The Impact of Temperature Shocks on the Credit Market

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Abstract

In this study, we conjecture that climate change, via extreme temperatures, has implications for the availability and pricing of credit in a region. We show that the severity of temperature extremes translates into a lower availability of credit in a region. We also document that for certain loan types, such as a revolving line of credit, the price of credit is increasing in the likelihood of extreme temperatures. We also find that extreme temperatures in one region may affect firm-level outcomes in other regions via a bank lending channel.

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1 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. As climate change advances, temperatures that were considered extreme may become *'a new normal'*; thus, intense climate disasters could become a permanent characteristic of the future. Heterogeneity in geographical topography dictates asymmetries in the occurrence of extreme temperatures and severe disasters. In this study, we exploit such asymmetries to show that the severity of extreme temperatures has implications for the availability and pricing of credit in a region. This finding is the main contribution of this study to the nascent literature of climate finance.

Extreme temperatures are likely to exacerbate the intensity of climate-related disasters. Furthermore, 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.[1] 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?

Our research question is important from a policy perspective. If the climate continues to change at its current rate, then extreme temperatures, as well as extreme events such as Hurricanes Katrina and Harvey, may become more frequent in the future. Such severe climate-related disasters are associated with the destruction of capital. Credit may play an essential role in replenishing the capital stock in a post-climate-disaster recovery phase and may foster subsequent economic advancement in

[1] By 'ration', we mean the bank refuses credit, the approved amount is lower than the required amount, the interest rate charged is higher, or other stringent conditions are imposed on the party in need of credit.

an affected region. Banks are a significant source of credit, and as such, a reduction in credit, in regions more prone to temperature and climate extremes, hold direct consequences for the well-being of entities in that region. An understanding of how credit sufficiency differs across regions could guide future policy work, especially when we are facing the next Hurricane Katrina.

We have two main results. First, temperature extremes adversely impact loan volume and the likelihood of a decline in loan volume in a region. A 1 percent increase in probability of extreme temperature leads to a 4 to 10 (1 to 2) percent decrease (increase) in the loan volume (likelihood of a decline in loan volume). Second, the extreme temperature effect, on average, is absent for the price of credit, which we measure by spread over LIBOR. In one of our tests, however, there is positive association between spread charged for relationship dependent loan types, such as a line of credit, and the likelihood of extreme temperatures.

There are two key empirical challenges in attaining our results. The first challenge relates to the measurement of the likelihood of extreme temperatures. We construct and validate intuitive measures of observing extreme temperatures in a region using monthly temperature data from the National Oceanic and Atmospheric Administration (NOAA). The constructed measures are well-behaved concerning the association between temperature and climate extremes.

The second challenge is due to two concurrent issues related to the identification and loan-level data that are available to us. To arrive at causal effects of temperature shocks on credit supplied in a region, we need to control for credit demand. An 'as-is' implementation of the Khwaja and Mian [2008] approach, which relies on firm-year fixed effects to control for credit demand, on the Reuters Loan Pricing Corporation (LPC) Dealscan dataset is not recommended for two reasons. First, the majority of the borrowing firms in Dealscan are not multi-bank firms. Second, in Dealscan, a loan contract (called a facility) is observed only once during its tenure–at origination.

This hinders our ability to calculate variables of interest, such as a bank's growth in loan volume in a geographical region. We overcome the absence of these features by resorting to a cohort approach used in contexts similar to ours in Acharya et al. [2018], Popov and Horen [2014] and Berg et al. [2019]. We satiate our baseline model with cohort-year fixed effects to control for credit demand. Essentially, this assumes that demand for credit operates at the cohort level. In a recent study, Degryse et al. [2019] show the validity of these fixed effects as controls for credit demand to obtain near-accurate order and magnitude of credit supply shocks.

We have four main data sources. The state-level monthly temperature data are from NOAA. The disaster damages data are from the Spatial Hazard Events and Losses Database for the United States (SHELDUS), which we use to validate the proposed temperature shock measures. Our loan-level data are from the Reuters LPC Dealscan dataset. We believe that Dealscan is the right dataset, despite its lack of time-series data on loan contracts, for two main reasons. The first relates to the size of a loan contract. We are interested primarily in large loan contracts because for such contracts banks are likely to be more diligent in their decision making. Moreover, a lending bank with large loan contracts is likely to be large, with operations across geographies. Second, our analysis requires information on loan amount and pricing, and the geographical location of the borrowing firm. The Dealscan dataset provides loan information at the origination, including loan amount, maturity, and spreads. We source borrowing firms' and lending banks' financial data from Compustat.

The empirical approach follows two steps. The first step is to construct temperature shock measures and to demonstrate the validity of the temperature shock measures in our setting. Using $1951-1980$ as the reference period, we construct three measures that implicitly account for a location as well as seasonalities. Next, we establish the appropriateness of the temperature shock measures for our setting. We show that extreme temperatures exacerbate natural disasters. To illustrate this, we measure disaster intensities by the amount of dollar damages caused. We use data from SHELDUS and find that the damages are increasing in the temperature shock measures proposed in this study. Second, we show that the borrowers in regions with a higher frequency of extreme temperatures have lower and more variable profitability, which is an important determinant of debt-serviceability.

