WORKING paper

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The Credit Channel of Acute vs Chronic Climate Change-Related Risk[1]

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ABSTRACT

We construct a firm-bank level panel of French single-establishment micro and SME firms from 2010 to 2023 to investigate the differential impact of chronic versus acute heat events on banks' loan supply. We show that both chronic temperature increases and acute heat days significantly reduce loan growth, primarily through medium- and long-term lending, but that banks respond differently to these two types of climate risk. To account for demand-side effects, we investigate sectoral dynamics and uncover pronounced maturity and sectoral heterogeneity. While the trade, transport, accommodations, leisure,manufacturing and mining sectors are affected by both types of shocks, sectors such as real estate, construction, services, and ICT are more strongly impacted by acute heat shocks. Our results are robust to alternative exposure measures and to the inclusion of credit ratings, highlighting that temperature exposure constitutes an additional source of risk not yet captured by standard bank credit assessment models.

Keywords: Bank Loans, Climate Change, Environmental Risks, Credit Register, Acute and Chronic Heat Stress, Firms

JEL classification: C23, D22, G21, L25, Q54

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[1] Comments by participants in the 4th joint Annual Workshop of the ESCB Research Cluster Climate Change and NGFS Expert Network Research (December 2025), the Green Finance Research Advances International Conference (December 2025), the AFFI 4th Sustainable Finance Research Forum (December 2025), and the 7th Brunel Banking Conference (June 2025) on an earlier version of the paper are gratefully acknowledged. We also thank participants at the TEPP seminar (March 2025) for their helpful comments and suggestions. All remaining errors are our own.

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NON-TECHNICAL SUMMARY

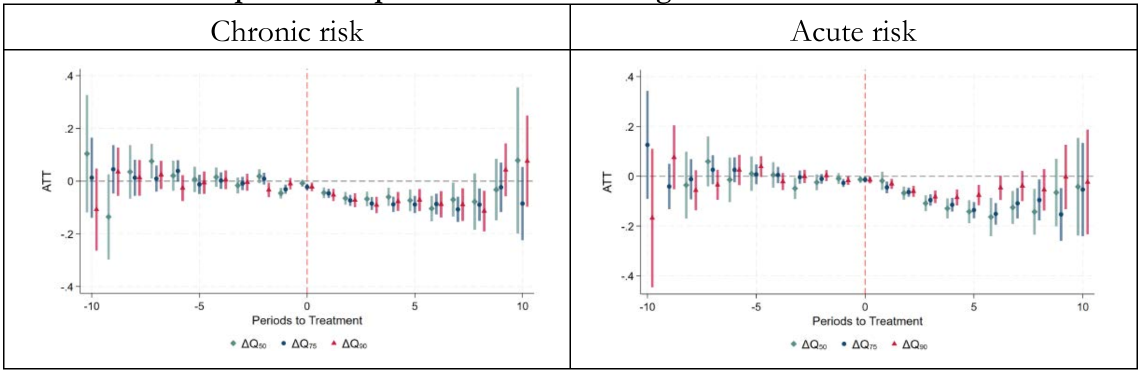
Physical climate risk is becoming increasingly salient for financial intermediation because it already affects firms' operating conditions, asset values, and borrowing capacity. Among its many dimensions, temperature is particularly important. It captures both gradual warming and the increasing incidence of extreme heat, two manifestations of climate change that may affect firms through distinct channels and over different horizons. Yet relatively little is known about how banks adjust credit supply in response to these temperature-related risks, especially at a granular level.

This paper examines how banks' lending to French single-establishment micro, small, and medium-sized enterprises (SMEs), measured using the Banque de France Fichier Central des Risques, responds to two distinct dimensions of temperature exposure: chronic warming and acute heat events. To do so, we combine station-level temperature observations from Météo-France with geocoded firm information to construct establishment level measures of local temperature exposure, providing a substantially finer geographic resolution than that used in the existing literature.

We document three main results. First, both chronic warming and acute heat exposure significantly reduce loan growth at high levels of temperature exposure, with effects concentrated in medium- and long-term credit. As illustrated in the Figure below, however, the dynamics differ markedly across the two dimensions of risk. Acute heat shocks generate sharp but transitory contractions in lending, persisting for up to five years at the 90th percentile of the exposure distribution. In contrast, chronic warming is associated with more persistent lending adjustments, lasting up to eight years at the same percentile, consistent with a longer-horizon reassessment of firm risk. Because chronic and acute temperature shocks are, on average, unevenly distributed across regions, the results suggest that these effects may also translate into geographically differentiated acess to credit. Second, the aggregate response masks substantial heterogeneity across industries. Trade and Transport, Accommodation and Leisure, as well as Manufacturing and Mining are vulnerable to both chronic warming and acute heat stress, whereas sectors such as Real Estate and Construction, Utilities, and Services and ICT respond more strongly to acute heat events. These patterns are consistent with heterogeneous transmission channels linking temperature exposure to firm performance and, ultimately, to bank lending. They also suggest that the observed contraction in credit largely reflects a supply-side adjustment. In this respect, our findings complement recent evidence that extreme temperatures reduce SME access to credit in other settings as well (Aguilar-Gomez et al., 2024). Third, the response to temperature exposure is not uniformly monotone. In some sectors, heightened temperature risk leads banks to shorten maturities rather than withdraw credit altogether, implying a shift toward short-term lending that partly offsets the contraction in medium- and long-term credit.

Overall, our results show that temperature-related climate risk already influences bank lending in economically meaningful ways. The effects differ across chronic and acute exposures, across sectors, and across loan maturities, and they persist over multi-year horizons. For policymakers and supervisors, these findings underscore the importance of climate-risk frameworks that are granular, sector-specific, and attentive to the maturity structure of lending. More broadly, they highlight the need to incorporate forward-looking climate-risk assessments into credit evaluation and portfolio monitoring practices.

Impact of temperature risk on credit growth to French firms


Chronic risk

Acute risk

Note: The figure displays the dynamic response of loan growth (measured as log-difference on y-axis) for single-establishment firms following a temperature shock. Estimates compare firms experiencing a temperature in year 0 with firms that have not yet experienced such an event. Coefficients are reported for the ten years following the shock as well as for the pre-treatment period. Temperature risk is defined as deviation from the establishment-specific 1976–2005 average exceeding the median, 75th and 90th percentiles of the annual cross-sectional distribution. We condider two dimensions of temperature exposure: chronic risk, measured by average annual temperature, and acute risk, measured by the annual number of days with temperatures above 35°C.

Le canal du crédit face aux risques climatiques : événements aigus vs réchauffement chronique

RÉSUMÉ

Nous construisons un panel entreprise-banque portant sur des microentreprises et des PME françaises mono-établissement sur la période 2010-2023 afin d'examiner l'impact différencié du réchauffement chronique et des épisodes de chaleur extrême sur l'offre de crédit bancaire. Nos résultats montrent que tant la hausse des températures moyennes que les épisodes aigus de chaleur réduisent significativement la croissance des prêts, principalement à travers les crédits à moyen et long termes. Les banques réagissent toutefois différemment à ces deux dimensions du risque climatique. Afin de distinguer les effets d'offre et de demande, nous analysons les dynamiques sectorielles et mettons en évidence une forte hétérogénéité selon les maturités et les secteurs d'activité. Alors que les secteurs du commerce, des transports, de loisirs et de l'industrie sont affectés par les deux types de chocs, des secteurs comme l'immobilier, la construction ou les services apparaissent davantage sensibles aux chocs de chaleur aiguë.

Les résultats sont robustes à l'utilisation de mesures alternatives de l'exposition thermique ainsi qu'à l'inclusion des notations de crédit. Cela suggère que l'exposition aux températures constitue un facteur de risque supplémentaire, encore imparfaitement pris en compte par les dispositifs traditionnels d'évaluation du risque de crédit.

Mots-clés : prêts bancaires, changement climatique, risques environnementaux, registre de crédit, stress thermique aigu et chronique, entreprises

1 Introduction

Physical climate risk is becoming increasingly salient for financial intermediation because it is already affecting firms' operating conditions, asset values, and borrowing capacity. Among its many dimensions, temperature is especially important. It captures both gradual warming and the growing incidence of extreme heat, two manifestations of climate change that may affect firms through different channels and over different horizons. Yet we still know relatively little about how banks adjust credit supply in response to these temperature-related risks, especially at a granular level.

This paper studies how banks' lending to French micro, small, and medium-sized firms responds to two distinct dimensions of temperature exposure: chronic increases in temperature and acute heat events. Distinguishing between the two is economically important because they need not affect firms, or banks, in the same way. Acute heat can generate immediate disruptions to labor productivity, operations, and local demand, whereas chronic warming is more likely to alter business conditions, operating costs, and expected firm risk over longer horizons. The distinction is also directly relevant for prudential policy. The European Central Bank (ECB, 2020), for instance, requires banks to integrate climate-related risks into their Internal Capital Adequacy Assessment Process (ICAAP) and explicitly differentiates between acute physical risks, such as extreme weather events, and chronic physical risks, such as rising average temperatures.

Recent policy and supervisory work has likewise emphasized that climate-related financial risk cannot be adequately understood through highly aggregated frameworks alone. The International Monetary Fund (IMF, 2022) and the Basel Committee on Banking Supervision (BCBS, 2021) both stress that sectoral, institutional, and geographic heterogeneity are central to the measurement of climate-risk transmission. Granular evidence is therefore essential, not only to capture uneven exposure across firms and regions, but also to understand how climate shocks propagate through credit markets by affecting repayment capacity, collateral values, and lending decisions. Recent micro-evidence in Europe reinforces this point by showing that climate-related losses can be substantially larger, and more unevenly distributed, than aggregate approaches suggest (Caggese et al., 2025).

Despite growing evidence that natural disasters and acute heat shocks affect firm outcomes and lending conditions, and that chronic warming depresses economic activity in the aggregate, there is still limited systematic evidence on how sustained increases in temperature affect credit supply at the firm-bank level (de Bandt et al., 2025). This gap matters because the firms most exposed to higher temperatures are often also those least able to adapt. Firm-level evidence suggests that smaller and less adaptable businesses are particularly vulnerable to rising energy costs and tighter labor constraints under heat exposure (Ponticelli et al., 2024), which can weaken entrepreneurship and firm resilience in hotter areas (Tarsia, 2025). What remains less well understood is how these risks translate into bank lending decisions over time, how they differ across sectors, and whether they affect the maturity structure of credit rather than only its overall volume.

France provides a particularly useful setting in which to study these questions. According to Météo-France's DRIAS 2020 projections (Météo-France, 2020), metropolitan France is expected to experience both a sustained rise in average temperatures and a higher frequency and intensity of acute heat episodes, with substantial local variation. This spatial heterogeneity makes France well suited to examining how localized temperature exposure maps into heterogeneous financial outcomes, and it underscores the value of integrating granular climate information into financial risk assessment, stress testing, and supervisory monitoring.

To address these questions, we match station-level temperature observations from Météo-France to geocoded firm information in order to measure local temperature exposure at the establishment level. This approach improves on the use of interpolated gridded climate data, which can smooth away localized phenomena such as urban heat islands and generate non-negligible measurement error (Auffhammer et al., 2013; Blanc and Schlenker, 2017). We combine these meteorological data with supervisory credit information to construct a rich firm-bank panel over 2010–2023 and estimate the effects of temperature exposure using a staggered difference-in-differences design. We report static two-way fixed-effects estimates as a benchmark and then use the heterogeneity-robust event-study framework of Callaway and Sant'Anna (2021) to trace the dynamic response of lending while explicitly assessing parallel trends and anticipatory behavior.

We document three main results. First, both chronic warming and acute heat exposure significantly reduce loan growth at higher levels of temperature exposure, with effects concentrated in medium- and long-term credit. The dynamic profiles differ, however, across the two dimensions of risk. Acute heat produces sharper but more transitory contractions in lending, whereas chronic temperature deviations are associated with more persistent adjustments, consistent with a longer-horizon reassessment of firm risk. Because chronic and acute temperature shocks are concentrated in different regions on average, these effects also imply climate-related disparities in credit access across space.

Second, the aggregate response conceals substantial heterogeneity across industries. Trade & Transport and Manufacturing & Mining are vulnerable to both chronic warming and acute heat stress, while sectors such as Real Estate & Construction, Utilities, Accommodation & Leisure, and Services & ICT respond more strongly to acute heat. These patterns are consistent with heterogeneous transmission channels linking temperature exposure to firm performance and, in turn, to bank lending. They also suggest that the observed contraction in credit largely reflects a supply-side adjustment. In that respect, our findings echo recent evidence that extreme temperatures reduce SME credit access in other settings as well (Aguilar-Gomez et al., 2024).

Third, banks adjust not only the volume of credit, but also its maturity structure. In some sectors, heightened temperature risk leads banks to shorten maturities rather than withdraw credit altogether, implying a shift toward short-term lending that partly offsets the contraction in medium- and long-term credit. More generally, the response to temperature exposure is non-linear: more severe deviations tend to trigger larger credit adjustments, although the sign and significance of the response are not monotonic across all industries.

These findings are robust to a wide range of alternative specifications. In particular, controlling for firm credit ratings leaves the estimates essentially unchanged, suggesting that current ratings do not yet embed temperature-related exposure and that banks' responses are at least partly forward-looking. Alternative temperature measures yield qualitatively similar results, and dropping sector controls under the unconditional parallel-trends assumption leaves the main dynamic patterns largely intact, validating our identification design. Crucially, when we absorb credit demand with industry×location×size×time fixed effects following Degryse et al. (2019), which identify supply shocks even for the single-bank firms that make up about 42% of our sample, the estimates are essentially unchanged, confirming that we capture a credit-supply rather than a demand response.

Taken together, our results show that temperature-related climate risk already influences bank lending in measurable and economically meaningful ways. The effects differ across chronic and acute exposure, across sectors, and across maturities, and they persist over multi-year horizons. For policymakers and supervisors, this underscores the importance of climate-risk frameworks that are granular, sector-specific, and attentive to the maturity structure of lending, while ensuring that forward-looking risk assessments are embedded in credit evaluation and portfolio monitoring.

The remainder of the paper is organized as follows. Section 2 reviews the literature on physical climate risk, temperature shocks, and credit markets. Sections 3 and 4 describe the data and empirical strategy. Section 5 presents the main results. Section 6 reports robustness checks and discusses the implications of the findings for policy and financial institutions. Section 7 concludes.

2 Related Literature

This paper contributes to a growing literature showing that physical climate risk affects the allocation of credit. Several studies document that lenders respond to exposure to natural hazards by tightening financing conditions. Faiella and Natoli (2018) find that flood risk reduces lending volumes to non-financial corporations. At the portfolio level, Meisenzahl (2023) show that large U.S. banks began reducing lending to counties with high climate risk, especially flood- and wildfire-exposed areas, with the pullback concentrated in riskier borrowers and loan types, while Blickle et al. (2025) provide a useful qualification to this literature by showing that disaster-related loan losses may be offset by stronger loan demand, resulting in limited net effects on bank profitability and stability. Despite this progress, there remains relatively little systematic evidence on how higher temperature exposures, and especially the distinction between chronic warming and acute heat exposure, affects the supply of bank credit.

A related literature studies how temperature shocks affect firm performance and, by implication, borrower risk. Acute temperature shocks have been shown to reduce profitability and earnings (Huang and Sugianto, 2024; Addoum et al., 2023; Pankratz et al., 2023), while Ginglinger and Moreau (2023) show that heat waves reduce leverage among the world's largest firms, consistent with both weaker borrowing demand and tighter credit conditions. Yet this evidence largely overlooks micro and SME firms, whose adaptation margins are often more limiteds. This distinction matters because smaller and less adaptable firms appear especially vulnerable to temperature exposure. Using U.S. plant-level data, Ponticelli et al. (2024) show that acute heat raises energy costs and reduces productivity in small plants, whereas large plants remain comparatively insulated; Tarsia (2025) document a similar pattern in Europe.[1] What remains less understood is how these heterogeneous firm-level damages translate into bank lending decisions over time, across sectors, and across credit maturities.

This paper also relates to a broader literature on the mechanisms through which temperature shocks affect economic activity. Existing work points to both supply-side and demand-side channels. On the supply side, heat impairs labor productivity, raises operating and energy costs, disrupts logistics and production networks, and can weaken collateral values.[2] On the demand side, temperature shocks can reshape consumption, tourism flows, and sectoral

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[1] Over longer horizons, Ponticelli et al. (2024) further show that sustained heat exposure can push smaller plants out of business and increase local concentration, while Tarsia (2025) argue that small-scale entrepreneurship becomes less viable in hotter regions.

