

# The Impact of Temperature Shocks on the Credit Market

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### Abstract

We show that the severity of temperature extremes translates into a lower availability of credit in a region. We also document that the price of credit is increasing in the likelihood of extreme temperatures.

### Introduction

According to the Intergovernmental Panel on Climate Change (IPCC) (2001) climate change or change in average weather affects the likelihood of extreme temperatures and that of intense climate-related disasters. An intense disaster adversely affects the serviceability of borrowers and the value of collateral held by a bank. To avoid problems such as repayment uncertainty, debt restructuring, and defaults, a bank may choose to ration credit in one or more ways. The asymmetries in the frequency of extreme temperatures imply that banks may provide credit disproportionately across regions. Therefore, we ask the following question: what are the implications of extreme temperatures for availability and pricing of credit in a region?

## **Empirical Strategy**

**Identification:** Temperature extremes increase the physical risk of intense climatic disasters that are likely to adversely affect borrowers' debt serviceability and the value of any collateral held by a bank. If banks are taking this into account, then, *ceteris paribus*, the terms and conditions of a loan contract, offered by banks, should vary across regions differing in the frequency of temperature extremes.

**Empirical Approach:** The empirical approach builds upon the work of Khawaja and Mian (2008). We resort to the cohort approach used in a context similar to ours in Acharya et al. (2018), Popov and Van Horen (2014), and Berg et al. (2019). The underlying assumption is that the shocks to credit demand operate at the cohort level. Therefore, including cohort-year fixed effects should absorb credit demanded by borrowing firms within a cohort. In our baseline results, we form cohorts by nine census regions and 10 Fama-French industry classification. The observation is at bank(b)-cohort(c)-year(t) level. Baseline Model Specification:

#### **Data Sources**

**Temperature Data:** State-month level data from the National Climatic Data Center of the National Oceanic and Atmospheric Administration (NOAA). Gridded temperature data from the University of Delaware used in small-firm analysis. **Natural Disasters Data:** The Spatial Hazard Events and Losses Database for the United States (SHELDUS).

Loan-Level Data: Reuter's Loan Pricing Corporate (LPC) Dealscan. Financial Data: Compustat.

Small Firms Lending Data: FFIEC CRA Dataset.

#### **Temperature Extremes**

**Choice of Base Reference Period:** 1951 - 1980Over the reference period, we estimate the following quantity  $Loan Outcome_{bct} = \beta_1 NPPOET_{bct-1} + Cohort_c \times Year_t + Bank_b \times Cohort_c + u_{bct}$ 

The specification includes bank-cohort fixed effects to control for bank-firm relationships. The primary independent variable is weighted (using loan amounts) and aggregated to the observation level. Loan Outcome is either  $\Delta Volume_{bct}$  defined as log growth in loan volume, Loan Decrease<sub>bct</sub> defined as a dichotomous variable that equals 1 if the bank decreased lending to a cohort and 0 otherwise or  $\Delta Spread_{bct}$  defined as the change in spread over LIBOR.

#### **Baseline Results**

Our main finding is that temperature extremes adversely affect the availability of credit in a region and lead to an increase in spread requirements. All tests include cohort-year and bank-cohort fixed effects, standard errors are clustered (banks), and the t-statistic is presented in  $(\cdot)$ .

#### **Dealscan Analysis**

 $\mathbb{T}_{sm,51-80}^{99^{th}} = P_{99}(\mathbb{T}_{smt})_{t \in \{1951,\cdots,1980\}}$ where  $\mathbb{T}$  represents temperature,  $P_{99}$  is an operator picking 99<sup>th</sup> percentile of the quantity inside (·), and *s*, *m*, and *t* index state, month, and year, respectively.

**Definition:** A temperature shock, denoted by  $\mathbb{E}_{smt}^{99^{th}}$ , is a dummy variable that equals 1 if  $\mathbb{T}_{smt} > \mathbb{T}_{sm,51-80}^{99^{th}}$  for all t > 1980, and equals 0 otherwise.

**Non-Parametric Probability of Extreme Temperature (NPPOET)** is defined as:  $NPPOET_{st} = MA_{Dec}^{36} \left[ \mathbb{E}_{smt}^{99^{th}} \right] \quad \forall t > 1980$ where  $MA_{Dec}^{36} \left[ \cdot \right]$  represents 36-month moving average (MA) observed in December of each year.



	$\Delta Volume_{bct}$	Loan Decrease <sub>bct</sub>	$\Delta Spread_{bct}$
NPPOET <sub>bct-1</sub>	-4.91***	1.10***	2.16**
	(3.63)	(3.05)	(2.15)
Ν	2,728	2,728	2,728

• Our baseline results remain economically and statistically robust to alternative cohort formations.

#### Small Firm Analysis

	$\Delta Volume_{bct}$	\[ \Delta Volume_{bct} \]	∆Volume <sub>bct</sub>	\[ \[ \] Volume_{bct} \]	∆Volume <sub>bct</sub>		
NPPOET <sub>bct-1</sub>	-2.78***	-2.33***	-2.94***	-8.67***	-16.034***		
	(9.34)	(5.04)	(6.22)	(5.36)	(5.06)		
Bank Size (\$B)	All	<1	[1, 10)	[10, 100)	>=100		
Ν	80,935	19,593	30,019	21,052	8,482		
	Loan Dec <sub>bct</sub>	Loan Dec <sub>bct</sub>	Loan Dec <sub>bct</sub>	Loan Dec <sub>bct</sub>	Loan Dec <sub>bct</sub>		
NPPOET <sub>bct-1</sub>	1.21***	0.69***	1.60***	3.53***	7.84***		
	(8.38)	(3.24)	(6.55)	(3.67)	(4.31)		
Bank Size (\$B)	All	<1	[1, 10)	[10, 100)	>=100		
Ν	80,935	19,593	30,019	21,052	8,482		
Conclusion							

This study focuses on the implications of extreme temperatures, which induce a

**Figure:** Time-series of cross-sectional average of NPPOET based on (>) 99<sup>th</sup> percentile and based on (<) 1<sup>st</sup> percentile.

new normal class of natural disasters that are more intense than their predecessors, for availability and pricing of credit in a region.

- We find that the severity of regional temperature extremes may go beyond known direct costs such as migration political security, and food and water security: it may decrease a region's access to credit and increase the price of credit.
- Our findings are more profound for relatively larger banks.

#### Contact

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#### References

- 1. Viral V Acharya, Tim Eisert, Christian Eufinger, and Christian Hirsch. Real Effects of the Sovereign Debt Crisis in Europe: Evidence from Syndicated Loans. The Review of Financial Studies, 31(8):2855–2896, 2018.
- Tobias Berg, Anthony Saunders, Larissa Schäfer, and Sascha Steffen. "Brexit" and the contraction of syndicated lending. Available at SSRN 874724, 2019.
- 3. IPCC. Climate change 2001: The scientific basis. Cambridge University Press, Cambridge., pages 101–165, 2001.
- 4. Asim Ijaz Khwaja and Atif Mian. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. American Economic Review, 8(4):1413–42, 2008.
- 5. Alexander Popov and Neeltje Van Horen. Exporting sovereign stress: Evidence from syndicated bank lending during the euro area sovereign debt crisis. Review of Finance, 19(5):1825–1866, 2014.