\phi_c^a]} = \frac{0.004}{0.067} = 0.060,$$

where $\widehat{\beta}_\delta$ is the linear-probability coefficient on the delinquency indicator. Thus, the

[17] The Central Bank's stress tests apply far more adverse credit-risk scenarios, and banks remain solvent (Central Bank of Chile, 2026).

0.4 percentage-point average increase in delinquency implies a 6.0 percentage-point increase among affected firms under the calibration. We impose the loss given default at $1 - \tau = 0.50$, above the Basel F-IRB senior-unsecured value of 0.40–0.45 because wildfires destroy the collateral backing the loan.

Multiplying the baseline values at the most exposed month gives:

$$(d^a - d^u)(1-\tau)\omega^W \mathbb{E}[\omega_c^a] \cdot \frac{S}{RWA} = 0.060 \times 0.50 \times 0.33 \times 0.025 \times 1.03 \approx 0.00026,$$

or about 0.025 percentage points of the capital ratio, an order of magnitude consistent with the small and insignificant bank-level provisioning response documented in Section 4.3. The credit share, $\mathbb{E}[\omega_c^a] = 0.025$, is well below the count share, $\mathbb{E}[\phi_c^a] = 0.067$, reflecting that firms that default after a wildfire are smaller than average, consistent with the concentration of effects among small firms in Section 3.2.

The counterfactual exercises in the next section use this benchmark calibration to illustrate how changes in portfolio composition affect the transmission of wildfire shocks to bank solvency.

5.3 Counterfactuals

Holding severity fixed, the capital hit depends on the two composition factors, ω^W and $\mathbb{E}[\omega_c^a]$. Figure 4 maps the capital hit over their plane: the color deepens toward the northeast as the hit increases, and the curve marks the 100 bps threshold, about one-third of the system's CET1 headroom. The marked point represents the most exposed configuration observed in the data: the highest monthly share of the loan book in wildfire-affected counties ($\omega^W = 0.33$), evaluated at the registry-average affected credit share ($\mathbb{E}[\omega_c^a] = 0.025$). This configuration remains well below the materiality threshold, with a capital hit of about 2.5 bps, roughly forty times smaller than 100 bps.

Under our benchmark calibration, reaching the 100 bps threshold while holding severity fixed would require the exposure product $\omega^W \mathbb{E}[\omega_c^a]$ to be approximately forty times larger than its benchmark value of $0.33 \times 0.025 = 0.008$, rising to about 0.325. The condition determines only the product, not either factor separately. Because both factors are shares bounded by one, reaching this level would require a substantial increase in the share of the loan book located in wildfire-affected counties, the affected credit share within those counties, or both. Such concentration appears implausible at the system level, although it could be more relevant for a bank heavily concentrated in a particular forestry or agricultural area.

Wildfire frequency provides an additional dimension of aggregate exposure. Absent nonlinear effects from the accumulation of successive events, more frequent wildfires would increase provisions, and the capital would be hit roughly proportionally. A material effect on bank solvency would therefore require substantially greater portfolio exposure, a higher frequency of wildfire shocks, or a combination of both.

6 Conclusions

This paper provides new evidence on how large wildfires affect firm credit risk, bank behavior, and bank solvency. Using granular firm-bank data matched with geospatial wildfire information from Chile, we document that these natural disasters reduce firms' repayment capacity. Delinquency increases persistently following wildfire events, with the strongest effects concentrated among small firms, those in the agriculture and forestry sector, and firms with weak firm-bank relationships. The effects are small in magnitude; however, they point to a contained deterioration in repayment behavior.

Wildfires shape bank behavior through different channels. First, banks raise interest rates and reduce lending in counties with high historical wildfire exposure, even when those counties are not directly affected by the wildfire itself. These results are consistent with banks reassessing wildfire exposure in vulnerable areas, which we interpret as evidence of their reassessment of future climate risk. Second, banks recognize the higher expected losses on wildfire-exposed loans by raising loan-loss provisions, with the largest effects concentrated among small firms.

At the aggregate level, once we consider total provisions across firms within a bank-county and, subsequently, at the bank level, the wildfire effects become small and statistically insignificant. The evidence shows that the deterioration in credit quality has been concentrated among relatively small borrowers, which account for a limited share of total bank lending. As a result, the rise in provisions is insufficient to materially affect bank solvency or local credit aggregates. Our findings suggest that portfolio composition is an important determinant of banking resilience. Resilience also rests on banks recognizing losses when they occur, as evidenced by the increase in provisions alongside rising delinquent debt in our data.

The analysis also offers guidance for assessing financial stability going forward. Our counterfactual exercise shows that even the most exposed month in the sample implies a negligible capital hit. Moreover, even the largest wildfire events in Chile have not generated detectable aggregate effects large enough to threaten bank solvency. Under our benchmark calibration, a material decline in solvency would require the exposure product to rise to many times its historical maximum, through some combination of a larger share of the book in burned counties and greater concentration on affected firms within them. Should future disasters push portfolios toward that region, the framework in this paper can locate the point at which resilience breaks down, tracing a shock from borrower delinquency through provisioning to bank capital.

The findings in this paper also matter for the climate-related financial stability policy agenda discussed at the Network of Central Banks and Supervisors for Greening the Financial System (NGFS), the Bank for International Settlements (BIS), and the Basel Committee. The portfolio composition that insulates the Chilean system is shared by many banking systems lending across a broad range of sectors and regions. In such countries, localized shocks can harm vulnerable firms and sectors without threatening financial stability. To the extent that policy action is warranted, the results in this paper support targeted assistance to the most exposed firms and sectors. However, natural shocks could become material for concentrated lenders, such as banks operating in small island states or in economies dependent on a narrow agricultural or forestry base. Those cases could benefit from mechanisms that hedge exposure to such shocks.

Lastly, one caveat of our analysis is that it captures the causal change in credit quality conditional on existing insurance coverage and government transfers. The relatively low credit deterioration among affected firms could result from larger firms having insurance and from government support for smaller firms. An increase in wildfire frequency and size could reduce insurance coverage, thereby increasing the probability of default for affected firms. Similarly, the reduction in default frequencies resulting from government transfers must be weighted against the fiscal cost of these measures. Future research could explore the effects of insurance or government transfers, provided that the information becomes available.

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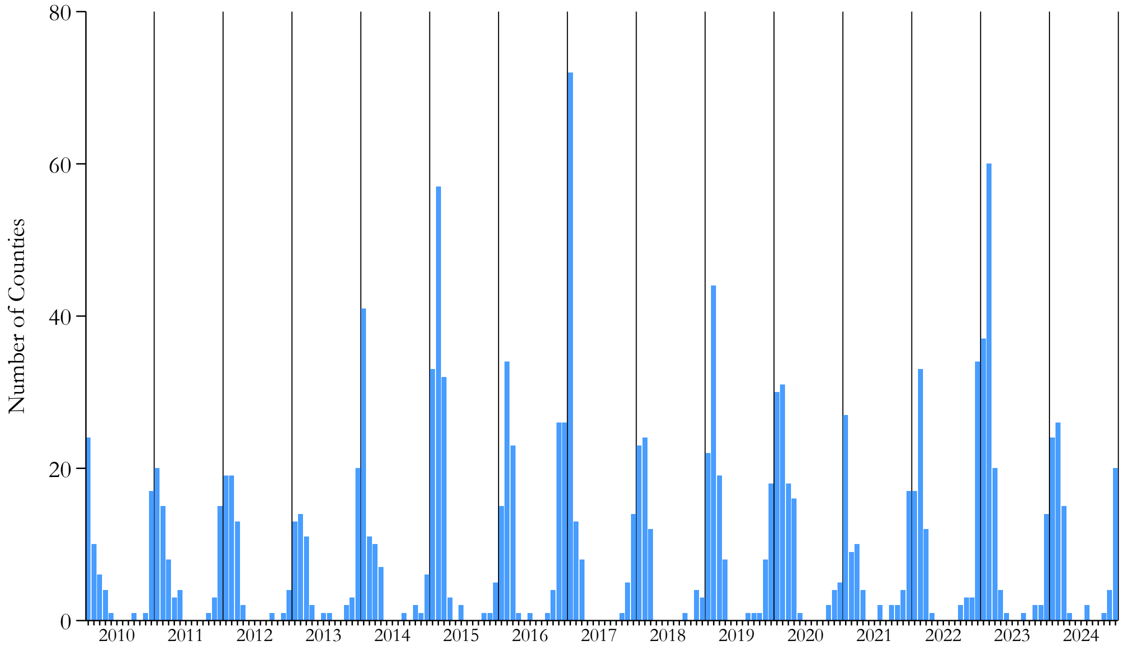
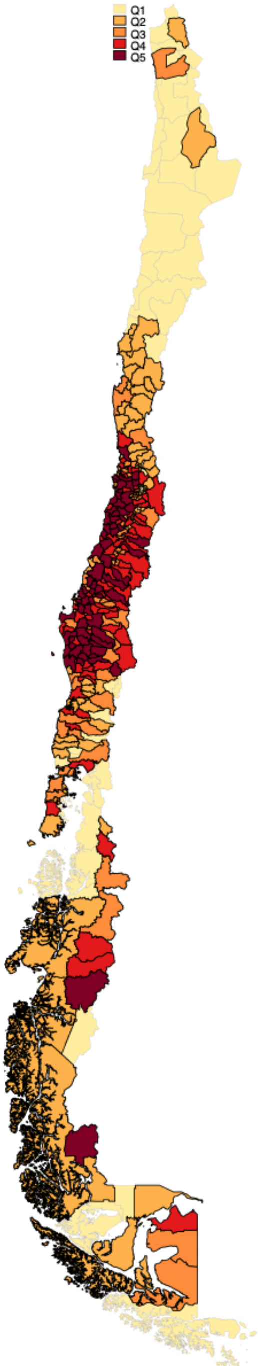
Figure 1
Number of Counties With a Large Wildfire