[2] For evidence on heat-related labor productivity losses, especially in heat-exposed sectors, see Graff Zivin and Neidell (2014), Burke et al. (2015), Zhang et al. (2018), and Acevedo et al. (2020). Heat exposure also raises health risks and excess mortality (Im et al., 2017; Ballester et al., 2023). On longer horizons, temperature has been shown to reduce export growth and productivity (Jones and Olken, 2010) and raise energy demand and transmission costs (Hsiang et al., 2017; Auffhammer et al., 2017).

sales. These mechanisms are likely to vary across sectors. In construction and transportation, for example, heat reduces productivity in outdoor work (Acevedo et al., 2020; Graff Zivin and Neidell, 2014; Han et al., 2024); in real estate, extreme weather can erode collateral through lower property values (Contat et al., 2024); in manufacturing, heat lowers revenues and operating income while raising labor and input costs (Pankratz et al., 2023); in utilities, higher temperatures raise cooling demand while lowering generation efficiency (Acharya et al., 2024); and in trade and transportation, localized shocks can propagate through supply chains and transport infrastructure: Barrot and Sauvagnat (2016) show that natural disasters hitting suppliers transmit downstream to their customers through input specificity, and Pankratz and Schiller (2024) document that realized heat specifically disrupts supplier relationships. Accommodation and leisure are exposed through both summer heat stress and winter warming, while services are relatively more sheltered but not fully insulated (Agulles et al., 2022; Falk and Lin, 2018; Groom et al., 2024).[3]

These firm-level damages have direct implications for credit markets. Aguilar-Gomez et al. (2024) show that unusually hot days reduce SME outstanding loans in Mexico and are followed by tighter credit access and worse credit scores, with adverse consequences for future borrowing and growth. A related informational channel operates in mortgage markets, where Duan and Li (2024) show that abnormally high temperatures reduce approval rates and loan amounts because loan officers update their beliefs about climate risk. More broadly, this mechanism is consistent with evidence that financial decisions increasingly reflect perceptions of climate-related risk, not only contemporaneous fundamentals (Baldauf et al., 2020; BCBS, 2021; IMF, 2022).[4] Collectively, this literature suggests that temperature risk can affect credit through several channels, including weaker cash flows, collateral deterioration, production-network propagation, and belief-driven reassessments of risk. Yet no study has systematically examined how chronic and acute temperature risks translate into differentiated lending responses across industries, credit maturities, and event time using granular

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[3] Several papers provide more detailed sectoral evidence that is directly relevant for interpreting heterogeneous lending responses. Han et al. (2024) report that roughly 60% of construction workers exposed to high temperatures experience significant productivity losses. Jones and Olken (2010) document that higher temperatures reduce light-manufacturing exports, consistent with lower factory productivity. Pankratz et al. (2023) show that a one-standard-deviation increase in hot days lowers revenues by 0.3% and operating income by 1.3%, while raising both wages and the cost of goods sold. In trade and transportation, Barrot and Sauvagnat (2016) estimate that \$1 of lost supplier sales translates into about \$2.4 of lost customer sales, while Pankratz and Schiller (2024) show more directly that customers are 7% more likely to terminate supplier relationships when realized heat exceeds expectations. Heat may also impair transportation directly through rail buckling, lower inland-waterway navigability, and air-cargo disruption (Mulholland and Feyen, 2021; Christodoulou and Demirel, 2018). In tourism-related activities, Falk and Lin (2018) find that a 1°C increase in winter temperature reduced accommodation guests in the South Tyrolean mountains by 8%, although adaptation through snowmaking has attenuated this sensitivity since the 1990s.

[4] Addoum et al. (2023) find limited contemporaneous stock-price responses to temperature shocks despite measurable effects on profitability, reflecting anlalysts' beliefs rather than the impact of heat exposure.

firm-bank data. This paper fills this gap.

3 Data

To investigate whether banks adjust their credit allocation in response to firms' exposure to excessive temperatures, we construct a new firm-bank panel dataset that includes granular information on credit exposure, firm financial information, geolocation and climate parameters. We retain only firms located in metropolitan France, explicitly excluding firms located in overseas territories. We restrict our sample to single-establishment firms, which are exclusively micro and small and medium-sized firms (SMEs), for which we can attribute a precise climate exposure without requiring geographic aggregation assumptions (Tarsia, 2025).[5] Each establishment is uniquely identified by its SIRET code, which maps to a SIREN firm identifier, enabling integration across administrative and financial datasets. This helps avoid capturing confounding effects.

Our analysis focuses on the period from 2010 to 2023. This period is chosen for three main reasons. First, climate-related physical risk did not become a salient issue in financial risk management until the early 2010s (Acharya et al., 2024). Second, the financial crisis of 2008 marked a structural reorganization of the French banking system, with several banks undergoing significant mergers and strategic adjustments. Third, new prudential regulations introduced in the aftermath of the 2008 financial crisis may have altered the baseline behavior of financial intermediaries. By focusing on the post-crisis, climate-aware period triggered in 2015 by the *Paris Climate Agreement*, and by the publication of the first draft of the *European Central Bank*'s climate-exposure guidelines in May 2020,[6] that required banks to integrate acute and chronic climate risks in their risk management frameworks, we aim to capture a regime in which climate exposure is a potentially meaningful determinant of credit allocation.

The granularity of the data— down to the level of individual establishments and banks— enables a uniquely detailed view of the interplay between physical climate risk and financial intermediation.

3.1 Loans

The core of our analysis is based on confidential monthly credit data from the *Service Central des Risques* (SCR), the French credit register maintained by the Banque de France. The

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[5] We refer the reader to a more detailed discussion on measurement error issues in Appendix A.

[6] ECB (2020) - Guide on climate-related and environmental risks, www.bankingsupervision.europa.eu, available as of Sep., 2025.

dataset includes the total outstanding loans greater than €25,000 issued in euros to local firms from 2006 to 2024. Each observation is recorded at the firm-bank-branch level and disaggregated by maturity at origination: short-term, medium/long-term, and credit types and purposes—where applicable. This dataset includes also firm credit ratings based on a periodic financial assessment conducted by the Banque de France and made available on a confidential basis to French banks. We aggregate these monthly data into yearly averages to align with the annual reporting frequency of firm-level fiscal declarations, and keep the most frequent rating in a given year for every company. Importantly, we include only observations for which corresponding firm-level data are available for the same year in the tax records.

3.2 Firm-level information

Firm-level variables are drawn from the BIC-IS dataset, maintained by the tax authorities, which compiles annual tax declarations of firms subject to the *Bénéfices Industriels et Commerciaux* (BIC) and *Impôt sur les Sociétés* (IS). This administrative dataset, available from 1992 to 2023, provides detailed information on balance sheets, income statements, and aggregate employment figures. It covers firms of all sizes, legal forms, and sectors operating in France. The BIC-IS dataset includes a highly disaggregated and annually updated sectoral classification based on tax declarations, which supports detailed sectoral controls in our empirical analysis.[7]

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[7] We acknowledge that, while economic researchers in France frequently rely on the INSEE's (the French national statistical agency) FARE database as a primary source for structural analysis, particularly due to its harmonized profiling of firms into economically meaningful units, we opt for BIC-IS due to its superior suitability for firm-level panel analysis. FARE's main advantage lies in its statistical design: through a process known as *"Profiling"*, it aggregates legal units (identified by SIREN codes) into coherent economic entities that more accurately reflect real production structures, especially in the case of corporate groups or cross-participation firms' net. It also eliminates artificially inflated intra-group sales, which are often not aligned with market conditions, thereby preventing double counting and enhancing the reliability of sector-level aggregates. These features make FARE particularly valuable for cross-sectional studies and macroeconomic monitoring. Nevertheless, caution is necessary when using FARE for longitudinal analysis. The database is subject to significant methodological changes—including modifications in *"Profiling"* scope, classification systems (such as sectoral reallocation) that introduce structural breaks, notably in 2013 and 2016. INSEE explicitly advises not to use FARE data for long period panel analysis, emphasizing instead its primarily purpose for analyzing year-on-year structural evolution. To help mitigate discontinuities, INSEE provides, for transitional years, two versions of the data—one using the former methodology and another based on the new approach. However, this backward harmonization is limited to the latest year before the change and is not extended to the entire historical series, due to substantial understandable operational constraints. Additionally, FARE may impute missing values for firms or variables in order to ensure internal coherence, which can obscure true firm-level dynamics. Although legal units can be mapped to profiled enterprises using auxiliary data such as LIFI, the original financial structure of individual legal units cannot be reverse-engineered once aggregated. This limits FARE's use for analyses requiring legally grounded financial data that are used for credit decisions by banks.

3.3 Establishment-level geolocation

The precise geolocation of each establishment is obtained from the *Geosirène* database, maintained by INSEE and publicly available from 1973 to 2024.[8] This dataset provides latitude and longitude coordinates for all active establishments in France, identified via their SIRET codes. It enables us to assign each establishment (as identified by the SIRET–its unique identifier) to the closest operating weather station in a given month and to compute direct measures of climate exposure at the local level.

3.4 Temperature deviation

Meteorological data are sourced from Météo-France, the national meteorological agency, which provides monthly climate observations at the station level from 1786 to 2025.[8] Unlike interpolated grid-level datasets, the Météo-France data consist of observed temperatures at each individual station, offering unmatched spatial and temporal accuracy. In fact, station-based observational data are capable of capturing localized phenomena such as urban heat islands, which are not detectable with global reanalysis models, widely used in this strand of the literature (see discussion in Appendix A). The challenge with observational data, however, lies in their limited availability. Meteorological station density tends to be sufficient only in high-income countries and mostly in urban or peri-urban zones. Fortunately, this aligns well with our empirical context. By linking each firm in our sample to its nearest active weather station, we obtain an average distance of just 5.65 km. On average, this corresponds to a station density of approximately one per 11 x 11 km grid cell ($\sim 0.1° \text{ x } 0.1°$). In contrast, most reanalysis datasets rely on interpolation and much larger grid cells and could potentially introduce serious biases when estimating the economic impact of climate change (Auffhammer et al., 2013). Our approach, by leveraging directly observed station-level measurements, substantially reduces measurement error relative to interpolated grids.

In our investigation, climate change is a deviation from a normal historical climate for the same location. In fact, different regions may have different local conditions (e.g. north *versus* south), relying on local deviations ensure we best capture local context and do not introduce an agregation bias. To derive precise exposures, we match each establishment to the nearest active station in a given month,[9] and then aggregate the obtained monthly parameters into annual indicators. Specifically, we calculate:

- The yearly average of daily mean temperatures (TM) and;

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[8] Source: `https://www.data.gouv.fr`

[9] We rely on monthly station–establishment matching, as stations may appear or disappear over the course of the year. Stations entering or exiting service within a month, and thus not covering the full month, are excluded.

- The yearly sum of days with maximum temperatures exceeding 35°C (JTX35).

The yearly average temperature is widely used as the main indicator to assess climate change. In this specific context, we consider that it could be highly relevant for banks' decision-makers to evaluate chronic temperature rise in a specific location, as it is a synthetic and straightforwardly observable benchmark.[10] In addition, JTX35 corresponds to the threshold used by Météo-France to characterize extremely hot days in France, whether or not these days occur within a heatwave episode. This indicator is particularly relevant in our setting because it captures daytime temperature extremes during periods when firms are normally operating and reflects acute operational disruptions. These two measures allow us to account for both, chronic, and acute temperature risks.

Météo-France defines the French baseline (normal) climate as the 1976–2005 period. This time span is considered as the most recent period with stable climate conditions before the onset of significant global warming trends. In this paper, we retain the same climate baseline period to compute yearly local deviations. We obtain average temperature deviations by calculating the difference between the 2010–2023 yearly realizations and the reference period yearly average for a same establishment. For 2023, for example, we calculate $\Delta TM_{2023} = TM_{2023} - \overline{TM}_{1976-2005}$ for each firm specific location and obtain a deviation distribution for all firms during 2023. We repeat the same calculation for all the years considered in our investigation period. Similarly, we derive the yearly deviation distributions of JTX35. Besides, we retain three distribution cutoffs to capture the severity of a deviation in a given year: the 50^{th}, 75^{th} and 90^{th} percentiles, noted Q_{50}, Q_{75} and Q_{90}, respectively. In the following, we refer to those indicators as $\Delta TM_t^{Q_{th}}$ and $\Delta JTX35_t^{Q_{th}}$.

For robustness checks and comparison to former findings in the literature, we also compute the yearly averages for daily maximum temperatures (TX). In fact, TX is used to calculate average temperatures (TM) –and partly accounts for higher average temperatures– but is also the main component to calculate more acute climate events, such as extreme temperatures and heat waves. We also calculte the yearly sum of days with TX exceeding 30°C (i.e. JTX30, high temperature days in France), and the corresponding deviations in terms of number of days. By contrast to other relatively arbitrary thresholds used in this strand of literature applied uniformly to different contexts, the considered thresholds are defined by Météo-France as most relevant to the French case and are readily available in the dataset.[11]

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[10] TM has a high media and (supra) national agencies coverage, as it is the ultimate target of global climate-related effort.

[11] Météo-France (2020) – Les Nouvelles Projections Climatiques De Référence DRIAS 2020 Pour La Métropole.

4 Methodology

To examine the impact of temperature deviations on bank loans' access of exposed firms, as compared to non-exposed firms, we opt for a difference-in-differences approach, by leveraging the constructed firm-bank level panel, to isolate the causal effect of temperature rise on credit supply, while controlling for unobserved heterogeneity across firms and banks.

4.1 Treatment design

In our investigation, firms enter the treatment group when they experience a temperature deviation greater than the considered percentile Q_{th} in a given year during 2010–2023. For example, a firm first assigned to the treatment arm in 2016 belongs to the group of firms that experienced a temperature deviation of at least the Q_{th} percentile in 2016 at their respective locations. This design allows us to i) get a location-specific approximation of temperature rise, ii) take into consideration the upward trend of temperature deviations and the resulting shifts in deviation distributions iii) keep the level of deviation severity constant across years, and, iv) mitigate the bias of exceptionally warm years.

However, firms become exposed to chronic temperature rise at different points in time depending on their geographic location. In our main empirical design, we assume that once a firm becomes exposed to excessive heat, it remains in the treated group for the remainder of the investigation period. This treatment assignment rule reflects two considerations. Firstly, from a climatological standpoint, the prevailing warming trends are not expected to reverse in the foreseeable future.[12] Thus, once a firm has experienced excessive heat, whether chronic or acute, its exposure is likely to persist or re-emerge periodically. Consistent with this, we checked that firms crossing the treatment threshold in a given year largely remain in that status in the subsequent years, for both the acute and chronic dimensions, which supports the absorbing-treatment assumption. Secondly, even in years when realized temperatures fall below critical thresholds, banks may still perceive such firms as exposed to latent climate risks, reflecting forward-looking credit assessments. Accordingly, our investigation assesses exposure to temperature risk rather than the effects of realized temperature shocks, which do not necessarily occur every year.

Within the difference-in-differences (DiD) framework, this setup corresponds to a staggered treatment design. In such a design, treatment occurs at different points in time across observational units, but the treatment status is assumed to be absorbing—that is, once treated, units do not revert to control status. Consequently, our main identification strategy does not permit firms to switch between treated and untreated states across time. While this frame-

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[12] IPCC, 2023; Météo-France, 2020.

work offers a natural structure for analyzing the onset of persistent heat exposure, several methodological challenges could arise in its implementation, particularly in the presence of treatment effect heterogeneity. We discuss these issues in detail below.

4.2 Sample selection

To ensure a high accuracy of our dataset, we exclude firms under the simplified tax declaration regime, as their data suffer from a rudimentary accounting system and lack of detail. Furthermore, some declarations are related to business activity longer than the standard 12 months declaration period. To avoid sporadic declaration patterns and compare firms based on the same consistent operating period, we exclude declarations with a reported activity period longer than 14 months for a given fiscal year (*millésime*). Besides, to limit the impact of outliers and administrative record errors, credit volumes are winsorised at the 2.5^{th} and 97.5^{th} percentiles. We further exclude public administrations, firms operating in the financial sector, and agricultural firms. The exclusion of agricultural firms is motivated by the specific sensitivity of these firms to climate conditions, which depends on crop type, timing of exposure (e.g., between flowering and harvest periods), heat-resistance characteristics, pest dynamics, and pesticide use—factors requiring an entirely different analytical framework. Furthermore, we leverage Banque de France ratings to exclude inactive as well as bankrupt firms, as their loan dynamics is not representative of a normal activity. Finally, for every temperature parameters, and treatment threshold, we exclude always-treated firms (i.e. firms that had already experienced annual temperature above the temperature percentile under study at the start of the sample period), as these do not have a pre-treatment period, a *sine qua non* condition for our DiD design. The "always-treated" status depends on the considered temperature parameter, as well as the exposure severity (deviation quantile), so our sample size varies accordingly.

4.3 Summary statistics

Table 1 presents summary statistics for loan growth at the firm-bank level, disaggregated across total, medium- and long-term (MLT), and short-term (ST) credit categories and temperature realisations and deviations from the baseline period (1976–2005). Loan growth is measured as the log-difference in outstanding credit between two consecutive years. This transformation captures proportional changes in lending and reduces the influence of scale heterogeneity across firms. The underlying dataset of outstanding loans spans the period from 2010 to 2023 and comprises 1,267,513 firm-bank-year observations for total loans. To reduce the influence of extreme values, all loans are winsorised at the 2.5% level on both tails of the distribution. Because loan growth is a year-on-year log-difference, the first available year (2010) is consumed in differencing, so our loan-growth sample spans 2011–2023.

Table 1. **Descriptive statistics**

Variable	**Obs.**	**Mean**	**Std. Dev.**	**25%**	**Median**	**75%**
Loans (Δ log)	1,157,313	-0.0629	0.5138	-0.2988	-0.1201	0.0819
Loans MLT (Δ log)	701,635	-0.1052	0.6975	-0.3483	-0.1609	0.0311
Loans ST (Δ log)	505,111	-0.0447	1.3306	-0.4465	0.0000	0.3857
TM (*Celsius*)	1,157,313	12.9865	1.8321	11.8500	12.8000	15.5167
JTX35 (*days*)	1,157,313	4.2043	5.5028	0.0000	2.0000	6.0000
ΔTM	1,157,313	1.1714	0.8704	0.6011	1.1978	1.7578
ΔJTX35	1,157,313	2.6263	4.8339	-0.3334	0.9667	4.2333

Notes: Loans refers to total outstanding loans at the firm-bank level. Loans MLT stands for medium- and long-term loans. Loans ST stands for short-term loans. All values represent year-on-year log-differences in loan amounts over the 2011-2023 period. ΔTM and ΔJTX35 refer to deviations from 1976-2005 realizations of average temperature (TM) and number of days $\geq$ 35°C, respectively. All temperature variables are aggregated to the firm-year level, rather than the firm-bank-year level, to avoid double-counting climate exposures for firms borrowing from multiple banks in a given year.

