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.

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:

\[ \text{Loan Outcome}_{bct} = \beta_1 \text{NPPOET}_{bct-1} + \text{Cohort}_{c} \times \text{Year}_{t} + \text{Banks} \times \text{Cohort}_{c} + \nu_{bct} \]

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, \(\text{Loan Decrease}_{bct}\), 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 ( ).

Dealscan Analysis

<table>
<thead>
<tr>
<th>(\Delta Volume_{bct})</th>
<th>(\text{Loan Decrease}_{bct})</th>
<th>(\Delta Spread_{bct})</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPPOET_{bct-1}</td>
<td>-4.91***</td>
<td>2.16**</td>
</tr>
<tr>
<td></td>
<td>(3.63)</td>
<td>(3.05)</td>
</tr>
<tr>
<td>N</td>
<td>2,728</td>
<td>2,728</td>
</tr>
</tbody>
</table>

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

Small Firm Analysis

<table>
<thead>
<tr>
<th>(\Delta Volume_{bct})</th>
<th>(\Delta Volume_{bct})</th>
<th>(\Delta Volume_{bct})</th>
<th>(\Delta Volume_{bct})</th>
<th>(\Delta Volume_{bct})</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPPOET_{bct-1}</td>
<td>-2.78***</td>
<td>-2.33***</td>
<td>-2.94***</td>
<td>-8.67***</td>
</tr>
<tr>
<td></td>
<td>(9.34)</td>
<td>(5.04)</td>
<td>(6.22)</td>
<td>(5.36)</td>
</tr>
<tr>
<td>N</td>
<td>80,935</td>
<td>19,593</td>
<td>30,019</td>
<td>21,052</td>
</tr>
</tbody>
</table>

• Bank Size (SB) All <1 (1, 10) (10, 100) >=100

Conclusion

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

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References


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 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: FiVEC Credit Database.

Temperature Extremes

Choice of Base Reference Period: 1951 – 1980

Over the reference period, we estimate the following quantity

\[ T_{m,51-80}^{99} = P_{m} (T_{m,51-80})_{c} \] (c:1951–1980)

where \( T \) represents temperature, \( P_{m} \) is an operating picking 99% percentile of the quantity inside (’), and \( m, T \) and \( m \) index state, month, and year, respectively.

Definition: A temperature shock, denoted by \( E_{m} \), is a dummy variable that equals 1 if \( T_{m,51} > T_{m,51}^{99} \) for all \( m > 1980 \), and equals 0 otherwise.

Non-Parametric Probability of Extreme Temperature (NPPOET) is defined as:

\[ \text{NPPOET}_{m} = MA_{1} [E_{m} T_{m,51}^{99}] \forall \ m > 1980 \]

where \( MA_{1} [\cdot] \) represents 36-month moving average (MA) observed in each year.

Figure: Time-series of cross-sectional average of NPPOET based on (> 99) percentile and based on (> 1) percentile.

References