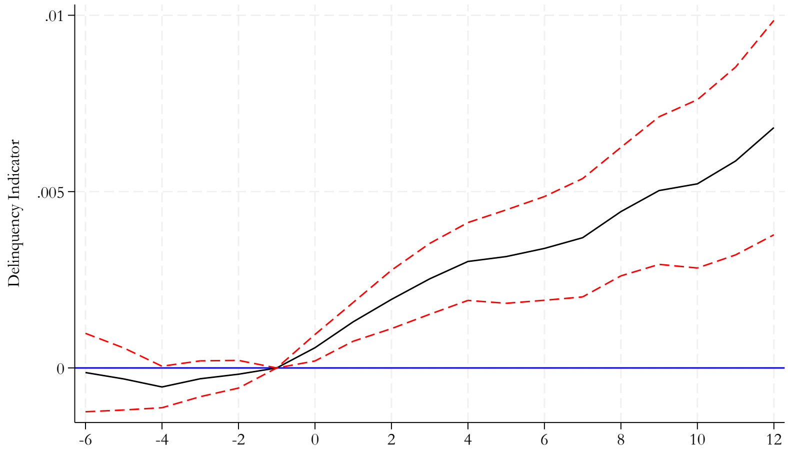
This figure shows the evolution over time of the number of counties experiencing large wildfires. A county-month is classified as experiencing a large wildfire when the burned area in that county during that month exceeds the 90th percentile (p90) of the burned-hectare distribution. Each bar represents one month and reports the number of counties whose wildfire activity exceeds this threshold in that month. The 12 bars within each year correspond to January through December. Counties are counted separately in each month in which they experience a large wildfire.

Figure 2
Spatial Distribution of Large Wildfire Activity

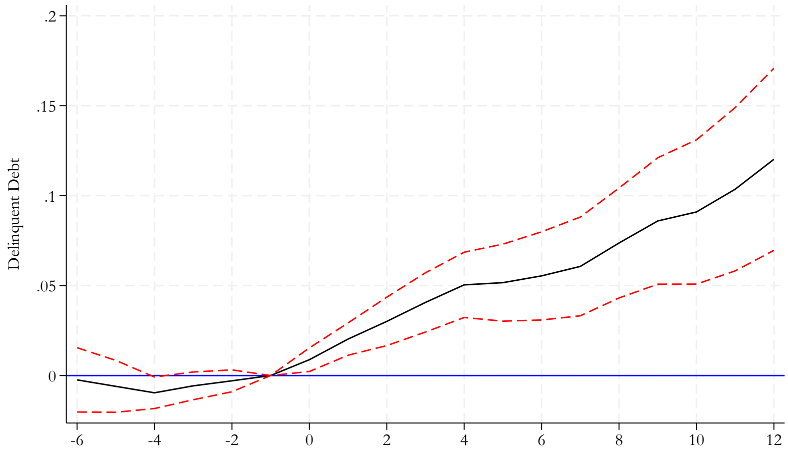


This figure maps the spatial distribution of large wildfire activity across Chilean counties, shaded by quintile of cumulative hectares burned over 2010–2024, computed from Corporación Nacional Forestal (CONAF) records at the county-year-month level. Wildfire activity is heavily concentrated in central-southern Chile, the country's main agricultural and forestry belt.

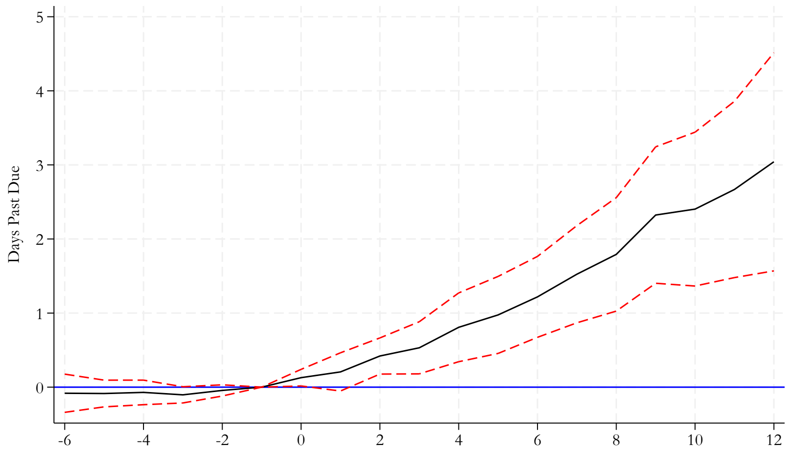
Figure 3
Impact of Large Wildfires on Firm-Bank Delinquency



A. Delinquency Indicator



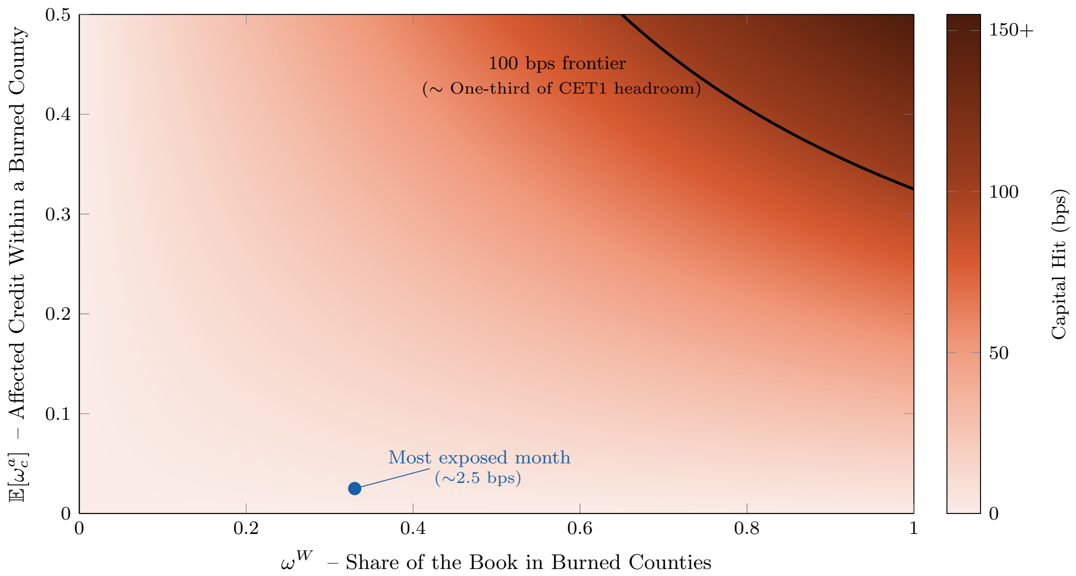
B. Delinquent Debt



C. Days Past Due

This figure reports Local Projections Difference-in-Differences (LP-DiD) estimates and 95% confidence bands of the dynamic effects of wildfire exposure on firm-bank delinquency outcomes. Panel A reports the Delinquency Indicator, Panel B reports the (log) Delinquent Debt, and Panel C reports Days Past Due. The horizontal axis is measured in months. The solid line shows point estimates and the dashed lines show confidence intervals. Estimations include firm and bank-time fixed effects as well as one lag of the dependent variable. Standard errors are two-way clustered at the county and year-month level.

Figure 4
Counterfactual Capital Hit Across Wildfire Exposure Combinations



This figure reports counterfactual capital hits over the plane of the two composition factors, ω^W (the share of the book in burned counties) and $\mathbb{E}[\omega_c^a]$ (affected credit within a burned county), holding severity fixed at $(d^a - d^u)(1-\tau) = 0.030$ and $S/RWA = 1.03$. The color becomes darker toward the northeast, where exposure is larger. The curve is the 100 basis points (bps) frontier, about one-third of the system's CET1 headroom. The marked point is the most exposed month of the 2010–2024 sample, $\omega^W = 0.33$ and $\mathbb{E}[\omega_c^a] = 0.025$, which implies a capital hit of about 2.5 bps.

Table 1
Summary Statistics

	Mean	Median	Std. Dev.	Min	Max	Observations
Panel A. Stock of Credit and Credit Risk						
Normal Debt (thousand USD)	473.8	14.0	5,083.9	0.0	1,729,192.8	23,219,668
Delinquent Debt (thousand USD)	14.1	0.0	413.5	0.0	145,002.5	23,219,668
Delinquency Indicator	0.09	0.00	0.3	0.0	1.0	23,219,668
Days Past Due	16.5	0.0	69.8	0.0	1,097.0	16,024,610
Panel B. Flow of New Credit						
Annual Interest Rate (percentage points)	9.7	8.6	5.9	1.2	31.1	712,157
Loan Amount (thousand USD)	516.1	113.8	2,300.7	0.9	275,331.6	712,157
Annual Interest Rate, CLP (percentage points)	11.3	10.7	5.6	1.2	31.1	559,227
Loan Amount, CLP loans (thousand USD)	424.3	81.0	2,099.8	0.9	179,275.6	559,227
Annual Interest Rate, UF (percentage points)	3.4	2.9	1.9	1.2	14.6	125,035
Loan Amount, UF loans (thousand USD)	753.3	333.9	2,150.6	1.0	153,161.2	125,035
Panel C. Portfolio Composition						
Debt-Weighted Shares						
Share of Debt Held by Small Firms	8.3	7.3	2.4	6.0	14.5	180
Share of Debt Held by Firms in Agriculture and Forestry Sector	5.5	5.5	0.3	4.9	6.1	180
Share of Debt Held by Small Firms in Agriculture and Forestry	0.8	0.8	0.1	0.7	0.9	180
Borrower-Count Shares						
Share of Borrowers that are Small Firms	69.4	68.9	5.0	62.1	77.6	180
Share of Borrowers in Agriculture and Forestry Sector	5.8	5.4	0.9	4.7	7.8	180
Share of Borrowers that are Small Firms in Agriculture and Forestry	3.8	3.6	0.5	3.3	5.0	180

This table reports firm-bank summary statistics of the main variables from 2010 to 2024. UF (*Unidad de Fomento*) is a Chilean indexed unit of account that evolves according to the previous month's inflation. All monetary values are expressed in thousands of U.S. dollars (USD).