The obtained panel is naturally unbalanced, reflecting variation in firm-bank relationships over time. Some firms are observed to hold only medium- and long-term loans, while others rely exclusively on short-term credit for certain periods. Sample sizes vary depending on the treatment metric and deviation severity. As noted earlier, firms that are always treated (depending on the treatment parameter and deviation severity) or observed only once are excluded from the analysis, consistent with the requirements of our difference-in-differences design.

In Figures 1–2, we document the evolution of chronic and acute temperature risks across France during the period 2010–2023, relative to the historical baseline of 1976–2005.[13] Chronic risk is proxied by deviations in mean temperature (TM), while acute risk is measured by the number of days exceeding 35°C (JTX35). These two dimensions exhibit distinct statistical properties and spatial distributions, which are critical for understanding firm-level exposures. In fact, Figure 1 clearly shows a rightward shift in the distributions of both chronic and acute risks at the regional level, suggesting an increasing risk of heat exposure. However, the distributions of deviations for both risks may indicate potential spatial heterogeneity, as they exhibit both positive and negative realisations (see Appendix B, Figure 7). These patterns are central to our identification strategy and to the definition of the appropriate comparison group. For example, in Figure 2, we observe that some regions are exclusively exposed to acute heat risk but not to chronic temperature increases. When estimating the impact of the latter, firms in such regions are not valid controls and must be excluded, and the reverse holds as well. A further concern arises for regions that are neither exposed to chronic nor acute

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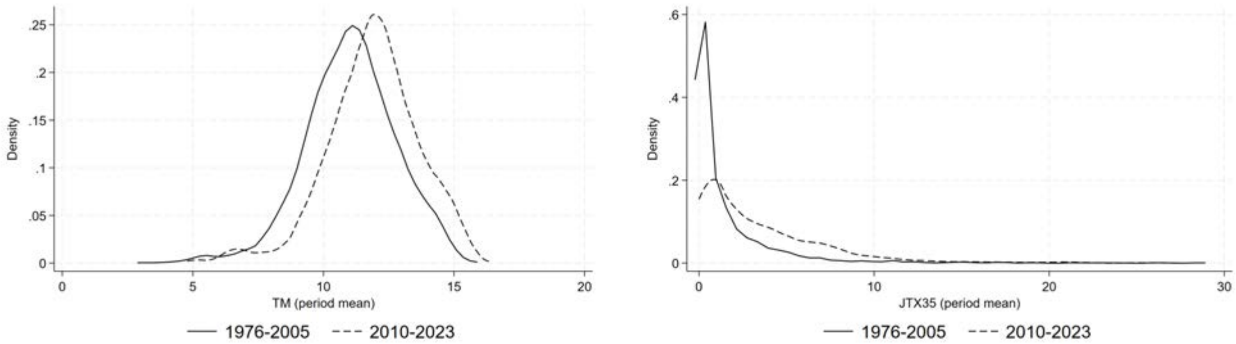
[13] Here, we aggregate station-level observations to the NUTS-3 level for illustrative purposes.

risks but may face other unobservable or unaccounted climate-related hazards. Coastal areas, for instance, are potentially subject to sea-level rise and flood risk. These regions, too, must be excluded from the comparison group, as they are structurally distinct. Accordingly, we adopt not-yet-treated firms as the appropriate comparison group to minimize contamination of the control group by other unpriced risks.

Figure 1. **Climate parameters distributions**

Average Temperature (chronic) **Days ≥ 35°C (acute)**



Notes: The figure shows kernel density estimates of deviations from the 1976–2005 baseline for two climate risk measures: mean temperature (TM, left panel) and the number of days exceeding 35°C (JTX35, right panel). Each panel compares the historical period (1976–2005) with the recent period (2010–2023).

Viewed jointly, these descriptive patterns highlight a dual climate challenge for French firms. Chronic warming affects a wide range of regions (*"départements"*), particularly in the north, while acute heat events are mostly concentrated in the south. These patterns motivate our identification strategy, which separately identifies the effects of chronic and acute climate risks on firm outcomes.

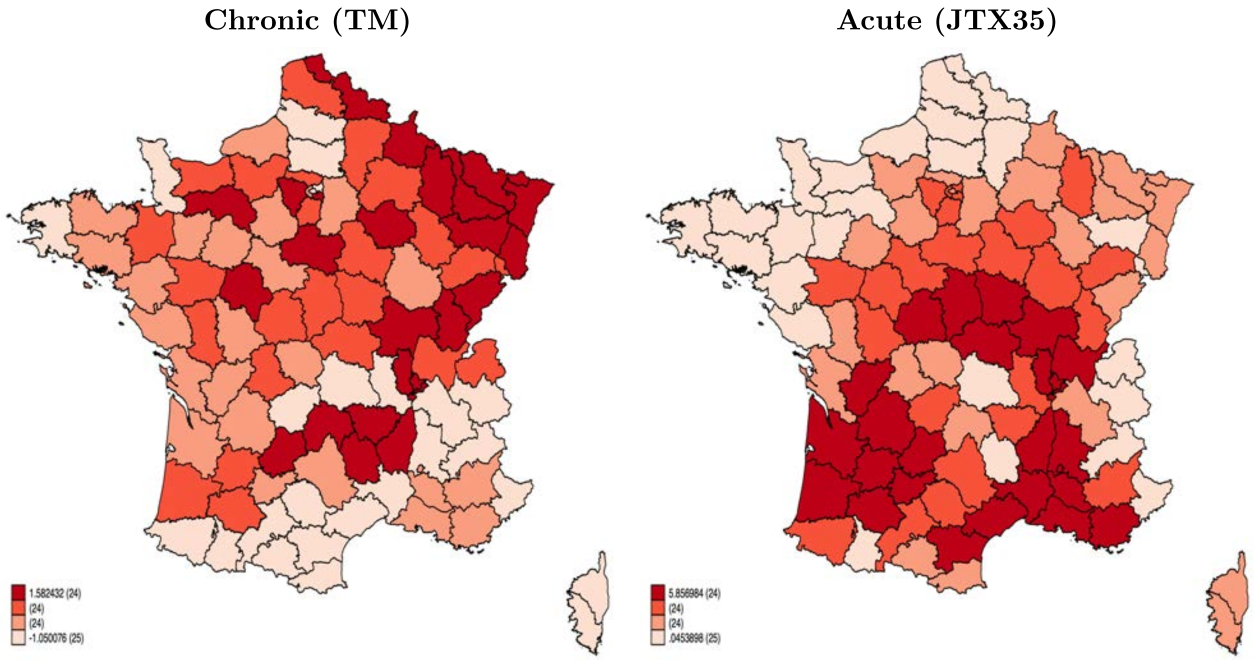
4.4 Empirical strategy

We implement two different modelling frameworks that should answer the three following questions:

Q1. Do firms exposed to chronic or acute temperature deviation shock subsequently experience a reduction in outstanding bank loans' growth?

Following many studies that investigated the impact of weather shocks on economic outcomes (e.g. Addoum et al., 2020; Javadi and Masum, 2021), we started by specifying a static TWFE model. By incorporating fixed-effect parameters, this approach provides a causal interpretation of the coefficient of interest assimilated to a difference-in-differences framework (Blanc and Schlenker, 2017):

Figure 2. **Spatial distribution of climate risk deviations (2010–2023 average)**



Chronic (TM)

Acute (JTX35)

Notes: The maps display deviations from the 1976–2005 baseline for mean temperature (TM, left panel) and the number of days exceeding 35°C (JTX35, right panel) across French departments for 2010–2023. Color gradients represent percentile ranges: for TM, values range from −1.05 to 1.58 (IQR: 0.74–1.02); for JTX35, values range from 0.05 to 5.86 (IQR: 1.13–2.36).

$$Y_{ibt} = \alpha_{ib} + \lambda_t + \beta \cdot \varDelta HeatExposure_{it}^{Q_{th}} + \phi \cdot \mathbf{X}_{it} + \epsilon_{ibt} \tag{1}$$

where Y_{ibt} denotes the outcome of interest (i.e. yearly average outstanding loans growth) for firm i borrowing from bank b in year t ; Observations at the firm-bank level should capture the specific relationship nature that a firm has with its lending bank. Firm-bank and time fixed-effects are represented by α_{ib} and λ_t, respectively.[14] The binary indicator $\varDelta HeatExposure_{it}^{Q_{th}}$ equals one if a firm experienced a heat exposure deviation at the Q_{th} percentile for the considred temperature dimension (TM for chronic, and $JTX35$ for acute). For instance, $\varDelta TM_{it}^{Q_{75}} = 1$ means that, at year t, firm i experienced a temperature exposure among the highest 25% deviations for that year. As per our staggered design, this indicator does not switch back to 0 once firm i starts being exposed. Therefore, β is our coefficient of interest, indicating the causality relationship as well as the magnitude of excess heat impact on the outcome of interest. Finally, $\mathbf{X}_{it}$ is a vector including a set of control variables. Specifically, we include firm size, age category and industry controls. We did not include covariates such as sales, profitability, or total assets' size to avoid confounding issues, as such indicators could be directly impacted by the investigated temperature exposure through the

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[14] Since each firm operates a single establishment, firm fixed effects absorb location fixed effects and thus account for time-invariant spatial characteristics.

channels described above, or through adaptation efforts (financed by bank loans), if any. Furthermore, including many controls could cause potential overcontrolling issues (Dell et al., 2014; Addoum et al., 2020). The idiosyncratic error term is denoted by ϵ_{ibt}. Standard-errors are clustered at the firm level.

Q2. Are these results robust to heterogeneous treatment effects and temperature exposure timing?

The static TWFE model specified above is useful to compare our findings to the existing literature investigating the impact of temperature on various economic outcomes. However, although TWFE specifications were used in a wide variety of applications among researchers, a fast-growing literature in causal inference models raised serious concerns about its validity in staggered designs, especially when treatment timing and/or treatment effects are heterogeneous (e.g. de Chaisemartin and D'Haultfœuille, 2020; Goodman-Bacon, 2021; Borusyak et al., 2024). These issues and existing alternatives are well documented in the related literature surveys by de Chaisemartin and D'Haultfœuille (2023) and Roth et al. (2023).[15]

Thus, to answer our second question, we chose a more credible estimator proposed by Callaway and Sant'Anna (2021) that is robust to heterogeneous treatment effects in staggered designs. We estimate the following Average Treatment Effect on the Treated (ATT), for all $t \geq g$, under the conditional parallel trends assumption :

$$\text{ATT}(g,t) = \mathbb{E}\left[Y_t(g) - Y_t(0) \mid X, G = g\right] \tag{2}$$

where $Y_t(g)$ denotes the observed growth in outstanding loans at date t for firms whose first exposure to excess heat occurs at date g, and $Y_t(0)$ denotes their potential outcome at date t in the absence of such exposure. In our design, firms not-yet-treated by date t serve as the counterfactual group. In the main specification, X includes sector controls, so we rely on the conditional parallel-trends assumption (PTA). As a robustness check, we also estimate the

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[15] A growing body of literature has highlighted significant biases in conventional two-way fixed effects (TWFE) estimators when used in staggered treatment settings with heterogeneous treatment effects. In such settings, TWFE models may inadvertently rely on inappropriate comparisons between units treated at different times—so-called "forbidden comparisons"—which could lead to inconsistent and even sign-reversed estimates of treatment effects. Alternative estimation strategies such as event-study specifications or difference-in-differences local projection regressions (DiD-LP) have also been shown to potentially produce misleading results in staggered adoption settings. For instance, when revisiting the empirical strategy of Favara and Imbs (2015) who investigate the impact of credit supply on price of housing, de Chaisemartin and D'Haultfoeuille (2022) demonstrate that local projection estimators may be biased and prone to incorrect inferences regarding the direction and magnitude of treatment effects.

model without controls, relying instead on the, strong, unconditional PTA.

At this stage, our estimand of interest is the overall ATT, which is a weighted average of individual ATT's, accounting for group and period-specific heterogeneity. Formally, ATT is given by:

$$\text{ATT} \;=\; \sum_{g=2}^{\mathcal{T}} \text{ATT}(g)\; P(G = g \mid G \leq \mathcal{T}) \tag{3}$$

In equation (3), ATT denotes the overall (sample-wide) average treatment effect obtained by aggregating cohort-specific summary effects across all first-treatment cohorts $g \in \{2, \ldots, \mathcal{T}\}$. The term ATT$(g)$ is the *cohort-level summary effect* for cohort g constructed from the collection of group–time effects $\{ATT(g,t) : t \geq g\}$, representing the average effect for cohort g over its observable post-treatment horizon. The weights $P(G = g)$ are the population shares of cohort g, ensuring that ATT is a properly weighted average across cohorts. Finally, $\mathcal{T}$ denotes the total number of observed periods.

Accordingly, it is possible to compare ATT's and $\beta' s$ obtained from the static TWFE.

Q3. Do banks adjust dynamically their behavior according to exposure and firms patterns?

In order to assess the impact of temperature exposure, it is useful to understand the dynamic response of bank lending to firms according to the time spent since the occurrence of the first actual shock. Banks may take time to acknowledge that firms are getting more fragile, whatever the year of the shock.

To answer this question, we developed a set of strategies to design our dynamic event-study estimand. Compared to the difference-in-differences' overall ATT, an event-study estimator, ATT(g, ℓ), calculates the treatment effect after ℓ period of treatment of a group g. This provides another perspective on the dynamic effects of exposure and banks' behavior toward firms with earlier exposure to excessive temperatures and those exposed later during the investigation period. Here again, researchers used to rely on a TWFE model, in its dynamic version, or a panel regression adapted version of the local projections approach proposed initially by Jordà (2005). However, since the recent methodological developments demonstrate that both are prone to incorrect inferences regarding the direction and magnitude of treatment effects in presence of heterogeneous treatment patterns, we discarded them.[16] Besides, the Callaway and Sant'Anna (2021) framework offers the possibility to infer a heterogeneity robust event-study estimator. For an average effect across all groups for a given exposure length (ℓ), the group-time average treatment effects ATT(g, ℓ) are aggregated as follow:

$$ATT_\ell \;=\; \sum_{g=2}^{\mathcal{T}} \mathbf{1}\{\, g+\ell \leq \mathcal{T} \,\}\; ATT(g,\, g+\ell)\; P(G=g \mid G+\ell \leq \mathcal{T}) \tag{4}$$

The term ℓ in equation (4) denotes the exposure length of a group first treated at g. The indicator $\mathbf{1}\{g+\ell \leq \mathcal{T}\}$ restricts attention to cohorts that remain observed ℓ periods after treatment, and $P(G = g \mid G+\ell \leq \mathcal{T})$ is the aggregation weight for group g, conditional on the group being observable at the relative time $G + \ell$.

5 Results

This section presents the empirical findings in four steps. First, we present the estimation results of the aggregate impact of temperature deviations on banks' loan supply using the two-way fixed effects specification as well as the heterogeneity-robust approach. In both cases, we break down the estimated effects by loan maturity to assess whether short- and long-term lending respond differently. Scond, we explore the dynamic adjustment of lending around temperature shocks through the event-study framework, tracing the timing and persistence of the effects. Finally, we examine heterogeneity across sectors to assess whether the impact of temperature deviations on credit supply varies with borrowers' industry characteristics.

5.1 Impact of temperature deviations on banks' loan supply

Static TWFE estimates Table 2 reports two-way fixed-effects (TWFE) estimates of the impact of chronic (TM) and acute (JTX35) temperature deviations on annual loan growth at the 50^{th}, 75^{th}, and 90^{th} quantiles.

All specifications compare treated firm-bank-year observations, where the deviation exceeds the relevant quantile, to not-yet controls, and include firm size, age category, as well as firm-bank and sector-time fixed effects.

In the pooled "All Maturities" sample, chronic warming (TM) reduces loan growth by approximately -9.8 (percentage points) pp at the median and the 75^{th} percentile temperature deviation shocks, and -8.9 pp at the 90^{th} percentile, all highly significant. Acute heat-day exposure (JTX35) produces even larger contractions: -12.0 pp at the median, -10.8 pp at

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[16] For a discussion of the underlying limitations of Local-projections design, we refer the reader to de de Chaisemartin and D'Haultfoeuille (2022).