Table 2
Distribution of Counties by Occurrence of Large Wildfires

	Number	Percentage
Zero Events	115	33.4%
1	63	18.3%
2	31	9.0%
3	15	4.4%
4	17	4.9%
5 or More Events	103	29.9%
Total	344	100%

This table shows the distribution of counties by the number of large wildfires experienced over the period 2010–2024. Large wildfires are defined as those above the 90th percentile of the burned-hectare distribution. The counties Isla de Pascua and Juan Fernández are excluded.

Table 3
Heterogeneous Impact of Large Wildfires on Delinquency by Firm Size

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. All Firms			
Treated	0.004***	0.061***	1.032***
	(0.001)	(0.013)	(0.310)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.5	6.3	6.9
Panel B. Small Firms			
Treated	0.005***	0.087***	0.793**
	(0.001)	(0.015)	(0.306)
Observations	13,893,222	13,893,222	10,018,863
R-squared	0.362	0.358	0.577
Effect / Pre-mean (%)	5.8	9.1	5.0
Panel C. Medium Firms			
Treated	0.002	0.027	0.958*
	(0.001)	(0.020)	(0.483)
Observations	5,053,222	5,053,222	3,301,954
R-squared	0.269	0.271	0.534
Effect / Pre-mean (%)	2.2	2.8	6.4
Panel D. Large Firms			
Treated	0.001	0.024	1.214
	(0.002)	(0.031)	(0.760)
Observations	4,050,374	4,050,374	2,442,222
R-squared	0.224	0.224	0.506
Effect / Pre-mean (%)	2.7	2.4	13.1
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' debt outcomes for a firm exposed to large wildfires, by firm size. The dependent variables are the average post-treatment change in each outcome over horizons $= 0, \dots, 12$ relative to month -1. Size definition follows the Chilean Tax Authority criteria based on annual sales. Firms with no reported sales information are excluded from the size-specific samples. All columns and panels include firm and bank-time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for Delinquency Indicator and Days Past Due, while for Delinquent Debt is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 4
Heterogeneous Impact of Large Wildfires on Delinquency by Sector

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Agriculture and Forestry			
Treated	0.004***	0.067**	1.256***
	(0.002)	(0.027)	(0.458)
Observations	1,054,943	1,054,943	651,165
R-squared	0.333	0.325	0.561
Effect / Pre-mean (%)	4.0	6.9	4.0
Panel B. Manufacturing			
Treated	0.002	0.034	0.528
	(0.002)	(0.029)	(0.854)
Observations	2,590,730	2,590,730	1,670,914
R-squared	0.312	0.304	0.550
Effect / Pre-mean (%)	1.9	3.5	3.4
Panel C. Utilities and Construction			
Treated	0.003	0.060	-0.163
	(0.003)	(0.042)	(0.680)
Observations	2,579,692	2,579,692	1,773,496
R-squared	0.346	0.339	0.572
Effect / Pre-mean (%)	3.0	6.2	-0.7
Panel D. Commerce, Transportation, and Tourism			
Treated	0.003***	0.052***	1.557***
	(0.001)	(0.017)	(0.418)
Observations	8,737,532	8,737,532	6,190,937
R-squared	0.340	0.333	0.569
Effect / Pre-mean (%)	3.5	5.3	9.7
Panel E. Services			
Treated	0.004***	0.062***	0.626*
	(0.001)	(0.016)	(0.325)
Observations	7,968,216	7,968,216	5,439,976
R-squared	0.325	0.315	0.558
Effect / Pre-mean (%)	7.0	6.4	5.7
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' debt outcomes for a firm exposed to large wildfires, by firm sector. The dependent variables are the average post-treatment change in each outcome over horizons $= 0, \ldots, 12$ relative to month -1. Sectors are aggregated into five macro-groups. All columns and panels include firm and bank-time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for Delinquency Indicator and Days Past Due, while for Delinquent debt is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5
Heterogeneous Impact of Large Wildfires on Delinquency:
Firm-Bank Relationship Strength – Small Firms

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Main-Bank Relationship			
Treated	0.010***	0.175***	2.055***
	(0.002)	(0.029)	(0.699)
Treated × Main bank	-0.006***	-0.109***	-1.573***
	(0.002)	(0.031)	(0.570)
Observations	13,893,222	13,893,222	10,018,863
R-squared	0.362	0.358	0.577
Treated / Pre-mean (%)	9.6	19.1	6.5
Interaction / Pre-mean (%)	-5.9	-10.3	-5.0
Panel B. Bank Share of Firm's Outstanding Debt			
Treated	0.013***	0.221***	3.088***
	(0.003)	(0.041)	(0.873)
Treated × Share (%)	-0.010***	-0.167***	-2.886***
	(0.003)	(0.049)	(0.778)
Observations	13,893,222	13,893,222	10,018,863
R-squared	0.363	0.358	0.577
Treated / Pre-mean (%)	11.9	24.7	9.8
Interaction / Pre-mean (%)	-8.9	-15.4	-9.1
Panel C. Single Bank Relationships			
Treated	0.007***	0.122***	1.863***
	(0.002)	(0.029)	(0.603)
Treated × Single Bank	-0.004*	-0.075*	-1.882***
	(0.002)	(0.040)	(0.561)
Observations	13,893,222	13,893,222	10,018,863
R-squared	0.364	0.360	0.578
Treated / Pre-mean (%)	6.8	13.0	5.9
Interaction / Pre-mean (%)	-4.1	-7.2	-6.0
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of wildfire treatment on firm-bank delinquency outcomes, interacting treatment with alternative measures of bank-firm relationship strength. Panel A uses an indicator for whether the bank is the firm's main bank, defined as the bank with the largest share of the firm's total borrowing in a given month. Panel B uses the bank's share of the firm's total outstanding debt. Panel C uses an indicator for firms borrowing from a single bank. The dependent variables are the average post-treatment change in each outcome over horizons $= 0, \dots, 12$ relative to month -1. All columns include firm and bank-time fixed effects, as well as one lag of the dependent variable. Standard errors are in parentheses and two-way clustered at the county and year-month level. Treated reports the estimated effect for the omitted relationship group or for a relationship measure equal to zero. Treated × relationship reports the differential effect associated with the corresponding relationship measure. Treated / Pre-mean and Interaction / Pre-mean (%) are the treatment and interaction coefficient variable scaled by the pre-treatment mean for Delinquency Indicator and Days Past Due, while for Delinquent Debt is computed as $100 \times (\exp(\beta) - 1)$. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Effects of Large Wildfires on New Lending:
Reassessment of Wildfire Credit Risk

	Exposure Percentile		
	p75th	p80th	p90th
Panel A. Interest Rate			
0–3 Months Since WF × High Exposure	0.370***	0.452***	0.463***
	(0.030)	(0.047)	(0.064)
4–6 Months Since WF × High Exposure	0.327***	0.400***	0.441***
	(0.077)	(0.067)	(0.152)
Observations	712,157	712,157	712,157
R-squared	0.854	0.854	0.854
Panel B. (Log) Loan Amount			
0–3 Months Since WF × High Exposure	-0.175***	-0.327***	-0.288***
	(0.053)	(0.013)	(0.011)
4–6 Months since WF × High Exposure	-0.155**	-0.329***	-0.219***
	(0.062)	(0.016)	(0.009)
Observations	712,157	712,157	712,157
R-squared	0.804	0.804	0.804
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports transaction-level regressions of loan terms on firms' ex ante wildfire risk exposure and loan-level characteristics, using the loan-level dataset. WF stands for large wildfire. Panel A reports effects on the interest rate. The reported interest rate effects are between 3.4% and 4.8% of the average pre-shock interest rate. Panel B reports effects on the log loan amount. Loan-level controls include interest rate type, loan maturity, currency type, a restructured loan indicator, and an uncollateralized loan indicator. Each column reports estimates for a different definition of high ex ante wildfire exposure: a county is classified as highly exposed if its cumulative affected surface area over 2002–2009 is above the 75th, 80th, or 90th percentile of the distribution across counties, respectively. The indirect exposure indicators interact these county-level classifications with the occurrence of a large wildfire anywhere in the country within the previous 0–3 and 4–6 months. All columns and panels include firm and bank-time fixed effects. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7
Impact of Large Wildfires on Firm-Bank Loan-Loss Provisions

	Provisioning Ratio	(Log) Total Provisions	Delinquent Provisions
Panel A. All Firms			
Treated	0.001***	0.001	0.057***
	(0.000)	(0.010)	(0.012)
Observations	23,219,668	23,219,668	23,219,668
R-squared	0.288	0.418	0.324
Effect / Pre-mean (%)	0.1	0.1	5.9
Panel B. Small Firms			
Treated	0.001***	0.021**	0.080***
	(0.000)	(0.010)	(0.014)
Observations	13,893,222	13,893,222	13,893,222
R-squared	0.314	0.493	0.356
Effect / Pre-mean (%)	2.3	2.1	8.3
Panel C. Medium Firms			
Treated	0.001	-0.010	0.028
	(0.001)	(0.019)	(0.019)
Observations	5,053,222	5,053,222	5,053,222
R-squared	0.224	0.404	0.269
Effect / Pre-mean (%)	1.4	-1.0	2.8
Panel D. Large Firms			
Treated	0.001	0.000	0.024
	(0.001)	(0.025)	(0.030)
Observations	4,050,374	4,050,374	4,050,374
R-squared	0.185	0.322	0.222
Effect / Pre-mean (%)	0.01	0.02	2.4
Firm FE	Yes	Yes	Yes
Bank $\times$ Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firm-bank loan-loss provisioning outcomes for a firm exposed to large wildfires, by firm size. The Provisioning Ratio is total loan-loss provisions over outstanding debt, Total Provisions is the log of total loan-loss provisions, and Delinquent Provisions is the log of loan-loss provisions on Delinquent Debt; both logged outcomes use the $\log(1 + y)$ transformation. Size definition follows the Chilean Tax Authority criteria based on annual sales. Firms with no reported sales information are excluded from the size-specific samples. All columns and panels include firm and bank-time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for Provisioning Ratio, while for Total Provisions and Delinquent Provisions it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8
Impact of Large Wildfires on Bank-County Loan-Loss Provisions

	Provisioning Ratio	(Log) Total Provisions	Delinquent Provisions
Panel A. All Firms			
Treated	-0.001	0.015	0.044
	(0.001)	(0.037)	(0.077)
Observations	326,504	338,058	338,058
R-squared	0.181	0.255	0.241
Effect / Pre-mean (%)	-1.3	1.5	4.5
Panel B. Small Firms			
Treated	0.000	0.069*	0.174***
	(0.001)	(0.037)	(0.066)
Observations	269,131	284,821	284,821
R-squared	0.225	0.276	0.255
Effect / Pre-mean (%)	0.8	7.1	19.0
Panel C. Medium Firms			
Treated	-0.001	-0.022	-0.172*
	(0.002)	(0.047)	(0.102)
Observations	237,493	252,798	252,798
R-squared	0.339	0.268	0.241
Effect / Pre-mean (%)	-0.3	-2.2	-15.8
Panel D. Large Firms			
Treated	0.001	-0.005	-0.031
	(0.001)	(0.056)	(0.110)
Observations	229,241	245,014	245,014
R-squared	0.149	0.252	0.233
Effect / Pre-mean (%)	1.4	-0.5	-3.1
County FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

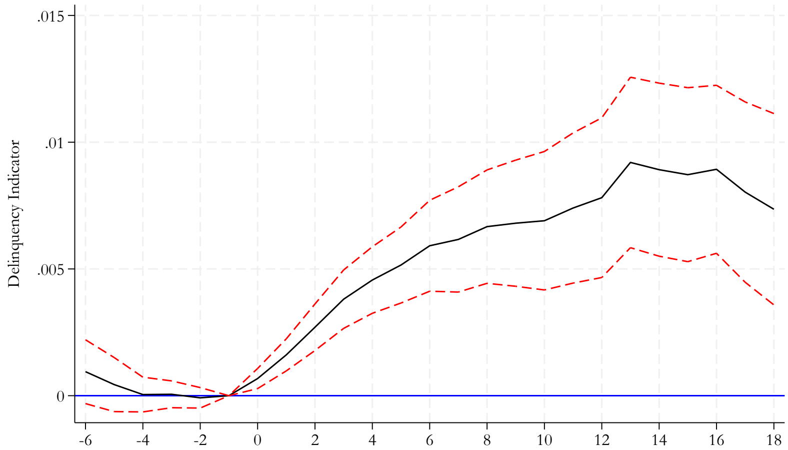
This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' provisioning outcomes for a firm exposed to large wildfires, aggregated at the bank-county level. The Provisioning Ratio is total loan-loss provisions over outstanding debt, Total Provisions is the log of total loan-loss provisions, and Delinquent Provisions is the log of loan-loss provisions on Delinquent Debt; both logged outcomes use the $\log(1+y)$ transformation. All columns and panels include county and bank-time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for Provisioning Ratio, while for Total Provisions and Delinquent Provisions it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 9
Impact of Large Wildfires on Bank-Level Delinquency and Provisions

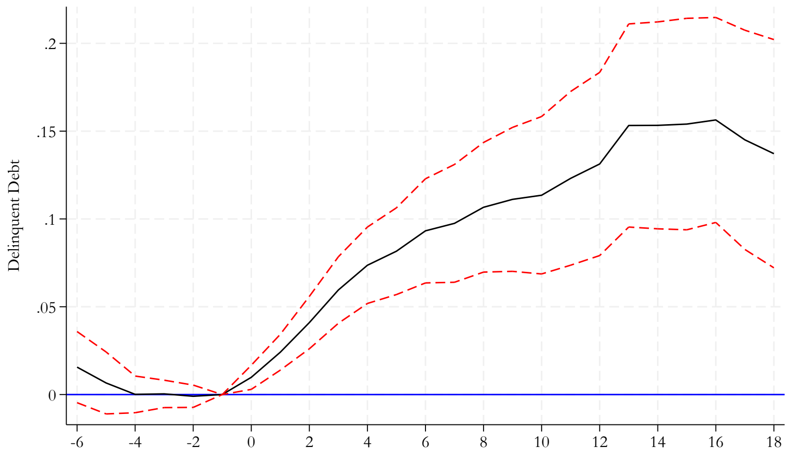
Panel A. Bank Delinquency Outcomes			
	Delinquent Debt	Delinquency Ratio	% Delinquent Firms
Bank exposure (%)	0.0784**	0.0007	0.0004**
	(0.0322)	(0.0005)	(0.0001)
Observations	2,901	2,893	2,893
R-squared	0.2758	0.7076	0.5872
Effect / Pre-mean (%)	8.2	1.8	0.4
Panel B. Bank Provisioning Outcomes			
	Provisioning Ratio	(Log) Total Provisions	Delinquent Provisions
Bank exposure (%)	-0.0000	0.0002	0.0733**
	(0.0001)	(0.0056)	(0.0317)
Observations	2,893	2,901	2,901
R-squared	0.8333	0.3122	0.2619
Effect / Pre-mean (%)	-0.0	0.0	7.6
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

This table reports pooled Panel Local Projections regressions of bank-level outcomes on wildfire exposure. Bank exposure measures the share of each bank's lending located in counties experiencing a large wildfire in that month. For Panel A, Delinquent Debt is the log of the bank's outstanding Delinquent Debt. Delinquency Ratio is Delinquent Debt over total outstanding debt, and % Delinquent Firms is the share of the bank's borrowers holding Delinquent Debt. For Panel B, Provisioning Ratio is total loan-loss provisions over outstanding debt, Total Provisions is the log of total loan-loss provisions, and Delinquent Provisions is the log of loan-loss provisions on Delinquent Debt; both logged outcomes use the $\log(1 + y)$ transformation. All columns and panels include bank and time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for the Provisioning Ratio, Delinquency Ratio, and % Delinquent Firms, while for Total Provisions, Delinquent Debt, and Delinquent Provisions it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and clustered at the bank level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

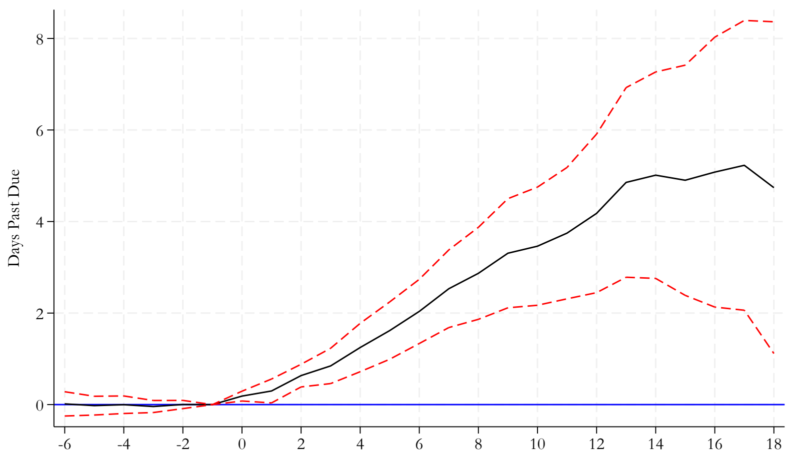
Appendix Figure 1
Impact of Large Wildfires on Firm-Bank Delinquency – Extended Horizon of 18 Months