Table 2. **Static TWFE – Impact of TM and JTX35 on Loan Growth**

	TM			**JTX35**		
	ΔQ_{50}	ΔQ_{75}	ΔQ_{90}	ΔQ_{50}	ΔQ_{75}	ΔQ_{90}
Panel A: All Loans						
Impact	-0.0978***	-0.0976***	-0.0888***	-0.119***	-0.108***	-0.0968***
Std. deviation	(0.00446)	(0.00423)	(0.00586)	(0.00369)	(0.00351)	(0.00464)
Adj. R^2	.0221877	.021234	.0205014	.0248896	.0230129	.021085
Firm-Bank	14,956	15,608	7,607	23,361	22,747	12,310
Observations	170,452	184,837	94,582	253,499	269,666	151,616
Panel B: Medium & Long-Term						
Impact	-0.138***	-0.129***	-0.116***	-0.169***	-0.153***	-0.131***
Std. deviation	(0.00727)	(0.00690)	(0.0101)	(0.00611)	(0.00574)	(0.00765)
Adj. R^2	.0328784	.0266453	.0190454	.032207	.0316361	.0256544
Firm-Bank	12,034	12,797	6,255	18,479	18,559	10,093
Observations	106,806	116,858	58,785	157,519	169,716	94,830
Panel C: Short-Term						
Impact	-0.0768***	-0.0742***	-0.0990***	-0.117***	-0.0986***	-0.0889***
Std. deviation	(0.0167)	(0.0154)	(0.0216)	(0.0145)	(0.0131)	(0.0166)
Adj. R^2	-.0040563	.0019135	.0068666	-.0126534	-.006567	.0013626
Firm-Bank	7,487	7,997	4,091	11,134	11,678	6,533
Observations	65,923	71,595	37,347	93,932	104,261	61,361
Size	Yes	Yes	Yes	Yes	Yes	Yes
Age category	Yes	Yes	Yes	Yes	Yes	Yes
Sectors x Time	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Static TWFE estimates of TM (chronic temperature rise) and JTX35 (acute heat days) at 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on overall, medium-long term, and short-term loans' annual growth. Firm-bank and time FEs are included in all specifications. Omitted: SME-sized firms and Age >= 10 years. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the 75^{th}, and -9.7 pp at the 90^{th}, again all highly significant. Heuristically, firms exposed to mean temperature deviations over the median experienced an overall loan growth rate lower by -9.8 pp as compared to non-exposed firms, implying a contraction in credit supply for that group.

Disaggregating by maturity reveals that medium- and long-term (MLT) credit bears the brunt of these static effects. TM shocks reduce MLT loan growth by -13.8 pp at the median, -12.9 pp at the 75^{th}, and -11.6 pp at the 90^{th}. JTX35 shocks compress MLT lending by -16.9 pp at the median, -15.3 pp at the 75^{th}, and -13.1 pp at the 90^{th} percentile, all highly significant. Short-term (ST) loans are markedly less sensitive: TM's median effect is -7.68 pp, -7.42 pp at the 75^{th}, and -9.9 pp at the 90^{th}, while JTX35 reduces ST growth by -11.7 pp at the median, -9.86 pp at the 75^{th}, and -8.9 pp at the 90^{th} percentile.

Interestingly, the absolute magnitudes of the coefficients tend to decline at higher deviation thresholds. Three non-mutually-exclusive mechanisms could explain this pattern. First, at the 75^{th} and 90^{th} percentiles, the control group may already include firms treated at lower thresholds, if banks begin incorporating temperature-risk considerations well before extreme deviations occur. Second, firms persistently exposed to high temperatures may have adapted operationally or financially, reducing their marginal vulnerability to additional deviations. Third, the TWFE estimator itself may be affected by the well-documented issues in staggered-adoption settings, including “forbidden comparisons” (treated units serving as controls for other treated units) and negative weighting, which can attenuate or even reverse average effects.

Despite these caveats, the static TWFE estimates are informative. They offer modelling flexibility, facilitate comparability with earlier studies using the same framework, and provide a first-pass diagnostic of treatment effects with low computational cost. However, the static TWFE specification imposes homogeneous, time-invariant treatment effects and cannot test for or properly accommodate violations of parallel trends, nor does it reveal the timing of credit adjustments. To address these limitations, we turn to the heterogeneity-robust event-study estimator of Callaway and Sant’Anna (2021), which allows for dynamic treatment effects and explicit tests for anticipatory behavior.

Average event-study effects (ATT) Table 3 reports average pre-treatment and post-treatment changes in loan growth from the Callaway-Sant’Anna framework. For all maturities, Pre-treatment coefficients are statistically indistinguishable from zero in nearly all specifications, supporting the conditional parallel-trends and non-anticipation assumptions. The exception is the medium- and long-term TM specification at the 90th percentile, where the average pre-trend is significant, so we flag the corresponding ATT and rely instead on the lower-quantile MLT estimates and the JTX35 MLT results, which pass.

Post-treatment, the results corroborate the previous findings for overall Loans and for MLT maturities. Temperature deviations have an impact on Loans’ growth. However, we note that TWFE magnitudes are more inflated in terms of magnitude. In fact, following this estimation approach, TM reduces loan growth by roughly -4.4 pp, -6.7 pp, and -5.2 pp at the 50^{th}, 75^{th}, and 90^{th} percentiles, respectively; and JTX35 compresses growth by -10.7 pp at the median, -8.3 pp at the 75^{th}, and -4.4 pp at the 90^{th}. MLT Loans (Panel B of Table 3) mirror these magnitudes closely. In contrast to the TWFE results (Table 2), ST Loans (Panel C of Table 3) show no statistically significant average effects in the heterogeneity-robust framework, indicating, at this stage, that the negative impact on aggregate loan growth is driven almost entirely by adjustments in longer-maturity credit.

5.2 Dynamic event-study profiles

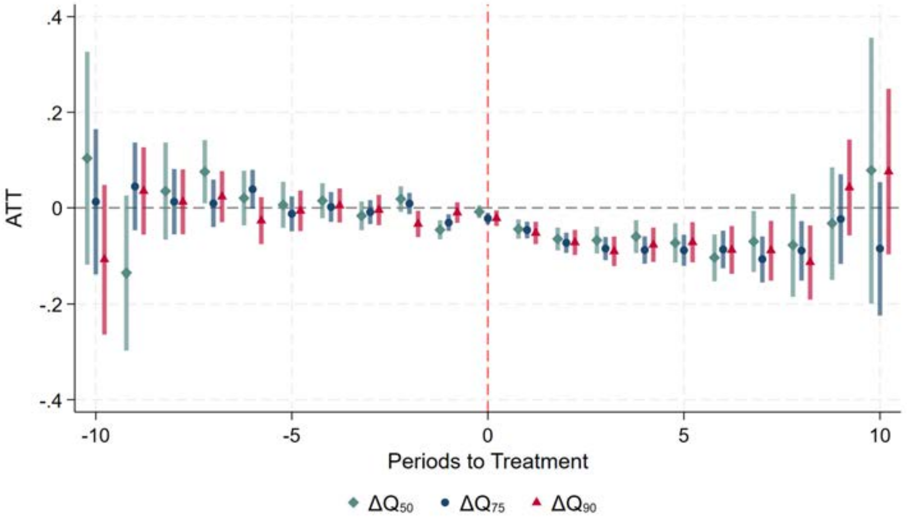
We next examine the full dynamic path of treatment effects using the Callaway-Sant’Anna event-study specification. Figures 3-6 plot the ATT coefficients and 95% confidence intervals for TM and JTX35 at the 50^{th}, 75^{th}, and 90^{th} percentiles. We begin with the pooled “All Maturities” sample before disaggregating by MLT and ST Loans.

Table 3. **Aggregate impact of TM and JTX35 on loans growth (ATT)**

	TM			**JTX35**		
	ΔQ_{50}	ΔQ_{75}	ΔQ_{90}	ΔQ_{50}	ΔQ_{75}	ΔQ_{90}
Panel A: All Loans						
Pre-trend (average)	0.00482	0.00562	-0.00857	0.00292	0.00929	-0.00686
	(0.0104)	(0.00748)	(0.00716)	(0.0137)	(0.0109)	(0.0114)
ATT	-0.0443**	-0.0672***	-0.0518***	-0.107***	-0.0834***	-0.0438**
	(0.0211)	(0.0139)	(0.0175)	(0.0270)	(0.0154)	(0.0202)
Clusters	56,424	37,275	16,199	69,464	46,905	22,289
Observations	153,873	166,478	84,769	229,194	244,689	137,392
Panel B: Medium & Long-Term						
Pre-trend (average)	-0.0169	-0.00299	-0.0300***	0.0341	-0.0151	-0.0185
	(0.0189)	(0.0110)	(0.0108)	(0.0238)	(0.0184)	(0.0182)
ATT	-0.0582**	-0.0611***	-0.103***	-0.106**	-0.109***	-0.0701**
	(0.0273)	(0.0223)	(0.0266)	(0.0532)	(0.0247)	(0.0327)
Clusters	47,901	32,111	14,055	59,719	40,727	19,409
Observations	96,528	105,266	52,696	142,689	154,102	85,765
Panel C: Short-Term						
Pre-trend (average)	0.0590	-0.00531	0.0301	0.0717	0.0369	-0.0279
	(0.0540)	(0.0361)	(0.0325)	(0.0668)	(0.0439)	(0.0363)
ATT	0.0219	-0.000531	0.0789	-0.0794	0.0760	0.0918
	(0.0666)	(0.0639)	(0.0671)	(0.0796)	(0.0665)	(0.0894)
Clusters	35,098	24,081	10,695	43,881	30,996	14,942
Observations	60,671	65,507	34,012	86,378	95,501	56,202
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of TM and JTX35 at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

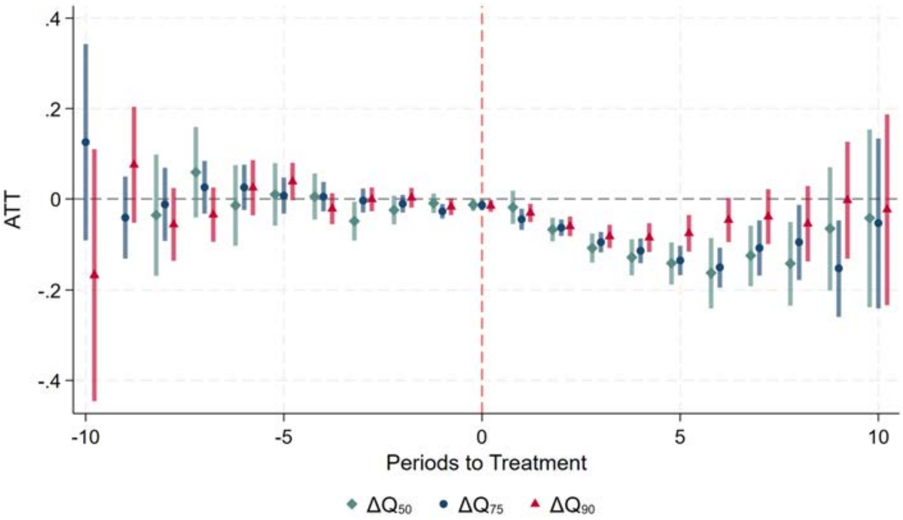
Figure 3. **Impact of TM on total loans for different deviation thresholds**



Notes: Callaway-Sant'Anna's (2021) event-study annual impact of TM at 50%, 75% and 90% temperature deviation thresholds on overall loans' annual growth from -10 years to +10 years to treatment. Confidence bands at 95%.

Figure 3 shows that pre-treatment TM coefficients for total Loans are indistinguishable from zero at the 75th and 90th quantiles, supporting parallel trends under more extreme warming. At the median, an isolated anticipatory dip appears one year before treatment, but other pre-period estimates are small and imprecise. For JTX35 (Figure 4), pre-treatment effects are again null except for a modest dip three years before treatment at the median. Post-treatment, lending contracts more rapidly, however.

Figure 4. **Impact of JTX35 on total loans for different deviation thresholds**



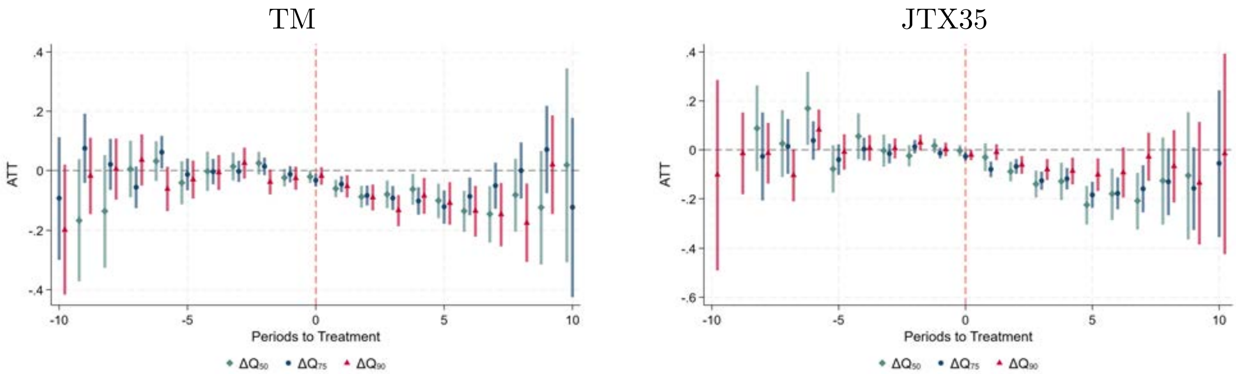
Notes: Callaway-Sant'Anna's (2021) event-study annual impact of JTX35 at 50%, 75% and 90% temperature deviation thresholds on overall loans' annual growth from -10 years to +10 years to treatment. Confidence bands at 95%.

Both measures produce clear contractions in loan growth, but they differ systematically in timing, peak magnitude, and persistence across the distribution of exposure. These differences are economically meaningful and point to distinct transmission dynamics through the credit channel depending on whether exposure is acute or chronic.

At the median the two measures diverge in shape. Acute exposure as measured by JTX35 yields a deeper median trough, on the order of -16.4 pp, that is materially negative for several post-treatment periods and vanishes only after a longer horizon. Chronic exposure as measured by TM produces a smaller median contraction, near -10.4 pp, which attenuates sooner. These two patterns suggest that for the typical firm banks tighten lending more sharply when an acute event occurs, whereas mean temperature deviations elicit a milder median response that recovers one period earlier. At intermediate exposure levels (Q_{75}) both acute events and chronic warming can lead to notable credit tightening, with a larger impact for acute risks (-15.3 pp and -10.7 pp, respectively), albeit with modest differences in timing. However, at the extreme upper tail, the ordering flips and TM produces the larger and more persistent contraction, with a trough of roughly -11.4 pp and negative effects that persist to a later horizon (up to period 8). By contrast JTX35 shows a maximum decline of roughly -8.5 pp and a return to negligible effects within fewer post-treatment periods (up to period 5). In other words, banks appear to react more durably to chronic mean deviations for the most exposed firms, while acute days drive a shorter lived response.

Across specifications, the cross-quantile patterns are consistent with distinct economic mechanisms, but the persistence ordering is exposure-dependent and should be stated as such. At the median and intermediate exposure, the acute (JTX35) response is the deeper and the more persistent of the two—materially negative for several post-treatment periods. Only at the upper tail (Q_{90}) does the ordering reverse where chronic (TM) deviations then produce the more persistent contraction (negative to period 8), while acute effects fade sooner (by period 5). This tail pattern is consistent with chronic warming eroding expected income streams and long-run viability for the most exposed firms, whereas the median pattern indicates that acute episodes, though transitory in the aggregate, generate the more drawn-out adjustment for the average firm.

Figure 5. **Impact on medium and long-term loans for different deviation thresholds**



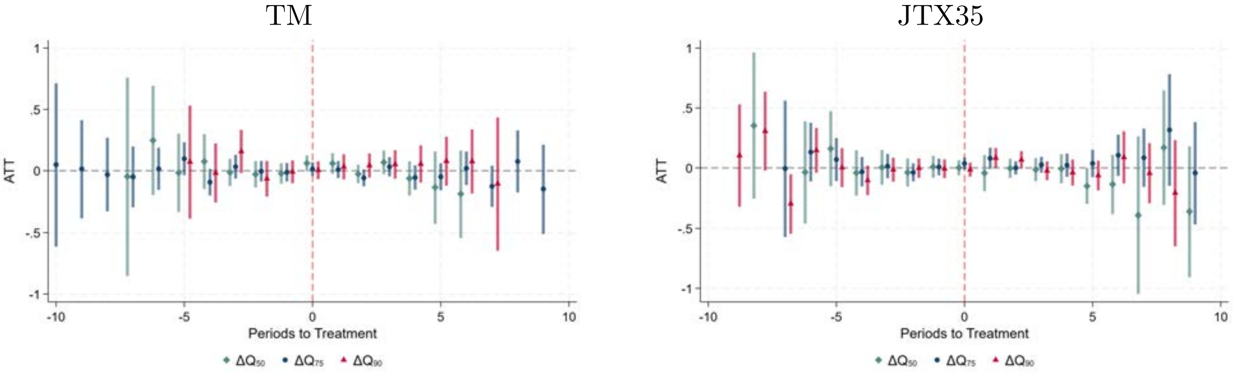
Notes: Callaway-Sant'Anna's (2021) event-study annual impact of TM and JTX35 at 50%, 75% and 90% temperature deviation thresholds on medium-long term loans' annual growth from -10 years to +10 years to treatment. Confidence bands at 95%. For readability purposes, ATT$_{10}$ of $\Delta JTX35_{Q_{50}}$ was dropped (CI too wide).

Maturity heterogeneity The MLT-only profiles (Figure 5) show even sharper and more persistent contractions. Chronically hot years trigger a -6.1 pp decline at year 2 (median), deepening to -13.4 pp by year 3 at Q_{90}, with negative effects persisting through year 8. Acute heat yields larger cuts still: the median falls by -22.5 pp in year 5 and the 75th percentile by -18.4 pp in year 5, followed by a gradual rebound.