A. Delinquency Indicator



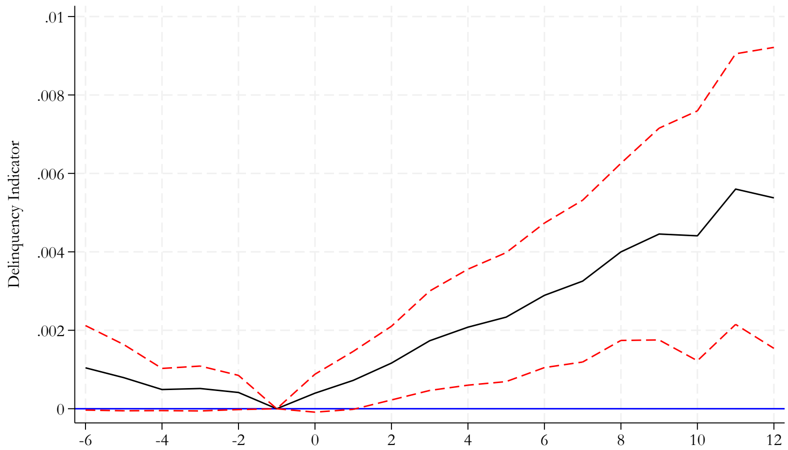
B. Delinquent Debt



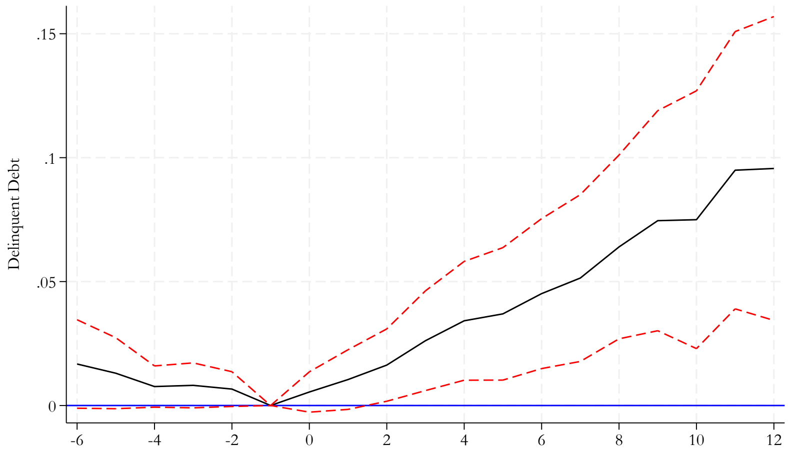
C. Days Past Due

This figure reports Local Projections Difference-in-Differences (LP-DiD) estimates and 95% confidence bands of the dynamic effects of wildfire exposure on firm-bank delinquency outcomes, extending the horizon to 18 months after the wildfire, and the clean condition to 18 months before the event. Panel A reports the Delinquency Indicator, Panel B reports the (log) Delinquent Debt, and Panel C reports Days Past Due. The horizontal axis is measured in months. The solid line shows point estimates and the dashed lines show confidence intervals. Estimations include firm and bank-time fixed effects, as well as one lag of the dependent variable. Standard errors are two-way clustered at the county and year-month level.

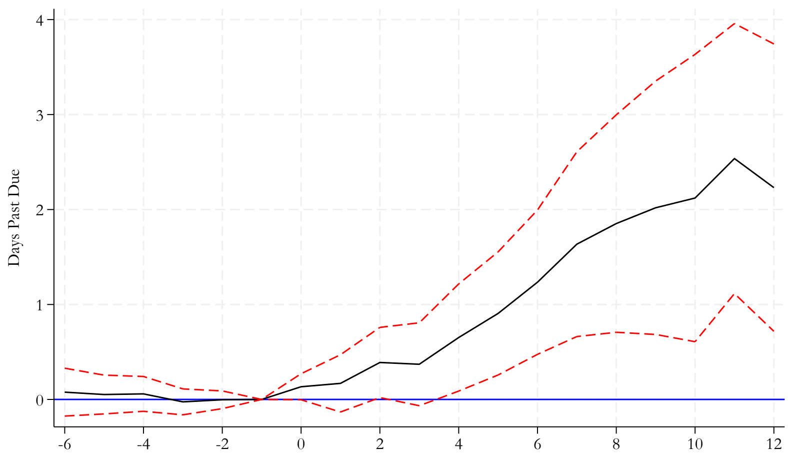
Appendix Figure 2
Impact of Large Wildfires on Firm-Bank Delinquency – Clean Pre- and Post-Treatment Windows



A. Delinquency Indicator



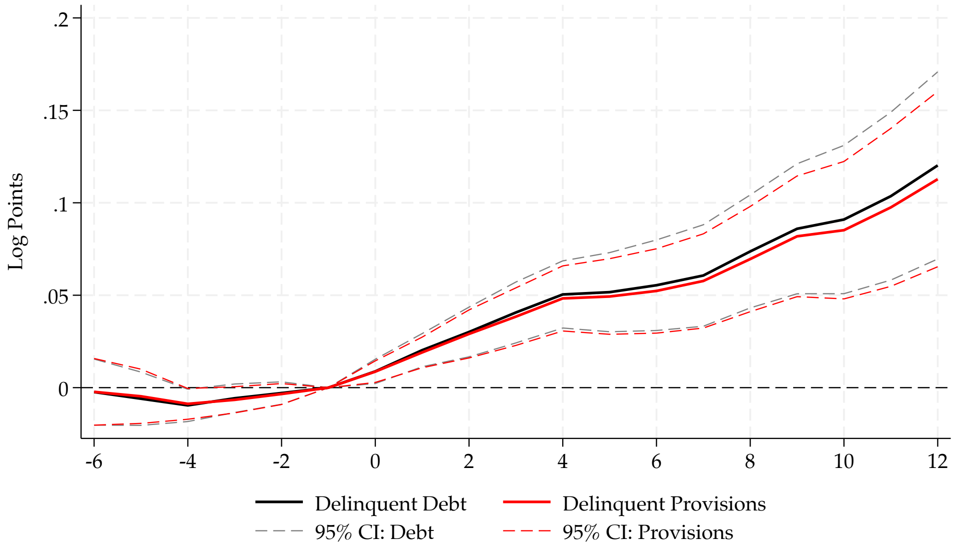
B. Delinquent Debt



C. Days Past Due

This figure reports Local Projections Difference-in-Differences (LP-DiD) estimates and 95% confidence bands of the dynamic effects of wildfire exposure on firm-bank delinquency outcomes. The sample requires both treated and control observations to be free of large wildfire exposure over the relevant pre- and post-treatment windows, except for the treatment event itself. Panel A reports the Delinquency Indicator, Panel B reports the (log) Delinquent Debt, and Panel C reports Days Past Due. The horizontal axis is measured in months. Estimations include firm and bank-time fixed effects, as well as one lag of the dependent variable. The solid line shows point estimates and the dashed lines show 95% confidence intervals. Standard errors are two-way clustered at the county and year-month level.

Appendix Figure 3
Joint Dynamics of Delinquent Debt and Delinquent Provisions



This figure reports Local Projections Difference-in-Differences (LP-DiD) estimates of the dynamic effects of wildfire exposure on firm-level Delinquent Debt and Delinquent Provisions. Both outcomes are measured in log points, so the two series are directly comparable. The solid black line reports the effect on Delinquent Debt, while the solid red line reports the effect on Delinquent Provisions. Dashed lines report 95% confidence bands for each outcome. Estimations include firm and bank-time fixed effects, as well as one lag of the dependent variable. Standard errors are two-way clustered at the county and year-month level.

Appendix Table 1
Pre Trends – LP-DiD Estimates by Horizon

Horizon	Delinquency Indicator	Delinquent Debt	Days Past Due
-6	-0.000	-0.002	-0.082
	(0.001)	(0.009)	(0.132)
-5	-0.000	-0.006	-0.086
	(0.000)	(0.007)	(0.092)
-4	-0.001^{*}	-0.010^{**}	-0.071
	(0.000)	(0.005)	(0.085)
-3	-0.000	-0.006	-0.104^{*}
	(0.000)	(0.004)	(0.056)
-2	-0.000	-0.003	-0.044
	(0.000)	(0.003)	(0.039)
-1 (Reference)	0.000	0.000	0.000

This table reports pre-treatment Local Projections Difference-in-Differences (LP-DiD) coefficients by time horizon. For each horizon and outcome, the table shows the estimated coefficient, its standard error, and significance stars based on the pointwise p-value from the horizon-by-horizon LP-DiD regressions. All columns include firm and bank-time fixed effects, as well as one lag of the dependent variable. Standard errors are two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 2
Permutation Placebo Test Stratified by Ex ante Wildfire Risk
Fixed-Sample Randomization Inference

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Randomization within Above/Below Median Exposure			
Actual Baseline Coefficient	0.004	0.061	1.032
Placebo Distribution (500 Permutations):			
Mean	-0.000	-0.001	0.035
Std. Dev.	0.000	0.006	0.151
2.5th pct.	-0.001	-0.014	-0.270
97.5th pct.	0.001	0.012	0.339
RI p-value	0.002	0.002	0.002
Panel B. Randomization within Exposure Quartiles			
Actual Baseline Coefficient	0.004	0.061	1.032
Placebo Distribution (500 permutations):			
Mean	-0.000	-0.001	0.045
Std. Dev.	0.000	0.006	0.125
2.5th pct.	-0.001	-0.014	-0.204
97.5th pct.	0.001	0.011	0.286
RI p-value	0.002	0.002	0.002

This table reports placebo test for the estimation sample of Figure 3. Actual coefficients are from the baseline pooled Local Projections Difference-in-Differences (LP-DiD) of Table 3. For each outcome, the baseline estimation sample is held fixed using the original clean-event rule, and treatment is then randomly reassigned across county-month cells within each month and within strata of predetermined ex ante wildfire exposure, preserving the number of treated county-month cells per stratum-month. Panel A uses two exposure strata defined by the median of cumulative pre-sample affected area, with zero-exposure counties in the bottom bin; Panel B uses exposure quartiles. Because large wildfires are concentrated in the high-exposure stratum, placebo assignments within strata necessarily overlap with actual treatment in peak months; with a fixed estimation sample, this leaves the placebo distribution centered at zero but widens it, so stratified Randomization Inference (RI) p-values are conservative relative to the unstratified test. The RI p-value reports the share of placebo estimates whose absolute value is at least as large as the actual baseline coefficient, using the small-sample correction $(s+1)/(R+1)$; a p-value of $0.002 = 1/(R+1)$ indicates that no placebo estimate reached the actual coefficient in any of the 500 permutations. All regressions include firm and bank-time fixed effects. Standard errors are two-way clustered at the county and year-month level in the baseline regressions.

Appendix Table 3
Heterogeneous Impact of Large Wildfires on Firm-level Delinquency:
Firm-Bank Relationship Strength – Medium and Large Firms

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Main Bank Relationship			
Treated	0.001	0.018	0.963*
	(0.001)	(0.019)	(0.541)
Treated × Main Bank	0.001	0.015	0.236
	(0.002)	(0.026)	(0.449)
Observations	9,103,665	9,103,665	5,744,215
R-squared	0.256	0.256	0.527
Treated / Pre-mean (%)	0.9	1.8	3.0
Interaction / Pre-mean (%)	0.8	1.5	0.7
Panel B. Bank Share of Firm's Outstanding Debt			
Treated	0.001	0.012	1.112*
	(0.001)	(0.023)	(0.618)
Treated × Share (%)	0.001	0.023	-0.078
	(0.002)	(0.042)	(0.709)
Observations	9,103,665	9,103,665	5,744,215
R-squared	0.256	0.256	0.527
Treated / Pre-mean (%)	0.5	1.2	3.5
Interaction / Pre-mean (%)	1.4	2.4	-0.2
Panel C. Number of Bank Relationships			
Treated	0.001	0.012	0.987**
	(0.001)	(0.018)	(0.496)
Treated × Single Bank	0.002	0.031	0.190
	(0.002)	(0.038)	(0.675)
Observations	9,103,665	9,103,665	5,744,215
R-squared	0.257	0.257	0.527
Treated / Pre-mean (%)	0.7	1.2	3.1
Interaction / Pre-mean (%)	1.5	3.1	0.6
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of wildfire treatment on firm-bank delinquency outcomes, interacting treatment with alternative measures of bank-firm relationship strength. Panel A uses an indicator for whether the bank is the firm's main bank, defined as the bank with the largest share of the firm's total borrowing in a given month. Panel B uses the bank's share of the firm's total outstanding debt. Panel C uses an indicator for firms borrowing from a single bank. The dependent variables are long differences in Delinquent Debt, the Delinquency Indicator, and Days Past Due. Treated reports the estimated effect for the omitted relationship group or for a relationship measure equal to zero. Treated × Relationship reports the differential effect associated with the corresponding relationship measure. All columns include firm and bank-time fixed effects, as well as one lag of the dependent variable. Treated / Pre-mean and Interaction / Pre-mean (%) are the treatment and interaction coefficient variable scaled by the pre-treatment mean for Delinquency Indicator and Days Past Due, while for Delinquent Debt is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 4
Bank Relationships, Reprogramming, and Loan Terms:
Small Firms

	Main Bank		
	Reprogrammed	Int. Rate	Amount
Main Bank	0.009***	-0.072	0.265***
	(0.002)	(0.050)	(0.013)
(Log) Loan Amount	-0.002	-1.314***	
	(0.002)	(0.105)	
No Guarantee	0.015**	-0.455***	-0.346***
	(0.006)	(0.112)	(0.021)
Reprogrammed Loan		-0.321***	-0.018
		(0.121)	(0.022)
Observations	381,854	381,854	381,854
R-squared	0.483	0.783	0.787
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports transaction-level regressions examining the association between main-bank relationships, reprogramming, and loan terms for small firms. The main-bank indicator is defined as a bank holding the largest share of the firm's outstanding bank debt. The dependent variables are an indicator for reprogrammed loans, the annual interest rate, and the log loan amount. All columns include firm and bank-time fixed effects. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 5
Prior Wildfire Exposure and Firm-level Delinquency

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Baseline			
Treated	0.004***	0.061***	1.032***
	(0.001)	(0.013)	(0.310)
Observations	23,219,668	23,219,668	15,913,073
Treated Observations	411,907	411,907	411,907
R-squared	0.334	0.326	0.566
Effect Size (%)	4.5	6.3	6.9
Panel B. Mutually Exclusive Treatment Groups			
Treated, No Prior Wildfire	0.004***	0.068***	1.167***
	(0.001)	(0.014)	(0.313)
Treated, Prior Wildfire	0.002	0.038*	0.534
	(0.001)	(0.021)	(0.656)
Observations	23,219,668	23,219,668	15,913,073
Treated Observations: No Prior	273,689	273,689	273,689
Treated Observations: Prior	138,218	138,218	138,218
R-squared	0.334	0.326	0.566
Effect Size: No Prior (%)	5.3	7.1	7.9
Effect Size: Prior (%)	2.4	3.9	3.6
Firm FE	Yes	Yes	Yes
Bank $\times$ Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' debt outcomes after large wildfires. Panel A reports the baseline treatment effect. Panel B estimates a single regression with two mutually exclusive treatment variables: current wildfires with no wildfire in months $t-13$ to $t-24$ and current wildfires with at least one wildfire in months $t-13$ to $t-24$. All panels use the clean-control condition, include firm and bank-time fixed effects, and include one lag of the dependent variable. Effect size is the treatment coefficient scaled by the pre-treatment mean for the Delinquency Indicator and Days Past Due, while for Delinquent Debt it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 6
Relationship Between Wildfires and Heatwaves

Panel A. Overlap Between Large Wildfires and Heatwaves

	No Heatwave	Heatwave	Total
Panel A.1. Heatwave Defined by p90 Threshold			
No Wildfire	164,290	21,430	185,720
	(87.80%)	(11.45%)	(99.25%)
Wildfire	816	592	1,408
	(0.44%)	(0.32%)	(0.75%)
Total	165,106	22,022	187,128
	(88.23%)	(11.77%)	(100.00%)
Panel A.2. Heatwave Defined by 30C Threshold			
No Wildfire	177,732	7,988	185,720
	(94.98%)	(4.27%)	(99.25%)
Wildfire	1,084	324	1,408
	(0.58%)	(0.17%)	(0.75%)
Total	178,816	8,312	187,128
	(95.56%)	(4.44%)	(100.00%)

Panel B. Probability of Large Wildfires During Heatwaves

	p90 Heatwave	30C Heatwave
Heatwave	0.0041***	0.0072**
	(0.0015)	(0.0034)
Heatwave, lag 1	0.0036**	-0.0073***
	(0.0016)	(0.0028)
Observations	186,238	186,238
R-squared	0.092	0.092
County FE	Yes	Yes
Month FE	Yes	Yes

This table reports the relationship between large wildfires and heatwaves. Panel A reports the overlap between large wildfire county-months and heatwave county-months. Each cell reports the number of county-month observations, with the share of all county-months in parentheses. Panel B reports regressions of large wildfire occurrence on contemporaneous and lagged heatwave indicators at the county-month level. Column 1 defines heatwaves using the p90 threshold. Column 2 defines heatwaves using the 30°C threshold. Panel B includes county and month fixed effects. Standard errors are in parentheses and clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 7
Wildfires and Heatwaves

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Baseline			
Treated	0.004***	0.061***	1.032***
	(0.001)	(0.013)	(0.310)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.5	6.3	6.9
Panel B. Baseline + Heatwave p90			
Treated	0.004***	0.061***	1.030***
	(0.001)	(0.013)	(0.310)
Heatwave (p90)	0.001	0.010	0.032
	(0.000)	(0.007)	(0.055)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.5	6.3	6.9
Panel C. Baseline + Heatwave 30 Celsius			
Treated	0.004***	0.061***	1.036***
	(0.001)	(0.013)	(0.308)
Heatwave 30 Celsius	0.000	0.005	0.099
	(0.000)	(0.005)	(0.141)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.5	6.3	6.9
Panel D. Heatwave p90			
Heatwave (p90)	0.001**	0.012**	0.107**
	(0.000)	(0.006)	(0.052)
Observations	23,462,566	23,462,566	16,080,500
R-squared	0.333	0.325	0.565
Effect / Pre-mean (%)	0.8	1.2	0.7
Panel E. Heatwave 30 Celsius			
Heatwave 30 Celsius	0.001**	0.013*	0.225
	(0.000)	(0.007)	(0.144)
Observations	23,293,637	23,293,637	15,957,031
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	1.1	1.3	1.4
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions examining the joint role of wildfires and heatwaves. Panels A to C include wildfire treatment alone or jointly with heatwave indicators; Panels D and E replace wildfire treatment with heatwave treatment only. All columns include firm and bank-time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for the Delinquency Indicator and Days Past Due, while for Delinquent Debt it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 8
Alternative Treatment Definitions