By contrast, ST loan dynamics (Figure 6) show negligible responses to TM, with coefficients hovering near zero throughout. JTX35 generates only an isolated -15 pp drop in year 5 at the median, with no systematic pattern at higher quantiles.

The dynamic event-study results confirm that both sustained warming and acute heat

Figure 6. **Impact on short-term loans for different deviation thresholds**



Notes: Callaway-Sant'Anna's (2021) event-study annual impact of TM and JTX35 at 50%, 75% and 90% temperature deviation thresholds on short-term loans' annual growth from -10 years to +10 years to treatment. Confidence bands at 95%. For readability purposes ATT$_{-7}$ of $\Delta JTX35_{Q_{50}}$ was dropped (CI too wide).

episodes prompt banks to tighten credit supply, with the adjustment concentrated in medium- and long-term lending. The static TWFE estimates provide a useful benchmark and facilitate comparison with prior literature, but the heterogeneity-robust event-study framework reveals the temporal structure of the response: effects emerge within one to two years of treatment, peak between years 2 and 6, and dissipate by year 10. Anticipation effects are minimal, and the maturity split underscores that climate-risk shocks primarily affect the supply of longer-term credit. The dissipation of the effect in later years may reflect several factors. On the supply side, banks may update risk assessments and become more accustomed to lending to firms operating in hotter environments. On the demand side, firms may adapt through operational changes, investment in resilience, or adjustments to financing strategies. The attenuation could also be influenced by market-wide disruptions, such as the COVID-19 pandemic, during which the French government implemented unprecedented support measures, particularly through the credit channel, that may have altered lending patterns independently of temperature conditions. Finally, the number of observations declines at longer horizons, as not all firms are observed for the full event window, especially more recent entrants to the credit market, which may contribute to the apparent fade-out. However, taken together, these patterns highlight the importance of modelling dynamic, quantile-specific treatment effects when evaluating the financial stability implications of climate risk.

5.3 Heterogeneity across sectors

By conducting a sector-specific analysis, we now control for heterogeneous demand conditions across industries, in order to be able to attribute the observed changes in loan growth to banks' portfolio adjustments toward climate-exposed firms rather than to shifts in sectoral credit demand. Using the Callaway and Sant'Anna (2021) event-study framework, we uncover pronounced heterogeneity in how chronic temperature deviations (TM) and acute heat-day risks (JTX35) shape bank lending across sectors. Tables 4 and 5 report ATT estimates for six sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT, at the 50^{th}, 75^{th}, and 90^{th} percentile thresholds of TM and JTX35 deviations. Pre-trend estimates serve as a test of the parallel-trends assumption, while post-treatment ATTs measure the average shift in yearly loan growth following a deviation above each threshold.

Table 4. **Sectoral effects of TM deviation on loans by percentile**

	TM					
	Sector (1)	**Sector (2)**	**Sector (3)**	**Sector (4)**	**Sector (5)**	**Sector (6)**
Panel A: $\Delta Q_{50^{th}}$						
Pre-trend (average)	-0.0122	0.00886	-0.0922	0.00742	0.00600	0.267^{***}
	(0.0166)	(0.0300)	(0.0589)	(0.0182)	(0.0147)	(0.0304)
ATT	-0.0577^{*}	-0.00988	-0.0319	-0.0779	-0.0602^{**}	0.352^{***}
	(0.0299)	(0.0713)	(0.153)	(0.0504)	(0.0307)	(0.0499)
Clusters	26,723	9,422	587	6,178	8,488	5,846
Observations	69,367	22,993	1,106	14,090	35,434	9,624
Panel B: $\Delta Q_{75^{th}}$						
Pre-trend (average)	0.0116	0.00119	-0.0250	-0.00720	-0.0136	0.0825^{*}
	(0.00801)	(0.0199)	(0.0581)	(0.0380)	(0.0176)	(0.0432)
ATT	-0.0897^{***}	-0.0369	-0.158	-0.0635	-0.0591^{**}	0.0622
	(0.0179)	(0.0399)	(0.0972)	(0.0522)	(0.0263)	(0.0736)
Clusters	17,801	6,223	343	4,039	5,701	3,674
Observations	75,497	24,794	1,355	14,844	37,414	11,506
Panel C: $\Delta Q_{90^{th}}$						
Pre-trend (average)	-0.00110	-0.00958	-0.0255	-0.0103	-0.0245^{*}	0.0495
	(0.00980)	(0.0215)	(0.0385)	(0.0250)	(0.0141)	(0.0408)
ATT	-0.0481^{*}	0.0143	0.203^{**}	-0.147^{***}	-0.0583	-0.151^{**}
	(0.0247)	(0.0574)	(0.0883)	(0.0440)	(0.0371)	(0.0649)
Clusters	7,702	2,690	149	1,720	2,654	1,492
Observations	37,022	13,191	565	7,440	20,410	5,581
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of TM at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Total lending Three key insights emerge from this sectoral breakdown. First, Trade & Transport and Manufacturing & Mining are the sectors most affected by chronic temperature rise, with loan growth contracting at both the 50^{th} and 75^{th} percentiles, and showing similar magnitudes of response under acute shocks of the same severity (see Table 4). Real Estate & Construction, by contrast, is fully insulated against chronic warming across total loan growth and medium- to long-term maturities, yet proves more vulnerable to acute shocks at comparable thresholds. Utilities and Services & ICT also display stronger responsiveness

Table 5. **Sectoral effects of JTX35 deviation on loans by percentile**

	JTX35					
	Sector (1)	**Sector (2)**	**Sector (3)**	**Sector (4)**	**Sector (5)**	**Sector (6)**
Panel A: $\Delta Q_{50^{th}}$						
Pre-trend (average)	0.0133	-0.00362	-0.0120	-0.0114	-0.00915	0.00355
	(0.0232)	(0.0385)	(0.0542)	(0.0184)	(0.0370)	(0.0258)
ATT	-0.112**	-0.110*	-0.258***	-0.0303	-0.0599**	-0.111**
	(0.0471)	(0.0563)	(0.0813)	(0.0419)	(0.0233)	(0.0496)
Clusters	32,817	11,675	735	7,890	10,324	7,047
Observations	99,927	36,074	1,641	21,888	53,215	14,367
Panel B: $\Delta Q_{75^{th}}$						
Pre-trend (average)	-0.00271	0.0277*	0.00813	0.0395	0.0191	-0.0163
	(0.0153)	(0.0164)	(0.0300)	(0.0441)	(0.0271)	(0.0439)
ATT	-0.0805***	-0.0992***	-0.192***	-0.150**	-0.0577	-0.0778*
	(0.0202)	(0.0264)	(0.0702)	(0.0746)	(0.0360)	(0.0456)
Clusters	22,332	7,589	464	5,611	7,051	4,530
Observations	109,115	36,838	1,822	24,407	54,802	15,802
Panel C: $\Delta Q_{90^{th}}$						
Pre-trend (average)	-0.00839	-0.0469*	0.0637	0.0118	0.0144	-0.0407*
	(0.0171)	(0.0242)	(0.0823)	(0.0379)	(0.0198)	(0.0223)
ATT	-0.0211	0.0416	0.0666	0.0177	-0.150***	-0.107**
	(0.0333)	(0.0574)	(0.0994)	(0.0485)	(0.0343)	(0.0521)
Clusters	10,667	3,538	226	2,580	3,391	2,193
Observations	61,856	19,605	1,480	13,571	30,088	9,970
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of JTX35 at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

to acute shocks than to chronic warming, as shown in Table 5. The Accommodation & Leisure sector, which is expected to benefit from a warmer climate (Addoum et al., 2020), instead shows significant vulnerability: loan growth contracts sharply under extreme chronic deviations at the 90^{th} percentile and under acute stress at the 75^{th} percentile, with effects of roughly 15 pp.

Second, the severity of deviations magnifies credit contractions in a non-linear fashion, though the direction and significance are not monotonic across all industries. This is illustrated by the Service & ICT results under chronic warming (Table 4), where moderate deviations suggest responsiveness but fail the parallel-trends test, while extreme deviations yield large negative effects. Medium- to long-term maturity results reflect qualitatively the same dynamic (see Appendix B.2, Tables 7–8).

Third, identification limits shape the interpretation of extreme shocks. At the 90^{th} percentile of acute heat risk, most sectors that had already responded at lower thresholds show little to no additional effect, consistent with control groups being already treated at lower quantiles and are no longer valid for comparison. Manufacturing & Mining remains an exception, contracting by about 15 pp, likely because it exhibits no treatment effects at the 75^{th} quantiles and retains a relatively less contaminated control group at the extreme.

Overall, we find that chronic temperature rise affects mainly the Trade & Transport and Manufacturing & Mining sectors, while sectors such as Real Estate & Construction, Accommodation & Leisure, and Services & ICT, which may benefit operationally from rising average temperatures, are more vulnerable to acute heat episodes. In sum, the sector-specific approach, which nets out heterogeneous demand shocks, demonstrates that banks adjust credit supply in response to both chronic and acute temperature risks. These findings underscore the need for financial stress tests and macroprudential policies to incorporate sectoral risk profiles and non-linear climate-shock thresholds in order to preserve lending stability under evolving temperature extremes.

Substitution by short-term lending Short-term lending remains largely unresponsive to chronic shocks, with ATT estimates insignificantly different from zero for most sectors and deviation severities (see Appendix Table 9). Nevertheless, under extreme acute-heat shocks (Table 6), Real Estate & Construction, despite a -10 pp contraction in total loans at the 75^{th} percentile, records a +26 pp increase in short-term lending at the 90^{th} percentile. Likewise, Utilities and Manufacturing & Mining register +47 pp and +30 pp surges, respectively. Service & ICT initially shows a +23 pp rise at the JTX35 75^{th} percentile, but parallel-trend violations preclude causal interpretation; at the 90^{th} percentile, the effect switches to a -28 pp contraction, with a valid causal interpretation this time. Chronic warming yields a similar maturity-reallocation signal: at the TM 50^{th} percentile, Trade & Transport sees a +9 pp increase in short-term lending, whereas Real Estate & Construction experiences a -42 pp decline.

These divergent short-term responses highlight the presence of non-linear treatment effects and sectoral heterogeneity in banks' reallocation of credit across maturities under varying temperature-risk severities. They suggest that, in some cases, banks may respond to heightened climate risk not by withdrawing credit entirely, but by shortening maturities to reduce exposure, while in other cases they may contract both short- and long-term lending. Such patterns have important implications for understanding the channels through which climate shocks propagate to the real economy and for designing supervisory guidance that accounts for maturity structure as well as sectoral exposure.

Table 6. **Sectoral effects of JTX35 deviation on short-term loans by percentile**

	JTX35					
	Sector (1)	**Sector (2)**	**Sector (3)**	**Sector (4)**	**Sector (5)**	**Sector (6)**
Panel A: $\Delta Q_{50^{th}}$						
Pre-trend (average)	0.116	-0.166	-0.416	0.298^{*}	0.109	0.206^{***}
	(0.0937)	(0.216)	(0.309)	(0.159)	(0.0937)	(0.0732)
ATT	-0.0245	-0.331^{**}	-0.434	-0.305^{**}	-0.00771	0.0232
	(0.121)	(0.166)	(0.445)	(0.144)	(0.0684)	(0.119)
Clusters	20,502	7,153	341	5,373	7,136	3,930
Observations	41,444	11,665	305	5,918	21,810	3,736
Panel B: $\Delta Q_{75^{th}}$						
Pre-trend (average)	0.00961	0.0650	-0.490^{***}	-0.209	0.0612	0.172^{**}
	(0.0423)	(0.0479)	(0.128)	(0.138)	(0.106)	(0.0694)
ATT	0.0301	-0.0294	-0.00419	0.0641	0.167	0.233^{**}
	(0.0832)	(0.143)	(0.424)	(0.246)	(0.137)	(0.116)
Clusters	14,699	4,810	209	3,956	5,019	2,678
Observations	47,309	12,466	280	6,777	22,852	4,808
Panel C: $\Delta Q_{90^{th}}$						
Pre-trend (average)	-0.0150	0.0625	0.0121	-0.233^{*}	-0.0690	0.0586
	(0.0341)	(0.119)	(0.259)	(0.126)	(0.0817)	(0.154)
ATT	-0.0307	0.262^{**}	0.467^{**}	-0.198	0.303^{*}	-0.283^{**}
	(0.134)	(0.133)	(0.207)	(0.146)	(0.179)	(0.140)
Clusters	7,163	2,301	110	1,803	2,429	1,309
Observations	27,642	7,176	330	3,702	13,828	3,096
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of JTX35 at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6 Discussion and Policy Implications

6.1 Discussion

This subsection discusses the economic interpretation of the results and assesses their robustness. We first relate the dynamic lending response to plausible transmission channels linking temperature shocks to firm credit. We then examine sectoral heterogeneity to show how these channels vary with firms' exposure, asset structure, and vulnerabilities. Next, we discuss what the concentration of the effects in medium- and long-term credit implies for bank loan supply and the maturity structure of lending. Finally, we show that the results are robust to the inclusion of credit-rating controls, alternative exposure measures, and alternative identifying assumptions.

Transmission channels Our empirical analysis reveals a consistent and economically meaningful contraction in bank lending following both chronic (TM) and acute (JTX35) temperature shocks. Heterogeneity-robust event-study estimates show that these effects are concentrated in medium- and long-term (MLT) credit, emerge within one to two years after treatment, peak between years two and six, and dissipate by year ten, with no evidence of anticipatory adjustment. At a broad level, these patterns are consistent with both supply-side channels, including labor productivity, health, energy, and logistics, and demand-side channels, including consumption and sectoral sales. Acute heat shocks are most plausibly associated with contemporaneous disruptions to labor productivity, health conditions, and short-run demand (Graff Zivin and Neidell, 2014; Acevedo et al., 2020; Im et al., 2017; Ballester et al., 2023), whereas chronic warming is more consistent with persistent changes in productivity, operating costs, and expected firm risk (Jones and Olken, 2010; Ponticelli et al., 2024). Besides, static TWFE estimates provide a useful and flexible benchmark and align closely with the dynamic estimates in both sign and magnitude, but the heterogeneity-robust event-study design is essential for confidently recovering the timing of the adjustment.

Sectoral heterogeneity The sectoral analysis shows that the aggregate patterns mask substantial cross-industry heterogeneity. Chronic warming has its largest and most persistent effects in Trade & Transport and Manufacturing & Mining, whereas acute heat-day shocks have a broader footprint, affecting also Real Estate & Construction, Utilities, Accommodation & Leisure, and Services & ICT. These patterns are consistent with sector-specific transmission channels and with differences across industries in exposure, asset structure, and vulnerabilities. In Trade & Transport, lending contracts under both chronic warming (TM: -9.0 pp at Q_{75}) and acute heat exposure (JTX35: -8.1 pp at Q_{75}), consistent with evidence that heat disrupts supplier relationships (Pankratz and Schiller, 2024) and propagates through production networks and supply chains (Barrot and Sauvagnat, 2016). This interpretation is reinforced by the classification of transportation as a particularly heat-exposed outdoor industry (Acevedo et al., 2020), and by evidence that high temperatures can directly disrupt the movement of goods and workers through transport-system failures.[17] Manufacturing & Mining exhibits comparable sensitivity to both shock types (TM: -5.9 pp at Q_{75}; JTX35: -6.0 pp at Q_{50}), in line with evidence that high temperatures reduce labor productivity (Jones and Olken, 2010; Somanathan et al., 2021; Pankratz et al., 2023) and raise energy costs, with especially strong effects for smaller plants (Ponticelli et al., 2024; Tarsia, 2025), which may be pushed out of business when they cannot absorb higher energy bills (Ponticelli et al., 2024), while revenues and operating income are also compressed as wage and input-cost pressures rise under heat exposure (Pankratz et al., 2023). By contrast, Real Estate & Construction and Utilities appear primarily exposed to acute rather than chronic temperature risk. In Real Estate & Construction, lending responds strongly to acute heat (JTX35: -11.0 pp at Q_{50}) but not to chronic warming. This pattern mirrors the sharp pro-

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[17] See Mulholland and Feyen (2021) on rail buckling, and Christodoulou and Demirel (2018) on reduced inland-waterway navigability and air-cargo disruptions in Europe under heat and low-water conditions.

ductivity losses in outdoor work once temperatures exceed critical thresholds documented in the literature (e.g. Graff Zivin and Neidell, 2014; Han et al., 2024). It is also consistent with construction being among the most temperature-exposed sectors across EU regions (Cipollini and Parla, 2026), while heat-related declines in property values may further weaken collateral and tighten credit supply (Contat et al., 2024). Utilities display the largest response to acute heat (JTX35: -25.8 pp at Q_{50} and -19.2 pp at Q_{75}), in line with a demand-supply squeeze in which cooling demand rises precisely when generation efficiency deteriorates (Acharya et al., 2024) and transmission costs rise at high temperatures (Auffhammer et al., 2017). Other sectors display more specific forms of temperature sensitivity. Accommodation & Leisure, where many activities are outdoor or place-based and therefore offer limited scope for adaptation, contracts under both extreme chronic warming (TM: -14.7 pp at Q_{90}) and acute heat (JTX35: -15.0 pp at Q_{75}), a pattern that aligns with losses linked to reduced winter snow cover (Falk and Lin, 2018) and heightened summer heat stress (Agulles et al., 2022), with such demand shocks likely to translate into persistent earnings erosion (Addoum et al., 2023). By contrast, Services & ICT, appears relatively insulated from moderate shocks (Acevedo et al., 2020), but still contracts under acute heat (JTX35: -7.8 pp at Q_{75}), consistent with evidence that high temperatures induce work-leisure substitution and reduce productivity even in predominantly indoor activities and in comparatively cold European regions (Groom et al., 2024). The fact that more severe deviations often magnify credit contractions, without generating monotonic responses in every sector, points to threshold effects in heat exposure and heterogeneous vulnerabilities across industries, including differences in the ability to protect labor productivity, absorb higher energy costs, preserve collateral values, or cushion demand losses.