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Baseline (p90)			
Treated (p90)	0.004***	0.061***	1.032***
	(0.001)	(0.013)	(0.310)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.5	6.3	6.9
Panel B. Wildfire > p75			
Treated (p75)	0.001***	0.021***	0.365**
	(0.000)	(0.006)	(0.150)
Observations	23,396,372	23,396,372	16,024,190
R-squared	0.333	0.325	0.566
Effect / Pre-mean (%)	1.7	2.1	2.5
Panel C. Wildfire > p95			
Treated (p95)	0.003**	0.041**	1.113***
	(0.001)	(0.018)	(0.323)
Observations	23,181,270	23,181,270	15,888,222
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	3.2	4.2	6.9
Panel D. Wildfire Share > P90 (county-normalized)			
Treated (Share p90)	0.003***	0.045***	0.573*
	(0.001)	(0.009)	(0.330)
Observations	21,580,298	21,580,298	14,517,948
R-squared	0.342	0.334	0.574
Effect / Pre-mean (%)	3.3	4.6	3.9
Panel E. Red Alert Wildfire (2015–2024)			
Treated (Red Alert)	0.002*	0.024*	0.195
	(0.001)	(0.012)	(0.173)
Observations	17,448,236	17,448,236	15,961,395
R-squared	0.371	0.362	0.566
Effect / Pre-mean (%)	2.0	2.5	1.5
Panel F. Red Alert × Wildfire > p90			
Treated (Red Alert x Wildfire > p90)	0.005***	0.075***	1.069***
	(0.001)	(0.010)	(0.232)
Observations	17,378,193	17,378,193	15,895,393
R-squared	0.371	0.362	0.566
Effect / Pre-mean (%)	6.4	7.8	6.1
Panel G. Log Area Affected (ha)			
Log Area Affected	0.000**	0.004**	0.071**
	(0.000)	(0.002)	(0.034)
Observations	23,961,697	23,961,697	16,536,401
R-squared	0.332	0.324	0.564
Doubling / Pre-mean (%)	0.3	0.2	0.4
Panel H. Log Area Affected (Conditional on Wildfire > p90)			
Log Area Affected (WF>p90)	0.001***	0.010***	0.163***
	(0.000)	(0.002)	(0.057)
Observations	22,979,543	22,979,543	15,913,073
R-squared	0.334	0.326	0.566
Doubling / Pre-mean (%)	0.5	0.5	0.8
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' debt outcomes under alternative treatment definitions. Panel A uses the baseline p90 threshold; Panels B and C use the p75 and p95 absolute thresholds. Panel D uses county-normalized burned area (>p90) to avoid mechanical bias toward larger counties. Panels E and F use official Red Alert declarations (2015 to 2024); Panels G and H use the log of hectares affected, unconditionally and conditional on exceeding p90. All columns include firm and bank-time fixed effects, as well as one lag of the dependent variable. For binary treatment panels (A to F), Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for the Delinquency Indicator and Days Past Due, while for Delinquent Debt it is computed as $100 \times (\exp(\beta) - 1)$. For log-treatment panels (G to H), Doubling / Pre-mean (%) reports the implied effect of doubling affected area, computed as $\beta \times \ln(2)$, and scaled by the same pre-treatment mean. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 9
Alternative Specifications

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Baseline			
Treated	0.004***	0.061***	1.032***
	(0.001)	(0.013)	(0.310)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.5	6.3	6.9
Panel B. Dropping High-Exposure Unburned Controls			
Treated	0.002***	0.039***	1.037***
	(0.001)	(0.014)	(0.377)
Observations	21,618,313	21,618,313	14,786,395
R-squared	0.332	0.324	0.564
Effect / Pre-mean (%)	2.8	4.0	6.9
Panel C. Without Outcome Lag			
Treated	0.003***	0.054***	0.861**
	(0.001)	(0.012)	(0.408)
Observations	23,219,668	23,219,668	15,913,073
R-squared	0.189	0.174	0.511
Effect / Pre-mean (%)	4.1	5.5	5.6
Panel D. Excluding Greater Santiago			
Treated	0.004***	0.059***	0.984***
	(0.001)	(0.013)	(0.341)
Observations	9,801,048	9,801,048	6,934,755
R-squared	0.355	0.346	0.570
Effect / Pre-mean (%)	4.0	6.0	6.2
Panel E. Sector-Time, Region-Time, Size-Time FE			
Treated	0.003***	0.059***	1.000***
	(0.001)	(0.013)	(0.350)
Observations	23,216,699	23,216,699	15,911,169
R-squared	0.338	0.329	0.569
Effect / Pre-mean (%)	4.1	6.0	6.8
Panel F. County-Month FE			
Treated	0.004***	0.060***	0.994***
	(0.001)	(0.014)	(0.315)
Observations	23,219,662	23,219,662	15,913,056
R-squared	0.334	0.326	0.566
Effect / Pre-mean (%)	4.4	6.1	6.7

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' debt outcomes under alternative specifications. Panel A is the baseline. Panel B keeps treated observations as in the baseline but drops high ex ante-exposure county-months from the control group when they are not currently burned, using the above 90th percentile of ex ante exposure as the predetermined high-exposure measure. Panel C drops the outcome lag; Panel D excludes the Greater Santiago area; Panel E includes a richer fixed effects structure. Panel F adds county-month fixed effects to account for lending seasonality. All columns include firm and bank-time fixed effects, as well as one lag of the dependent variable, unless otherwise stated. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for the Delinquency Indicator and Days Past Due, while for Delinquent Debt it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 10
Heterogeneous Impact of Large Wildfires on Firm-level Delinquency:
Firm Sector - Excluding Greater Santiago

	Delinquency Indicator	Delinquent Debt	Days Past Due
Panel A. Agriculture and Forestry			
Treated	0.005***	0.074**	1.374***
	(0.002)	(0.029)	(0.518)
Observations	851,616	851,616	527,117
R-squared	0.340	0.332	0.551
Effect / Pre-mean (%)	5.1	7.7	10.8
Panel B. Manufacturing			
Treated	0.001	0.025	0.016
	(0.002)	(0.027)	(0.707)
Observations	1,116,715	1,116,715	765,039
R-squared	0.344	0.335	0.550
Effect / Pre-mean (%)	1.4	2.5	0.1
Panel C. Utilities and Construction			
Treated	0.003	0.056	0.097
	(0.003)	(0.043)	(0.739)
Observations	1,254,742	1,254,742	897,753
R-squared	0.371	0.365	0.574
Effect / Pre-mean (%)	2.7	5.7	0.5
Panel D. Commerce, Transportation, and Tourism			
Treated	0.004***	0.058***	1.368***
	(0.001)	(0.018)	(0.447)
Observations	3,844,534	3,844,534	2,846,640
R-squared	0.363	0.355	0.569
Effect / Pre-mean (%)	4.1	6.0	8.9
Panel E. Services			
Treated	0.004***	0.060***	0.798**
	(0.001)	(0.018)	(0.372)
Observations	2,531,933	2,531,933	1,760,774
R-squared	0.355	0.346	0.564
Effect / Pre-mean (%)	6.2	6.2	6.7
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions of firms' debt outcomes for a firm exposed to large wildfires, by firm sector. The dependent variables are the average post-treatment change in each outcome over horizons $= 0, \ldots, 12$ relative to month -1. Sectors are aggregated into five macro-groups. All columns and panels include firm and bank-time fixed effects and one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for Delinquency Indicator and Days Past Due, while for Delinquent Debt is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 11
Wildfires and New Credit: Access and Borrower Composition

Panel A. Extensive Margin of Bank Credit Access

	All Firms	Small Firms	Agro/Forestry Firms
Treated	0.0537***	0.0591***	0.0539***
	(0.0054)	(0.0061)	(0.0054)
Observations	50,338,149	36,867,645	2,390,773
R-squared	0.413	0.419	0.414
Effect / Pre-mean (%)	11.8	13.6	12.6
Firm FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

Panel B. Share of Firms: Bank-County-Month Level

	Small	Agro/Forestry
Treated	-0.0013	0.0005
	(0.0014)	(0.0012)
Observations	276,374	276,308
R-squared	0.127	0.123
Effect / Pre-mean (%)	-0.2	0.2
County FE	Yes	Yes
Bank × Time FE	Yes	Yes

Panel C. Share of Firms: County-Month Level

	Small	Agro/Forestry
Treated	-0.0011	-0.0004
	(0.0016)	(0.0012)
Observations	40,476	40,476
R-squared	0.250	0.219
Effect / Pre-mean (%)	-0.2	-0.2
County FE	Yes	Yes
Month FE	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions studying whether large wildfires change credit access or the composition of firms receiving credit. Panel A estimates the extensive margin of bank credit access at the firm level. The dependent variable is the average post-treatment change in an indicator equal to one if the firm has positive bank debt, over horizons $h = 0, \ldots, 12$ relative to month -1. The firm panel starts when a firm first appears in the credit registry and treats firms as exiting after their last observed credit-registry month unless that month is December 2024. Columns in Panel A report all firms, small firms, and agriculture/forestry firms. Panel B aggregates the data at the bank-county-month level, and Panel C aggregates the data at the county-month level. Panels B and C report the average post-treatment changes in the shares of small firms and agriculture/forestry firms among borrowers with credit. Panel A includes firm and month fixed effects, Panel B includes county and bank-time fixed effects, and Panel C includes county and month fixed effects. All columns and panels include one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean. Standard errors are two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 12
Effects of Large Wildfires on New Lending:
Reassessment of Wildfire Credit Risk – Heckman Correction