Bank loan supply and maturity structure The concentration of the response in medium- and long-term credit is particularly informative about the nature of banks' adjustment. This finding echoes firm-level evidence in Aguilar-Gomez et al. (2024), who show that extreme heat reduces SME outstanding loans and weakens subsequent credit access in Mexico, with adverse consequences for future borrowing and firm growth. In our setting, the predominance of the contraction at longer maturities suggests that banks respond to heightened temperature risk primarily by reducing longer-horizon commitments rather than by withdrawing credit indiscriminately. This pattern is consistent with a credit-supply channel through which temperature shocks amplify real-economy damages by restricting the investment financing that exposed firms may need in order to adapt.

Short-term lending is generally less sensitive to temperature shocks, but several exceptions point to maturity reallocation rather than to a uniform contraction in credit supply. Under extreme acute-heat exposure, some sectors, including Real Estate & Construction, Utilities, and Manufacturing & Mining, experience sizeable increases in short-term credit despite concurrent contractions in total lending, suggesting that banks preserve short-horizon financing while limiting longer-term exposure. By contrast, in other cases, such as Services & ICT at the JTX35 90th percentile, both short-term and medium- and long-term credit contract, indicating a broader withdrawal of financing. Taken together, these patterns imply that high temperature exposures affect not only the volume of credit supplied, but also its maturity structure.

6.2 Robustness checks

We implemented various robustness checks which support the interpretation of the main results. We first probe the specification by introducing credit ratings, using alternative temperature metrics, and dropping sector controls. We then turn to the identification of the credit-supply channel, absorbing credit demand with fixed effects à la Degryse et al. (2019), separating acute from chronic exposure, and re-estimating with the de Chaisemartin and D'Haultfoeuille (2022) dose-response design. We finally address the sample composition. We exclude the COVID-19 pandemic years to rule out any contagion or broader market distortions from state-guaranteed lending, which, although already excluded from our sample, may have reshaped credit-market mechanisms more widely. Separately, we reintegrate inactive or defaulted firms to deal with survivorship.

Introducing credit ratings We first exploit the flexibility of the TWFE specification to add firm credit ratings, a time-varying control that cannot be included in our heterogeneity-robust design based on Callaway and Sant'Anna (2021), which restricts conditioning variables to time-invariant controls. Controlling for firm credit ratings, the coefficients on rating categories decline monotonically with borrower risk, as expected, while the estimated effects of temperature shocks remain virtually unchanged.[18] This pattern indicates that the lending response to excess heat is not simply capturing differences in observable credit quality as summarized by current ratings. Instead, temperature exposure appears to constitute an additional source of credit risk that is not fully reflected in standard credit assessments.

This result also points to a forward-looking component in banks' responses. If the estimates were driven only by contemporaneous deterioration in observable borrower quality, controlling for ratings would be expected to attenuate the temperature coefficients. The stability of the estimates suggests that banks adjust lending along a margin not fully captured

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[18] See Appendix B.3, Tables 10–11.

by existing ratings, such as expected repayment capacity, collateral values, or climate-related operating risk. This interpretation is in line with evidence that abnormally high temperatures reduce approval rates and loan amounts when loan officers update their beliefs about climate risk (Duan and Li, 2024). More broadly, it accords with evidence that financial decisions increasingly reflect perceived climate-related risk, rather than only contemporaneous fundamentals or historical performance (Baldauf et al., 2020; BCBS, 2021; IMF, 2022). In this sense, temperature shocks appear to introduce an additional risk factor not already captured by conventional bank screening.

Alternative excess temperature metrics Alternative exposure measures, yearly average maximal temperature (TX) and the number of days with temperatures above 30°C (JTX30), yield qualitatively similar results,[19] while sharpening sectoral contrasts and reinforcing the importance of matching the temperature metric and threshold to the operational realities of each industry. This strengthens the interpretation that the estimated effects capture economically meaningful dimensions of exposure rather than idiosyncrasies of the baseline specification. Similarly, dropping sector controls produces nearly identical dynamic profiles, with somewhat tighter confidence intervals,[20] indicating that the results are not an artifact of the control structure. If anything, this exercise confirms that the identification strategy is robust even under the stronger, unconditional parallel-trends assumption.

Disentangling credit demand from credit supply Our baseline results address the issue that the estimated contractions might reflect a temperature-driven decline in firms' credit *demand* rather than an adjustment in banks' credit *supply*, by implementing a sector-by-sector analysis. This is supported by the usual assumption that firms' demand is largely sector-specific. The canonical way to absorb firm-level demand is the firm-time fixed effect of Khwaja and Mian (2008), which is only identified for firms borrowing from multiple banks. In our setting, however, single-bank firms account for about 52% of the sample and are precisely the firms most exposed to credit-supply shocks. We therefore follow Degryse et al. (2019) and proxy credit demand with industry×location×size×time (ILST) fixed effects, which identify supply shocks using both single- and multi-bank firms. Because the heterogeneity-robust estimator of Callaway and Sant'Anna (2021) does not accommodate time-varying controls, we residualize loan growth on these demand fixed effects in a first step, and re-estimate our specification on the residualized outcome. Identification of the temperature effect is preserved because exposure is measured at the firm level, through each firm's nearest weather station

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[19] See Appendix B.3, Tables 12–15.

[20] See Appendix B.4, Figures 9–11.

and its own historical baseline, so that meaningful variation in deviations remains *within* each ILST cell (at the department level).

Because the residualized outcome is a generated regressand, we address the resulting inference issue in the standard way (Pagan, 1984): we run a 1,000 replication firm-clustered bootstrap that re-estimates the ILST fixed effects and re-residualizes inside every draw, so the first-step estimation error is reflected in the standard errors. The temperature effects are robust to this two-step bootstrap. We recover same dynamic patterns and comparable magnitudes, still statistically significant, supporting the interpretation that we identify a credit-supply response rather than a demand artifact.

Separating acute from chronic exposure We revisit our analysis that investifgates separately acute and chronic channels. Because warmer locations also tend to experience more extreme heat days, chronic (TM) and acute (JTX35) exposures are positively correlated, which could blur the attribution of effects to each channel. To isolate each dimension, we re-estimate the model on firms exposed *exclusively* to one risk (at $\geq Q_{75}$ and $\geq Q_{90}$, respectively), dropping entirely the upper quartile ($\geq Q_{75}$) of the other dimension from the sample. The contractions persist for each exposure taken in isolation, indicating that the two channels are not merely an artifact of their joint occurrence. This exercise recovers a more restrictive local effect, defined over firms that are highly exposed along one dimension while remaining little exposed along the other, and should therefore be read as evidence on channel separability rather than as an estimate for the full population.

Allowing for joint exposure through a dose-response design As a complementary strategy that retains, rather than discards, firms exposed to both risks, we re-estimate the impact using the de Chaisemartin and D'Haultfoeuille (2022) estimator, which accommodates non-binary treatment. We let the treatment take the values 0, 1, or 2 according to the number of temperature dimensions to which a firm is exposed, so that doubly exposed firms enter at the highest intensity. The results are robust to this change in both estimator and treatment definition. We interpret the ordering as a count of exposure dimensions rather than as a cardinal dose, since acute and chronic heat are qualitatively distinct risks rather than two units of the same exposure.

Excluding policy-driven credit interventions Our sample period spans the COVID-19 pandemic, during which the French government substantially altered the supply of credit through state-guaranteed loans (*Prêts Garantis par l'État*, PGE) to firms affected by the lockdowns. Although firms that received such guaranteed loans are already dropped at the data-cleaning stage, the intervention itself, together with the near-total shutdown of activity, may have altered credit-market mechanisms more broadly, affecting even non-guaranteed firms. To rule out any contamination from this exceptional environment, we re-estimate our specification on a window ending in 2019, thereby excluding the COVID and post-COVID years. The results are qualitatively unchanged, at the cost of a shorter post-treatment horizon for late-treated cohorts and correspondingly wider confidence intervals.

Addressing survivorship Finally, our baseline excludes firms that become inactive or default over the sample period. To verify that this selection does not understate the credit response, we reintegrate these firms. The estimates are robust, as expected. such firms mechanically exhibit negative loan growth, since at best they repay outstanding debt without obtaining new credit, so that excluding them is, if anything, conservative with respect to detecting a credit contraction.

Across these exercises, each additional layer of robustness considerably reduces the effective sample size and systematically widens the confidence intervals. Nonetheless, the sign, timing, and concentration of the effects in medium- and long-term credit remain stable throughout, reinforcing the interpretation that temperature shocks operate through a forward-looking bank credit-supply channel.

6.3 Policy implications

These results have several implications for financial stability policy, prudential supervision, and climate-risk management.

First, the concentration of lending contractions in medium- and long-term credit suggests that climate shocks primarily affect investment finance rather than working capital. This matters because reduced access to long-term credit may slow capital formation in exposed sectors and constrain firms' ability to invest in adaptation, including heat-resilient infrastructure, cooling technologies, collateral protection, and supply-chain diversification. Climate-related credit retrenchment may therefore be self-reinforcing as lower long-term finance limits resilience investment, which raises future risk and weakens borrower creditworthiness. For macroprudential authorities, the implication is that aggregate credit volumes are insufficient indicators of climate-related financial stress. Supervisors should also monitor the maturity structure of lending in climate-sensitive sectors and assess whether prudential responses to climate risk unintentionally restrict adaptation-enabling finance, especially for SMEs.

Second, the maturity-reallocation patterns observed in some sectors under extreme severities indicate that banks may respond to climate exposure by shortening loan maturities rather than withdrawing credit altogether. While this strategy can reduce long-term risk on bank balance sheets, it may increase refinancing risk for borrowers and shift liquidity risk elsewhere in the financial system. These effects may remain hidden if surveillance focuses only on total credit. A firm that retains short-term funding but loses access to longer-term finance may appear liquid in the near term while becoming more exposed to rollover risk and refinancing pressure. Macroprudential policy should therefore treat maturity shortening as a potential channel through which climate risk can reshape financial fragility even without an immediate decline in aggregate lending.

Third, the pronounced sectoral heterogeneity and non-linear responses to exposure severity argue for sector-specific climate impact assessment. Supervisory frameworks should incorporate differentiated exposure metrics and thresholds tailored to sectoral risk profiles. This distinction matters because acute and chronic temperature risks do not operate uniformly across sectors. Acute heat is more closely linked to contemporaneous disruptions in operations, whereas chronic warming is more likely to affect firms through persistent changes in business conditions. Climate impact assessments should also account for the spatial concentration of acute and chronic risks, since these exposures are not distributed evenly across regions and may generate geographically differentiated contractions in credit access.

Fourth, the evidence that banks adjust credit supply in a forward-looking manner, despite the absence of temperature-risk signals in current credit ratings, suggests that supervisory guidance and market discipline can influence behavior ahead of observable losses. The implication for supervision is therefore not simply that climate risk should enter governance frameworks in general terms, but that acute and chronic temperature exposures should be embedded more concretely in internal credit assessment, sectoral portfolio monitoring, underwriting standards, and capital planning. In particular, supervisory expectations should increasingly focus on how banks operationalize forward-looking climate judgments at the borrower and portfolio levels, especially where conventional ratings still fail to capture temperature-related vulnerabilities.

7 Conclusion

This paper examines how chronic and acute temperature deviations affect the supply of bank credit to French single-establishment micro and SME firms, using station-level climate data matched to each firm's location. We construct a rich firm–bank panel over 2010–2023 and implement a staggered difference-in-differences design that combines static two-way fixed-effects estimates with heterogeneity-robust event-study specifications to identify both the average magnitude and the dynamic adjustment of bank lending to climate-related temperature risk.

The evidence shows that both chronic warming and acute heat exposure already affect credit supply in economically meaningful ways, but not in the same manner. Loan growth declines significantly at higher levels of exposure, with the contraction concentrated in medium- and long-term credit. The dynamic profiles indicate that acute heat produces sharper but more transitory tightening, whereas chronic temperature deviations are associated with more persistent lending adjustments, consistent with a longer-horizon reassessment of firm risk. Because the two temperature dimensions are concentrated in different regions on average, these effects also imply climate-related disparities in credit access across space.

The results further show that the aggregate response conceals substantial cross-industry heterogeneity. Sectors such as Trade & Transport and Manufacturing & Mining are vulnerable to both chronic and acute temperature risk, whereas other sectors, including Real Estate & Construction, Utilities, Accommodation & Leisure, and Services & ICT, respond more strongly to acute heat stress. These sectoral patterns are consistent with heterogeneous transmission channels linking temperature exposure to firm performance, and they point to a predominantly supply-side adjustment in bank lending. Banks also adjust along the maturity dimension. In some industries, greater temperature risk leads to a shortening of maturities rather than a complete withdrawal of credit, indicating that climate shocks affect not only the volume of lending but also its structure. More generally, the results point to non-linear responses, with stronger shocks often generating larger credit contractions, although not in a uniform way across all sectors.

The main findings are robust to a wide range of alternative specifications. The estimated effects remain unchanged when controlling for firm credit ratings, suggesting that current ratings do not yet fully capture temperature-related exposure and that banks' responses are at least partly forward-looking. Alternative measures of both chronic and acute temperature risk yield similar results, while dropping sector controls under a stronger identification strategy leaves the dynamic patterns essentially unchanged.

Overall, the analysis suggests that chronic and acute temperature risks should not be treated as interchangeable manifestations of a single physical-risk factor. They differ in timing, persistence, sectoral footprint, and transmission, and banks translate those differences into distinct loan-supply adjustments across maturities and industries. Climate risk therefore affects the real economy not only through its direct impact on firms, but also through the way financial intermediaries reprice, restructure, or restrict credit in response to changing exposure. For policymakers and supervisors, this reinforces the case for climate-risk frameworks that are sector-specific, threshold-sensitive, and attentive to the maturity structure of lending, while ensuring that forward-looking risk assessments are embedded in credit evaluation and portfolio monitoring. More broadly, preserving access to longer-term finance for viable adaptation investment may be important to prevent climate-related credit tightening from undermining resilience itself. Future research could usefully examine the interaction of multiple physical climate risks and extend the analysis to larger, multi-establishment firms, for which geographic diversification and internal risk-sharing may alter both exposure and transmission through the credit channel.

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A Appendix – Discussion on Economic-Climate Impact Analysis

A.1 Chronic vs. acute temperature risk

Before selecting an appropriate climate dataset, it is essential to clarify several key conceptual distinctions. One such distinction pertains to whether the economic impact of temperature should be viewed through the lens of chronic or acute risk. The concept of excessive heat or thermal stress remains ambiguous in much of the economics literature. Yet this distinction carries regulatory implications, particularly within the banking sector. The European Central Bank (ECB), for instance, has mandated that banks integrate climate-related risks into their Internal Capital Adequacy Assessment Process (ICAAP) by the end of 2024. In doing so, it explicitly differentiates between acute risks—such as extreme weather events—and chronic risks, including gradual changes in climate patterns such as rising average temperatures.

In the context of temperature-related risk, heatwaves are typically categorized as acute events, while sustained increases in average temperature fall under chronic risk. This distinction, however, has not been consistently operationalized in the economic literature examining the relationship between temperature stress and macro- or microeconomic outcomes. Both dimensions—acute and chronic—are closely tied to the maximum daily temperature (TX), a commonly used climatic indicator. Heatwaves are often defined as a sequence of days during which TX exceeds a given absolute or relative threshold. Average temperature, by contrast, is commonly computed as the arithmetic mean of the daily minimum (TN) and maximum temperatures, i.e., (TN + TX)/2, over a 24-hour calendar day. Because this identity weights TN and TX equally, a rise in the daily mean reflects trends in both components rather than in TX alone; indeed, over much of the instrumental record minimum temperatures have risen at least as fast as maxima (the well-documented narrowing of the diurnal temperature range). Sustained warming in TM therefore embeds movements in both daytime and nighttime temperatures, which is one reason the chronic mean-deviation measure is not a mere restatement of the acute, upper-tail (TX-based) measure. Despite its importance, the economic literature has not yet adopted a standardized framework to distinguish or measure these temperature dynamics in relation to economic activity.

This lack of consensus is partly attributable to varying degrees of awareness regarding new regulatory frameworks—such as the ECB's guidance—and the absence of a clear mapping between temperature indicators and the types of risk they represent. Moreover, temperature is inherently local. What qualifies as moderately warm in a southern region (e.g., South Asia) may be considered extreme in northern climates (e.g., Scandinavia). For instance, Addoum et al. (2020) use a 30° Celsius (C) threshold, while Acharya et al. (2024) employs 100° Fahrenheit (F) in the U.S. context ($\sim$ 37.8°C). The wide climatic variability across U.S. regions—as previously documented by Lau and Nath (2012)—justifies such heterogeneity across studies in threshold selection, though it also contributes to divergent empirical conclusions.

Climate science has long employed more granular and context-sensitive approaches to defining and measuring heat exposure—practices that economists would benefit from adopting to enhance empirical precision.

A.2 Temperature indicators

The economic relevance of temperature as a risk factor begins with its direct impact on human beings—and, over the longer term, on the environment and biodiversity. This impact may be either amplified or mitigated by the degree of adaptation within the work environment. Less developed economies are more exposed Burke et al. (2015). Similarly, certain economic sectors—such as construction—are naturally more exposed than others, such as services.

In this context, the climatology literature offers a wide range of indicators to capture excessive heat. In a comprehensive review, Freitas and Grigorieva (2017) identified 165 different indices and classified them according to objective criteria. Their conclusion is that there is no universally "best" indicator—rather, the choice depends on the purpose of the study. The primary criterion should thus be the indicator's relevance to the specific object of analysis. For example, a study focusing on the impact of temperature on mortality would favor an indicator such as the wet-bulb temperature, which accounts for both temperature and humidity. It has been shown that exposure to a wet-bulb temperature of 35°C can result in death within a few hours (Im et al., 2017).

A.3 Defining extreme temperature thresholds

Recent work in the economics literature has typically employed absolute temperature thresholds ranging from 30°C to 38°C to define extreme heat (Acharya et al., 2024) or associated it . By contrast, the climate science literature tends to adopt a relative approach. This is generally implemented in two ways. One method involves the use of temperature anomalies—measuring deviations from a historical reference period. In such cases, the selection of the baseline period is essential. For instance, the European Union's Copernicus program, which provides global climate datasets, uses the 1971-2000 period as its standard reference. In the case of France, Météo-France, the national meteorological agency, uses the 1976-2005 period (DRIASS, 2020).[21]

A second approach defines extreme heat based on the historical distribution of a chosen temperature indicator. Here too, researchers must determine an appropriate percentile threshold. For example, Addoum et al. (2023) associate to their absolute threshold a relative measure at the 90th and 95th percentiles to account for time and location-specific definition of extreme temperature. Griffin et al. (2025) define heatwaves as episodes lasting at least two days on which temperatures exceed the 95th percentile of the past five years. Acknowledging the nonlinear effects of heat, they find that firm performance begins to decline beyond a critical threshold of 23°C. While such a temperature would not be considered extreme in Southern Europe, the threshold may reflect temperature anomalies in colder zones within their broader sample. The authors themselves note that their study spans a large geographic area—including the European Union and the United Kingdom—underscoring the value of more localized analyses. Similarly, Pankratz et al. (2023), in their global study of 93 countries, use an absolute threshold of 30°C, which they later combine with a relative metric—the 90th percentile. These methodological choices again highlight the challenge of applying a uniform definition of extreme heat across heterogeneous climates.

In our study, which focuses specifically on metropolitan France, we adopt the standards established by Météo-France. According to the agency, the threshold for excessive heat is 35°C (DRIASS Report, 2020). This choice offers three main advantages. First, it reflects the specific features of the local climate—both current and historical—drawing on the agency's technical expertise and deep contextual knowledge. Second, as the national authority responsible for issuing weather warnings and climate alerts, Météo-France plays a central role in shaping how extreme heat is perceived and managed by policymakers, employers, and the general public. Temperature, and more broadly, climate-change perception is of relevant interest if we consider that economic agents, and specifically investors, would adjust their decision process based on their belief on climate concerns, not only on objective measures (Baldauf et al., 2020; BCBS, 2021; IMF, 2022) Third, the use of air temperature as an index is both, intuitive, and accessible. It is widely understood by non-specialists and is commonly

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[21] Les Nouvelles Projections Climatiques De Référence DRIAS 2020 Pour La Métropole, Météo-France, 2020

used as a benchmark for designing adaptation and mitigation strategies. According to Freitas and Grigorieva (2017), it ranks among the most effective indicators—alongside wet-bulb temperature—for assessing the health risks posed by extreme heat.

For the purposes of our investigation, we rely on air temperature, which is both widely used and easy to interpret, and is considered on par with wet-bulb temperature in terms of relevance. We assume that while workers in French firms may indeed be exposed to extreme temperatures, the effect of humidity in indoor environments remains relatively marginal on average.

A.4 Selecting the appropriate climate data source

Due to practical considerations, particularly related to data availability and computational feasibility, most of the existing literature relies on gridded climate datasets—often with relatively coarse resolution—such as the CMIP6 models from the Copernicus program used in the IPCC's sixth assessment report , or the ERA5 reanalysis dataset. These sources offer a major advantage: they provide comprehensive climate data across wide geographic areas, including regions with sparse meteorological station coverage, by aggregating information from multiple origins (e.g., weather stations, satellite data, ship-based measurements). Furthermore, they enable long-term projections—spanning decades or even centuries—on a global scale while maintaining internal consistency across both space and time in the climatic indicators reported.

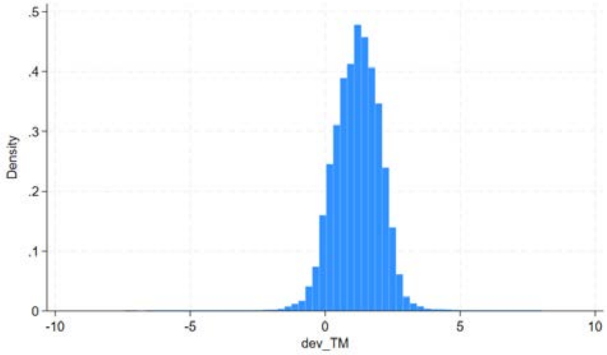
Due to practical considerations, particularly related to data availability and computational feasibility, most of the existing literature relies on gridded climate datasets. These fall into two conceptually distinct types that are often conflated. The first are coupled climate-model projections such as the CMIP6 ensemble, coordinated by the World Climate Research Programme and used in the IPCC's sixth assessment report (IPCC, 2023). These simulate the climate forward under emission scenarios and thus enable long-term projections spanning decades or even centuries, but at coarse spatial resolution (typically 80-250 km). The second is reanalysis, such as ERA5: a reanalysis assimilates historical observations into a fixed model to reconstruct the observed past at much finer resolution (about 0.25°, 31 km), and does not produce forward projections. Both share the advantage of comprehensive spatial coverage, including regions with sparse station networks. However, only the model projections extend into the future, and only the reanalysis approximates observed conditions at high resolution.

While these models—formerly referred to as expert systems—benefit from state-of-the-art climate science and have reached levels of precision previously unattainable, they still retain an inherent, undefined level of uncertainty. This stems from multiple sources: the interpolation techniques employed, the reliance on proxy variables, and the reanalysis approach itself, which uses sophisticated forecasting models that condition the final outputs. Additionally, their relatively coarse spatial resolution makes them ill-suited for local-scale analyses. As noted on the Copernicus project website, *"coarse resolution (from 80 km to 250 km) hinders the possibility of directly connecting their [GCM models] outputs to regional/local scale impact studies like hydrology, agriculture, tourism and energy sectors"*. NASA and climate scientists like Schmidt (2011) and Bosilovich et al. (2013) caution that although these models are valuable, their outputs should not be mistaken for actual observations and must be handled with care. Blanc and Schlenker (2017) and Auffhammer et al. (2013) emphasize that, in addition to reflecting true climatic signals, model-generated data also introduce measurement error such as serial and spatial correlations. In the context of panel data regressions—commonly used to assess the economic impacts of extreme temperatures—fixed effects may absorb a substantial portion of the true signal. This can lead to attenuation bias in estimating the variable of interest, with signal-to-noise ratios as low as 1:6. This issue is also acknowledged by Acharya et al. (2024).

Moreover, station-based observational data are capable of capturing localized phenomena such as urban heat islands, which are not detectable with global reanalysis models. The challenge with observational data, however, lies in their limited availability. Meteorological station density tends to be sufficient only in high-income countries and mostly in urban or peri-urban zones.

Figure 7. **Distribution of TM deviations (2011–2023)**

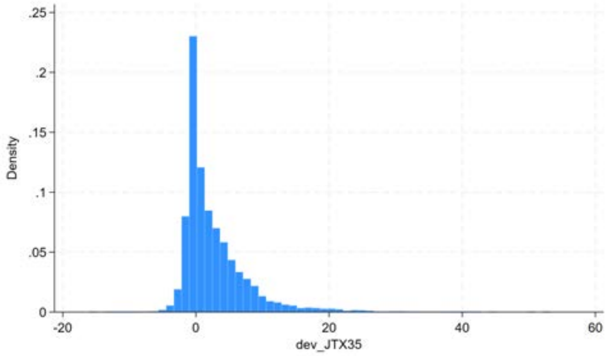
TM (Chronic)



Notes: Distributions of TM deviations (2011–2023) from the baseline period (1976–2005) at the firm level.

Figure 8. **Distribution of JTX35 deviations (2011–2023)**

JTX35 (Acute)



Notes: Distributions of JTX35 deviations (2011–2023) from the baseline period (1976–2005) at the firm level.

B Appendix – Additional Results

B.1 Distribution of temperature deviations

B.2 Impact by sector – complementary tables

Table 7. **Sectoral effects of TM deviation on medium & long-term loans**

	TM					
	Sector (1)	**Sector (2)**	**Sector (3)**	**Sector (4)**	**Sector (5)**	**Sector (6)**
Panel A: $\Delta Q_{50^{th}}$						
Pre-trend (average)	-0.0350	0.0218	0.0988	0.0185	-0.0497	0.248***
	(0.0331)	(0.0349)	(0.0645)	(0.0188)	(0.0418)	(0.0308)
ATT	-0.123***	0.00918	0.192	-0.108	-0.0352	0.325***
	(0.0442)	(0.0586)	(0.124)	(0.0808)	(0.0449)	(0.0653)
Clusters	23,386	7,504	457	5,683	6,941	4,616
Observations	45,229	13,160	516	11,249	19,913	5,699
Panel B: $\Delta Q_{75^{th}}$						
Pre-trend (average)	0.0123	-0.0260	0.0663	-0.00783	-0.0359	0.0982**
	(0.0118)	(0.0323)	(0.0523)	(0.0422)	(0.0263)	(0.0486)
ATT	-0.129***	0.0395	-0.158	-0.0632	-0.0467	0.0603
	(0.0366)	(0.0515)	(0.108)	(0.0532)	(0.0484)	(0.0690)
Clusters	15,803	5,029	268	3,747	4,787	2,908
Observations	49,897	14,022	701	11,892	21,657	6,448
Panel C: $\Delta Q_{90^{th}}$						
Pre-trend (average)	-0.0204	-0.0126	-0.0835**	-0.0164	-0.0747***	0.0367
	(0.0144)	(0.0319)	(0.0413)	(0.0269)	(0.0280)	(0.0286)
ATT	-0.130***	0.0387	0.149	-0.136**	-0.0994*	-0.182**
	(0.0381)	(0.0875)	(0.0945)	(0.0655)	(0.0566)	(0.0751)
Clusters	6,864	2,213	115	1,593	2,266	1,188
Observations	24,402	7,192	296	5,670	11,614	3,199
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of TM at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8. **Sectoral effects of JTX35 deviation on medium & long-term loans**

	JTX35					
	Sector (1)	**Sector (2)**	**Sector (3)**	**Sector (4)**	**Sector (5)**	**Sector (6)**
Panel A: $\Delta Q_{50^{th}}$						
Pre-trend (average)	0.0177	0.0522	0.0940	0.0672*	-0.0196	0.137
	(0.0421)	(0.0345)	(0.0590)	(0.0364)	(0.0236)	(0.130)
ATT	-0.0907	-0.122*	-1.179***	-0.0504	-0.0849*	0.0241
	(0.134)	(0.0665)	(0.111)	(0.0530)	(0.0457)	(0.0569)
Clusters	28,988	9,509	574	7,325	8,592	5,570
Observations	64,688	20,852	800	17,134	29,387	8,094
Panel B: $\Delta Q_{75^{th}}$						
Pre-trend (average)	0.00843	0.0587*	0.122	0.0462	-0.0550	-0.208
	(0.0169)	(0.0339)	(0.0799)	(0.0486)	(0.0354)	(0.191)
ATT	-0.0909***	-0.233***	-0.285***	-0.0827	-0.0785	-0.107*
	(0.0348)	(0.0692)	(0.108)	(0.0654)	(0.0546)	(0.0560)
Clusters	19,902	6,247	362	5,225	5,956	3,592
Observations	70,886	21,319	876	19,524	31,049	9,299
Panel C: $\Delta Q_{90^{th}}$						
Pre-trend (average)	-0.0182	-0.0728**	0.0128	0.155	-0.0465	-0.0301
	(0.0212)	(0.0318)	(0.0277)	(0.127)	(0.0678)	(0.0299)
ATT	-0.0336	-0.0449	-0.0918	-0.000957	-0.147**	-0.107*
	(0.0523)	(0.0841)	(0.102)	(0.0779)	(0.0672)	(0.0581)
Clusters	9,521	2,916	185	2,426	2,867	1,740
Observations	40,339	10,816	708	10,575	16,834	5,977
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of JTX35 at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9. **Sectoral effects of TM deviation on short-term loans**

	TM					
	Sector (1)	**Sector (2)**	**Sector (3)**	**Sector (4)**	**Sector (5)**	**Sector (6)**
Panel A: $\Delta Q_{50^{th}}$						
Pre-trend (average)	0.0843	0.0239	0.0760	-0.0250	0.0710	0.619***
	(0.0742)	(0.224)	(0.446)	(0.0928)	(0.0865)	(0.151)
ATT	0.0896**	-0.426***	1.671***	-0.00538	-0.00418	0.272*
	(0.0452)	(0.157)	(0.263)	(0.195)	(0.113)	(0.154)
Clusters	16,497	5,658	271	4,149	5,739	3,227
Observations	29,913	7,601	209	4,051	15,619	2,598
Panel B: $\Delta Q_{75^{th}}$						
Pre-trend (average)	0.0492	-0.0188	0.432***	-0.000308	-0.0990	-0.175**
	(0.0357)	(0.165)	(0.148)	(0.0711)	(0.0860)	(0.0831)
ATT	-0.0596	-0.381*	1.784***	0.258	0.174	0.0270
	(0.0796)	(0.200)	(0.412)	(0.191)	(0.120)	(0.151)
Clusters	11,430	3,851	158	2,805	3,992	2,123
Observations	31,938	8,606	326	4,093	16,580	3,452
Panel C: $\Delta Q_{90^{th}}$						
Pre-trend (average)	0.0437	-0.00652	-0.497***	-0.0506	0.0528	0.0493
	(0.0538)	(0.105)	(0.0320)	(0.0888)	(0.0512)	(0.132)
ATT	0.0404	0.180	0.0908	0.173	-0.0351	0.146
	(0.0891)	(0.153)	(0.618)	(0.249)	(0.110)	(0.168)
Clusters	5,053	1,689	64	1,244	1,866	895
Observations	15,769	4,943	59	2,287	8,872	1,841
Firm-Bank & Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of TM at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.3 Robustness check tables with credit ratings and alternative temperature metrics

Throughout the tables, *"Loans"* denotes the annual loan growth ($\Delta Loans$) for the specified maturity.