	Exposure Percentile		
	p75th	p80th	p90th
Panel A. Interest Rate			
0–3 Months Since WF × High Exposure	0.370***	0.445***	0.454***
	(0.028)	(0.046)	(0.063)
4–6 Months Since WF × High Exposure	0.319***	0.384***	0.424***
	(0.080)	(0.069)	(0.154)
Inverse Mills Ratio	0.060***	0.060***	0.060***
	(0.022)	(0.022)	(0.023)
Observations	712,157	712,157	712,157
R-squared	0.854	0.854	0.854
Panel B. (Log) Loan Amount			
0–3 Months Since WF × High Exposure	-0.175***	-0.333***	-0.295***
	(0.054)	(0.014)	(0.011)
4–6 Months Since WF × High Exposure	-0.156**	-0.336***	-0.232***
	(0.063)	(0.017)	(0.010)
Inverse Mills Ratio	0.051***	0.051***	0.051***
	(0.010)	(0.010)	(0.010)
Observations	712,157	712,157	712,157
R-squared	0.805	0.805	0.805
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports transaction-level regressions of loan terms on firms' ex ante wildfire risk exposure and loan-level characteristics, using the loan-level dataset. Panel A reports effects on the interest rate; Panel B reports effects on the log loan amount. Loan-level controls include interest rate type, loan maturity, currency type, a restructured loan indicator, and an uncollateralized loan indicator; the interest rate regressions (Panel A) additionally control for the log loan amount, which is the dependent variable in Panel B and therefore not included among its controls. Each column reports estimates for a different definition of high ex ante wildfire exposure: a county is classified as highly exposed if its cumulative affected surface area over 2002–2009 is above the 75th, 80th, or 90th percentile of the distribution across counties, respectively. Coefficients are the interaction between a county's ex ante exposure and a dummy equal to one if a large wildfire occurred within the previous 0–3 or 4–6 months, respectively. The first stage includes the number of banks operating in the county as an exclusion restriction, which shifts access to credit but is excluded from the loan-terms equation. The interest rate effect sizes are between 3.4% and 4.4% of the average pre-shock interest rate. All columns and panels include firm and bank-time fixed effects. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 13

Effects of Large Wildfires on New Lending by Relationship Length

	Exposure Percentile		
	p75th	p80th	p90th
Panel A. Interest Rate			
0–3 Months Since WF × High Exposure	0.320***	0.371***	0.351***
	(0.026)	(0.054)	(0.083)
0–3 Months Since WF × High Exposure × Relationship Length	0.002*	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
4–6 Months Since WF × High Exposure	0.261***	0.297***	0.285***
	(0.037)	(0.053)	(0.084)
4–6 Months Since WF × High Exposure × Relationship Length	0.002	0.002	0.002
	(0.004)	(0.002)	(0.003)
Observations	711,997	711,997	711,997
R-squared	0.854	0.854	0.854
Panel B. (Log) Loan Amount			
0–3 Months Since WF × High Exposure	-0.162***	-0.311***	-0.278***
	(0.050)	(0.012)	(0.019)
0–3 Months Since WF × High Exposure × Relationship Length	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
4–6 Months Since WF × High Exposure	-0.158**	-0.339***	-0.269***
	(0.062)	(0.012)	(0.029)
4–6 Months Since WF × High Exposure × Relationship Length	0.001**	0.001***	0.001
	(0.000)	(0.000)	(0.001)
Observations	711,997	711,997	711,997
R-squared	0.805	0.805	0.805
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table reports transaction-level regressions of firms' interest rate and loan amount on wildfire shocks, ex ante wildfire exposure, and firm-bank relationship length. Each column reports estimates for a different definition of high ex ante wildfire exposure: a county is classified as highly exposed if its cumulative affected surface area over 2002–2009 is above the 75th, 80th, or 90th percentile of the distribution across counties, respectively. Panel A reports effects on the interest rate. Panel B reports effects on the log loan amount. All columns and panels include firm and bank-time fixed effects. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 14
Effects of Heatwaves on New Lending by Ex Ante Wildfire Exposure

	Exposure Percentile		
	p75th	p80th	p90th
Panel A. Interest Rate			
0–3 Months Since Heatwave × High Exposure	0.012	-0.006	-0.143***
	(0.029)	(0.032)	(0.046)
4–6 Months Since Heatwave × High Exposure	-0.002	-0.022	-0.222***
	(0.029)	(0.031)	(0.052)
Observations	1,174,222	1,174,222	1,174,222
R-squared	0.839	0.839	0.839
Panel B. (Log) Loan Amount			
0–3 Months Since Heatwave × High Exposure	-0.010	-0.019*	-0.021
	(0.011)	(0.011)	(0.015)
4–6 Months Since Heatwave × High Exposure	-0.008	-0.014	-0.001
	(0.009)	(0.009)	(0.013)
Observations	1,174,222	1,174,222	1,174,222
R-squared	0.803	0.803	0.803
Firm FE	Yes	Yes	Yes
Bank × Time FE	Yes	Yes	Yes

This table re-estimates the reassessment specification of Equation (4) replacing wildfire episodes with heatwave episodes. Each column reports estimates for a different definition of high ex ante wildfire exposure: a county is classified as highly exposed if its cumulative affected surface area over 2002–2009 is above the 75th, 80th, or 90th percentile of the distribution across counties, respectively. Coefficients show the interaction between a county's ex ante wildfire exposure and an indicator equal to one if a heatwave occurred within the previous 0–3 and 4–6 months, respectively. Loan-level controls and fixed effects are as in Table 6. Standard errors are in parentheses and two-way clustered at the county and year-month level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 15

Impact of Large Wildfires at the Bank-Month Level: Small Banks

	Panel A. Banks Below Median Size		
Panel A.1. Bank Delinquency Outcomes			
	Delinquent Debt	Delinquency Ratio	% Delinquent Firms
Bank exposure (%)	0.0766	0.0008	0.0005*
	(0.0516)	(0.0006)	(0.0003)
Observations	974	966	966
R-squared	0.4053	0.6334	0.6630
Effect / Pre-mean (%)	7.9	2.3	1.2
Panel A.2. Bank Provisioning Outcomes			
	Provisioning Ratio	(Log) Total Provisions	Delinquent Provisions
Bank exposure (%)	-0.0000	0.0060	0.0731
	(0.0001)	(0.0112)	(0.0516)
Observations	966	974	974
R-squared	0.8660	0.4124	0.3918
Effect / Pre-mean (%)	-0.1	0.6	7.6
	Panel B. Banks in Lower Quartile		
Panel B.1. Bank Delinquency Outcomes			
	Delinquent Debt	Delinquency Ratio	% Delinquent Firms
Bank exposure (%)	0.0304***	0.0007	0.0006*
	(0.0086)	(0.0005)	(0.0003)
Observations	548	540	540
R-squared	0.5156	0.6908	0.6555
Effect / Pre-mean (%)	3.1	1.9	1.2
Panel B.2. Bank Provisioning Outcomes			
	Provisioning Ratio	(Log) Total Provisions	Delinquent Provisions
Bank exposure (%)	-0.0001	0.0038	0.0263**
	(0.0001)	(0.0184)	(0.0107)
Observations	540	548	548
R-squared	0.9090	0.5275	0.5031
Effect / Pre-mean (%)	-0.01	0.4	2.7
Bank FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

This table reports pooled Local Projections Difference-in-Differences (LP-DiD) regressions aggregated at the bank level for small banks. Bank exposure measures the share of each bank's lending located in counties experiencing a large wildfire in that month. Panel A restricts the sample to banks below the median of the bank-size distribution. Panel B restricts the sample to banks in the lower quartile of the bank-size distribution. Within each panel, subpanels report delinquency and provisioning outcomes separately. For Panel A.1 and B.1, Delinquent Debt is the log of the bank's outstanding Delinquent Debt. Delinquency Ratio is Delinquent Debt over total outstanding debt, and % Delinquent Firms is the share of the bank's borrowers holding Delinquent Debt. For Panel A.2 and B.2, Provisioning Ratio is total loan-loss provisions over outstanding debt, Total Provisions is the log of total loan-loss provisions, and Delinquent Provisions is the log of loan-loss provisions on Delinquent Debt; both logged outcomes use the $\log(1 + y)$ transformation. All columns include bank and time fixed effects, as well as one lag of the dependent variable. Effect / Pre-mean (%) is the treatment coefficient scaled by the pre-treatment mean for the Provisioning Ratio, Delinquency Ratio, and % Delinquent Firms, while for Total Provisions, Delinquent Debt, and Delinquent Provisions it is computed as $100 \times (\exp(\beta) - 1)$. Standard errors are in parentheses and clustered at the bank level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table 16
Baseline Calibration of the Capital-Hit Condition

Parameter	Value	Status	How It Is Obtained
$\hat{\beta}_\delta$	0.004	Estimated	`Treated` coefficient on the delinquency indicator, baseline LP-DiD
$\hat{\beta}_\rho$	0.001	Estimated	`Treated` coefficient on the provisioning ratio (consistency check)
$\mathbb{E}[\omega_c^a]$	0.025	Observed	Average affected credit share within a burned county, credit registry
$\mathbb{E}[\varphi_c^a]$	0.067	Observed	Average share of affected firms by count within a burned county, credit registry
ω^W	0.33	Observed	Maximum monthly share of the book in burned counties, 2010–2024
S/RWA	1.03	Observed	System loans over risk-weighted assets; exceeds one because average risk weights are below one
$1-\tau$	0.50	Imposed	Loss given default
$d^a - d^u$	0.060	Recovered	$\hat{\beta}_\delta/\mathbb{E}[\varphi_c^a] = 0.004/0.067$

This table reports the baseline calibration of the capital-hit condition derived in the text. Expectations denote averages across burned counties, taken over the treated firm-bank-month observations in the baseline Local Projections Difference-in-Differences (LP-DiD) sample. Observed values come from the credit registry or from supervisory balance-sheet aggregates, estimated values are coefficients from the baseline LP-DiD regressions, the imposed value is set on economic grounds, and the recovered value is obtained by inverting the identity $\hat{\beta}_\delta = \mathbb{E}[\varphi_c^a]\,(d^a - d^u)$. The loss given default is set above the Basel F-IRB senior-unsecured value of 0.40–0.45 because wildfires destroy the collateral backing the loan. The share of the book in burned counties, ω^W, is taken at the most exposed month of the 2010–2024 sample. The ratio S/RWA exceeds one because average risk weights in the system are below one.

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