Table 10. **Static TWFE - TM Impact on overall Loans**

	(1) Loans	(2) Loans	(3) Loans	(4) Loans	(5) Loans	(6) Loans
TM ΔQ_{50}=1	-0.0978***	-0.0976***				
	(0.00446)	(0.00445)				
TM ΔQ_{75}=1			-0.0976***	-0.0975***		
			(0.00423)	(0.00422)		
TM ΔQ_{90}=1					-0.0888***	-0.0880***
					(0.00586)	(0.00585)
Size (micro-firms)	-0.0202***	-0.0156**	-0.0106	-0.00701	-0.0234***	-0.0195**
	(0.00697)	(0.00697)	(0.00650)	(0.00649)	(0.00834)	(0.00836)
Age [0-3[	0.0136	0.0170	0.0396	0.0460	0.0607	0.0672*
	(0.0296)	(0.0293)	(0.0290)	(0.0291)	(0.0398)	(0.0401)
Age [3-9]	0.00710	0.0103	0.00584	0.00918	0.00598	0.00960
	(0.00665)	(0.00665)	(0.00649)	(0.00650)	(0.00889)	(0.00894)
Rating=1		0.0907***		0.0639***		0.0809***
		(0.0145)		(0.0140)		(0.0197)
Rating=2		0.0764***		0.0784***		0.0733***
		(0.0117)		(0.0112)		(0.0161)
Rating=3		0.0606***		0.0596***		0.0523***
		(0.00747)		(0.00716)		(0.00997)
Rating=4		0.0494***		0.0428***		0.0381***
		(0.00499)		(0.00480)		(0.00659)
Rating=6		-0.0561***		-0.0455***		-0.0444***
		(0.00920)		(0.00926)		(0.0143)
Rating=7		-0.0681***		-0.0720***		-0.0644***
		(0.0169)		(0.0150)		(0.0212)
Rating=8		-0.0958***		-0.0802***		-0.0538**
		(0.0182)		(0.0168)		(0.0245)
Rating=9		-0.118***		-0.124***		-0.0824
		(0.0367)		(0.0349)		(0.0587)
Year x Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm–Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Ratings	No	Yes	No	Yes	No	Yes
Adj. R^2	.0221877	.0236635	.021234	.0224316	.0205014	.0214269
Clusters	14,956	14,956	15,608	15,608	7,607	7,607
Observations	170,452	170,452	184,837	184,837	94,582	94,582

*Notes: Static TWFE estimates of TM at 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on annual Loans growth. Ratings from 1–9, rating = 1 being the most creditworthy. Omitted: rating = 5, size = SMEs, age $\geq$ 10 years. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 11. **Static TWFE - JTX35 Impact on overall Loans**

	(1) Loans	(2) Loans	(3) Loans	(4) Loans	(5) Loans	(6) Loans
JTX35 ΔQ_{50}=1	-0.119***	-0.120***				
	(0.00369)	(0.00368)				
JTX35 ΔQ_{75}=1			-0.108***	-0.108***		
			(0.00351)	(0.00351)		
JTX35 ΔQ_{90}=1					-0.0968***	-0.0968***
					(0.00464)	(0.00463)
Size (micro-firms)	-0.0294***	-0.0252***	-0.0280***	-0.0240***	-0.0186**	-0.0144*
	(0.00562)	(0.00561)	(0.00547)	(0.00546)	(0.00735)	(0.00737)
Age [0-3[	0.0333	0.0385*	0.0400*	0.0443**	0.0105	0.0127
	(0.0223)	(0.0224)	(0.0225)	(0.0223)	(0.0281)	(0.0279)
Age [3-9]	0.0000747	0.00208	0.00473	0.00725	-0.000898	0.00224
	(0.00562)	(0.00563)	(0.00540)	(0.00541)	(0.00721)	(0.00723)
Rating=1		0.0824***		0.0838***		0.0970***
		(0.0120)		(0.0119)		(0.0159)
Rating=2		0.0767***		0.0718***		0.0645***
		(0.00971)		(0.00925)		(0.0124)
Rating=3		0.0555***		0.0500***		0.0548***
		(0.00604)		(0.00592)		(0.00787)
Rating=4		0.0397***		0.0400***		0.0409***
		(0.00409)		(0.00389)		(0.00523)
Rating=6		-0.0517***		-0.0524***		-0.0695***
		(0.00788)		(0.00783)		(0.0115)
Rating=7		-0.0359***		-0.0519***		-0.0629***
		(0.0126)		(0.0134)		(0.0174)
Rating=8		-0.0899***		-0.0826***		-0.0739***
		(0.0138)		(0.0150)		(0.0194)
Rating=9		-0.0843***		-0.0716**		-0.150***
		(0.0278)		(0.0288)		(0.0416)
Year x Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm–Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Ratings	No	Yes	No	Yes	No	Yes
Adj. R^2	.0248896	.0259892	.0230129	.024082	.021085	.0223838
Clusters	23,361	23,361	22,747	22,747	12,310	12,310
Observations	253,499	253,499	269,666	269,666	151,616	151,616

*Notes: Static TWFE estimates of JTX35 at 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on annual Loans growth. Ratings from 1–9, rating = 1 being the most creditworthy. Omitted: rating = 5, size = SMEs, age $\geq$ 10 years. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 12. **Static TWFE - TX Impact on Loans**

	(1) Loans	(2) Loans	(3) Loans	(4) Loans	(5) Loans	(6) Loans
TX ΔQ_{50}=1	-0.103***	-0.103***				
	(0.00440)	(0.00440)				
TX ΔQ_{75}=1			-0.0920***	-0.0919***		
			(0.00438)	(0.00437)		
TX ΔQ_{90}=1					-0.0931***	-0.0927***
					(0.00588)	(0.00587)
Size (micro-firms)	-0.0238***	-0.0186***	-0.0192***	-0.0145**	-0.0198**	-0.0153*
	(0.00683)	(0.00682)	(0.00645)	(0.00645)	(0.00854)	(0.00856)
Age [0-3[	0.0399	0.0455	0.0433	0.0481*	0.0524	0.0558
	(0.0294)	(0.0294)	(0.0279)	(0.0278)	(0.0377)	(0.0377)
Age [3-9]	0.0204***	0.0237***	0.00311	0.00615	0.00494	0.00805
	(0.00663)	(0.00663)	(0.00655)	(0.00654)	(0.00887)	(0.00886)
Rating=1		0.0853***		0.0899***		0.0763***
		(0.0146)		(0.0149)		(0.0185)
Rating=2		0.0651***		0.0869***		0.0650***
		(0.0115)		(0.0116)		(0.0154)
Rating=3		0.0631***		0.0581***		0.0542***
		(0.00740)		(0.00738)		(0.00958)
Rating=4		0.0475***		0.0441***		0.0450***
		(0.00485)		(0.00492)		(0.00641)
Rating=6		-0.0486***		-0.0514***		-0.0559***
		(0.00929)		(0.00951)		(0.0135)
Rating=7		-0.0675***		-0.0501***		-0.0673***
		(0.0160)		(0.0154)		(0.0193)
Rating=8		-0.0841***		-0.0713***		-0.0843***
		(0.0182)		(0.0180)		(0.0240)
Rating=9		-0.0665*		-0.0562*		-0.0801
		(0.0399)		(0.0338)		(0.0566)
Year x Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm–Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Ratings	No	Yes	No	Yes	No	Yes
Adj. R^2	.0226962	.0240433	.0215181	.0227662	.0245252	.0257375
Clusters	14,855	14,855	14,381	14,381	7,741	7,741
Observations	171,886	171,886	172,519	172,519	97,578	97,578

*Notes: Static TWFE estimates of TX at 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on annual Loans growth. Ratings from 1–9, rating = 1 being the most creditworthy. Omitted: rating = 5, size = SMEs, age ≥ 10 years. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 13. **Sectoral effects of JTX30 on overall Loans**

	(1) Loans	(2) Loans	(3) Loans	(4) Loans	(5) Loans	(6) Loans
JTX30 ΔQ_{50}=1	-0.101***	-0.101***				
	(0.00408)	(0.00407)				
JTX30 ΔQ_{75}=1			-0.101***	-0.101***		
			(0.00416)	(0.00415)		
JTX30 ΔQ_{90}=1					-0.0961***	-0.0959***
					(0.00583)	(0.00581)
Size (micro-firms)	-0.0335***	-0.0285***	-0.0211***	-0.0172***	0.00264	0.00640
	(0.00600)	(0.00599)	(0.00621)	(0.00619)	(0.00884)	(0.00886)
Age [0-3[	0.0421*	0.0479**	0.0808***	0.0866***	0.0228	0.0261
	(0.0227)	(0.0225)	(0.0247)	(0.0247)	(0.0402)	(0.0404)
Age [3-9]	0.00505	0.00825	0.00668	0.00989	0.000547	0.00315
	(0.00618)	(0.00617)	(0.00611)	(0.00611)	(0.00908)	(0.00908)
Rating=1		0.0960***		0.0731***		0.0946***
		(0.0129)		(0.0137)		(0.0201)
Rating=2		0.0935***		0.0717***		0.0941***
		(0.0107)		(0.0109)		(0.0153)
Rating=3		0.0674***		0.0535***		0.0639***
		(0.00656)		(0.00681)		(0.00965)
Rating=4		0.0442***		0.0442***		0.0433***
		(0.00442)		(0.00455)		(0.00629)
Rating=6		-0.0549***		-0.0439***		-0.0284**
		(0.00901)		(0.00910)		(0.0136)
Rating=7		-0.0407***		-0.0532***		-0.0537***
		(0.0139)		(0.0151)		(0.0198)
Rating=8		-0.0709***		-0.0878***		-0.0637***
		(0.0156)		(0.0165)		(0.0205)
Rating=9		-0.121***		-0.0607		-0.0608
		(0.0433)		(0.0428)		(0.0514)
Year x Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm–Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Credit Ratings	No	Yes	No	Yes	No	Yes
Adj. R^2	.0208382	.0221987	.0216239	.0227232	.0217225	.0228324
Clusters	18,666	18,666	16,484	16,484	7,914	7,914
Observations	214,309	214,309	200,555	200,555	97,014	97,014

*Notes: Static TWFE estimates of JTX30 at 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on annual Loans growth. Ratings from 1–9, rating = 1 being the most creditworthy. Omitted: rating = 5, size = SMEs, age $\geq$ 10 years. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 14. **Sectoral effects of TX on overall Loans**

	Sector (1)	Sector (2)	Sector (3)	Sector (4)	Sector (5)	Sector(6)
Panel A: ΔQ_{50}						
Pre-trend (average)	0.0163	-0.0173	0.200***	0.0438	-0.0634*	-0.0143
	(0.0165)	(0.0248)	(0.0627)	(0.0382)	(0.0353)	(0.0179)
ATT	-0.0888***	0.0593	0.215***	-0.110**	-0.0278	-0.0866
	(0.0274)	(0.0804)	(0.0702)	(0.0447)	(0.0315)	(0.0671)
Clusters	26,900	9,516	587	6,556	8,409	5,929
Observations	69,864	24,258	1,017	15,624	33,890	9,946

Panel B: ΔQ_{75}

	Sector (1)	Sector (2)	Sector (3)	Sector (4)	Sector (5)	Sector(6)
Pre-trend (average)	0.0158	0.00643	0.116	-0.0124	-0.0250**	0.0906
	(0.0104)	(0.0257)	(0.0778)	(0.0225)	(0.0114)	(0.0656)
ATT	-0.0595***	0.0221	0.0736	-0.107***	-0.0841***	0.186
	(0.0191)	(0.0611)	(0.120)	(0.0365)	(0.0246)	(0.115)
Clusters	17,107	5,913	353	4,119	5,576	3,516
Observations	70,299	22,895	1,312	14,724	34,872	10,157

Panel C: ΔQ_{90}

	Sector (1)	Sector (2)	Sector (3)	Sector (4)	Sector (5)	Sector(6)
Pre-trend (average)	-0.00462	0.000632	-0.0191	-0.0293**	-0.00950	-0.00465
	(0.00907)	(0.0217)	(0.124)	(0.0116)	(0.0149)	(0.0161)
ATT	-0.0663**	-0.00793	0.146	-0.0888**	-0.0832**	-0.0364
	(0.0262)	(0.0605)	(0.141)	(0.0406)	(0.0363)	(0.0877)
Clusters	7,839	2,754	145	1,810	2,734	1,491
Observations	37,799	13,507	659	7,766	21,128	5,887

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of TX at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15. **Sectoral effects of JTX30 on overall Loans**

	Sector (1)	Sector (2)	Sector (3)	Sector (4)	Sector (5)	Sector(6)
Panel A: ΔQ_{50}						
Pre-trend (average)	0.0113	0.0208	0.0987**	-0.0238**	-0.0180	-0.00194
	(0.0147)	(0.0239)	(0.0448)	(0.0117)	(0.0251)	(0.0364)
ATT	-0.0780***	-0.139***	-0.181**	-0.293*	-0.0591*	-0.123**
	(0.0202)	(0.0442)	(0.0873)	(0.157)	(0.0312)	(0.0605)
Clusters	29,190	10,287	657	7,143	9,238	6,279
Observations	85,604	29,676	1,552	16,442	48,485	11,873

Panel B: ΔQ_{75}

	Sector (1)	Sector (2)	Sector (3)	Sector (4)	Sector (5)	Sector(6)
Pre-trend (average)	0.0134	0.00298	-0.0122	-0.00763	-0.0131	0.107***
	(0.0129)	(0.0281)	(0.0383)	(0.0441)	(0.0263)	(0.0391)
ATT	-0.0849***	-0.0186	-0.123	-0.0966***	-0.0504	-0.0584
	(0.0260)	(0.0441)	(0.0803)	(0.0359)	(0.0316)	(0.0453)
Clusters	18,648	6,384	385	4,691	5,801	3,847
Observations	80,130	28,136	1,489	17,690	41,717	11,312

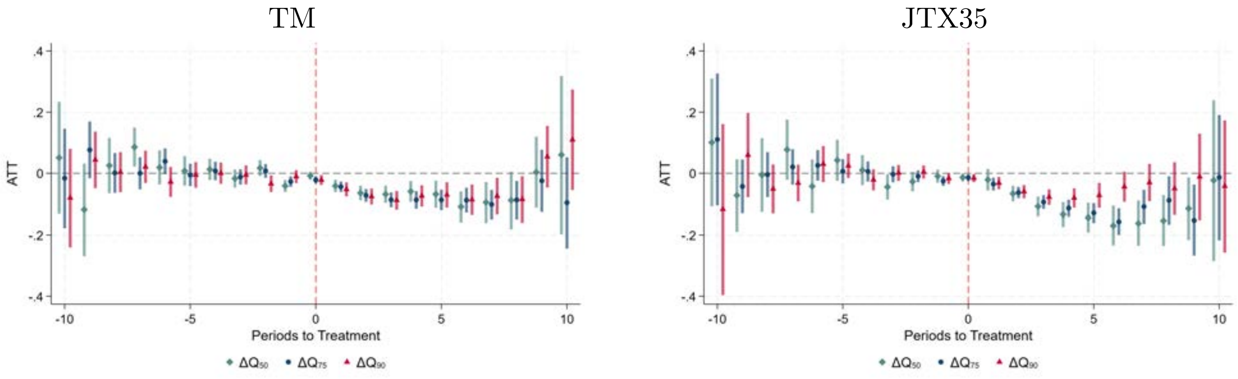
Panel C: ΔQ_{90}

	Sector (1)	Sector (2)	Sector (3)	Sector (4)	Sector (5)	Sector(6)
Pre-trend (average)	-0.0191	-0.0200	-0.0537	-0.0361**	0.0116	0.0178
	(0.0120)	(0.0335)	(0.0513)	(0.0169)	(0.0220)	(0.0194)
ATT	-0.121***	-0.0139	0.0913	-0.101	-0.00394	-0.0228
	(0.0229)	(0.0435)	(0.141)	(0.0621)	(0.0419)	(0.0680)
Clusters	8,312	2,767	161	2,008	2,542	1,683
Observations	38,567	13,284	603	8,323	20,163	5,985

Notes: Callaway-Sant'Anna's (2021) average treatment effects (ATT) of JTX30 at the 50%, 75% and 90% temperature deviation percentiles (ΔQ_{th}) on loans' annual growth. Pre-trend (average) controls for the parallel-trends and non-anticipation assumptions. Sectors: (1) Trade & Transport, (2) Real Estate & Construction, (3) Utilities, (4) Accommodation & Leisure, (5) Manufacturing & Mining, and (6) Service & ICT. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.4 ATT estimations under strong parallel-trends assumption

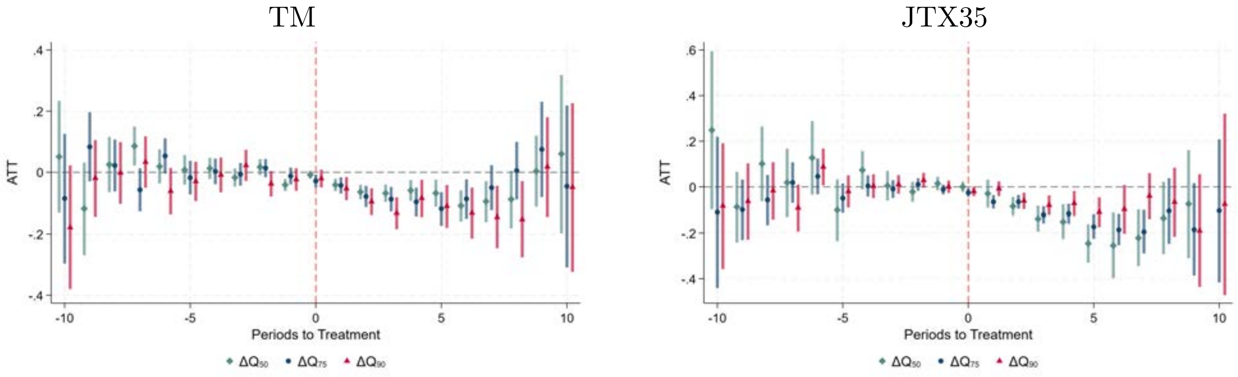
Figure 9. **Impact on overall loans**



TM

JTX35

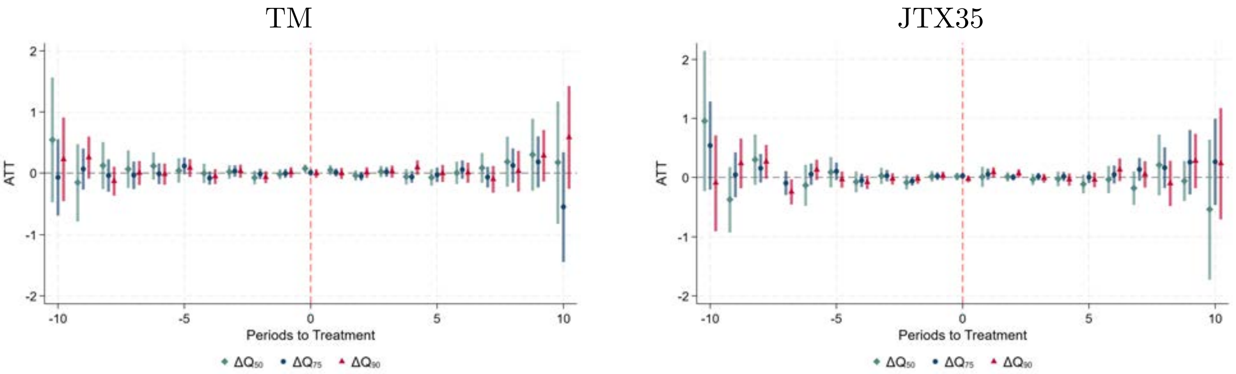
Figure 10. **Impact on medium & long-term loans**



TM

JTX35

Figure 11. **Impact on short-term loans**



Notes: Callaway-Sant'Anna's (2021) event-study. Impact of TM and JTX35 at 50%, 75% and 90% temperature deviation thresholds on loans' annual growth from -10 years to +10 years to treatment. Confidence bands at 95%.