The second step of our empirical approach is to show the effect of extreme temperatures on the availability and price of credit. To do so, we aggregate the LPC Dealscan dataset to the cohort-bank-year level. Doing so yields a panel data with a time-series on the amount a bank lends to a cohort. For a bank that lends to firms in different states within a census region, we aggregate the state-level temperature shock measures to the cohort-bank-year level using loan amounts. We then estimate a high-dimensional fixed effects model with weighted temperature shock measure as an independent variable.

This study is closely related to a relatively new literature that aims to link various aspects of climate change with finance. In a closely related work, Delis et al. [2018] find that banks charge marginally higher spreads to fossil fuel firms after the Paris Agreement. Our study differs from Delis et al. [2018] on two fronts. First, we work with temperature data. Second, we consider the implications of temperature shocks for credit in all industries. In a recent study, Addoum et al. [2019] use grid-level PRISM temperature data and the National Establishment Time-Series (NETS) database and find that temperature shocks have no impact on establishment-level sales. In Addoum et al. [2019], there is an overlap between the reference period for temperature shocks and the sample period.[2] Other work complementing this literature relates to heterogeneous beliefs about climate change and financial instruments from a climate change perspective; see Baldauf et al. [2018] and Baker et al. [2018].

[2] Addoum et al. [2019] work with three temperature shock measures. For the first, the authors arbitrarily choose 30 degrees Celsius and 0 degrees Celsius as extremes. The other two are based on 90^{th} and 95^{th} percentile of temperature distribution observed over the sample period under analysis.

Some researchers focus on the effect of *ex post* measures of climate change (that is, extreme disasters) on credit supply. For instance, Cortés [2014] shows that regions with a higher presence of local lenders fare better after a significant disaster strikes. Chavaz [2014] uses Hurricane Katrina as an exogenous shock and reports findings similar to those of Cortés [2014]. We differ from these studies as we focus on the implications of an *ex ante* measure of climate change for credit. From an identification standpoint, our approach is inspired by the literature that shows that exogenous shocks to banks can alter lending to firms. The shocks used vary from liquidity shocks in Khwaja and Mian [2008], financial crises in Acharya et al. [2018] and Popov and Horen [2014] to Brexit in Berg et al. [2019].

The results of our study suggest that the severity of regional temperature extremes may go beyond 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 for certain loan types. This study, to best of our knowledge, is the first one to establish an association between climate change and credit supplied in a region.

2 Data Description

2.1 Temperature Data

We source the temperature data from the National Climate Data Center (NCDC) at the National Oceanic and Atmospheric Administration (NOAA). The data are derived from area-weighted averages of grid-point estimates interpolated from station data from the Global Historical Climatology Network (GHCN). A nominal grid resolution of 5 kilometers is used to ensure that all divisions have sufficient sampling. All temperature data are corrected for biases that may arise due to observation time, station location, temperature instrumentation, and siting conditions.

The main advantage of this dataset is that it provides a complete time-series of monthly temperatures for a state. The full coverage of 48 contiguous US states is available from 1895, but for this study, our sample period is from 1951 to 2017. The data contain information on mean, minimum, and maximum monthly temperature. Our long-term temperature reference period, in line with that of the Goddard Institute of Space Studies Surface Temperature Analysis (GISTEMP), is 1951-1980. A fixed base period makes temperature anomalies consistent over time. In this study, we work with average monthly temperatures.

2.2 SHELDUS

The Spatial Hazard Events and Losses Database for the United States (SHELDUS) is a county-level hazard dataset for the US and covers natural hazards like thunderstorms, hurricanes, floods, wildfires, and tornadoes, as well as perils such as flash floods, heavy rainfall, et cetera. SHELDUS contains information on the date of an event, the affected location (county and state), and the direct losses caused by the event, such as property and crop losses, injuries, and fatalities from 1960 onwards. We keep observations where the reported hazard type is coastal, drought, flooding, hail, heat, hurricane, landslide, lightning, severe storm, tornado, wildfire, wind, winter weather, fog, and avalanche. We remove observations where the reported hazard type is an earthquake, volcano, tsunami, or seiche because climate scientists have not established a clear link between climate change and the occurrence of such hazards. The data are at the county-hazard-type-quarter level, and the sample used spans 27 years, starting 1990 and ending 2016.

2.3 Dealscan and Compustat

Our loan-level data are sourced from the Reuters Loan Pricing Corporation (LPC) Dealscan dataset, which satisfies two important requirements. The first relates to the size of a loan contract. We are interested primarily in large loan contracts because for such loan contracts, banks are likely to be more diligent in their decision making. Moreover, lending banks with large loan contracts are likely to be large in size and have operations across geographies. Second, our analysis requires information on loan amount, loan pricing, and the location of the borrowing firm. The Dealscan dataset provides loan information at the origination, including loan amount, maturity, and loan spreads.

In Dealscan, a loan contract is referred to as a package, which could be made up of many loans known as a 'facility'. We conduct our analysis at the facility level. Our Dealscan sample starts in 1990 and ends in 2017. To avoid country idiosyncrasies, we consider only US banks lending to borrowers based in the US. We source borrower and lender information from Compustat. We merge the Dealscan and Compustat data using borrower links from Chava and Roberts [2008] and lender links from Schwert [2017]. We remove observations with missing data on 'all-in-drawn' spread, which is our measure of the cost of credit.

Note that in Dealscan, a lender can be a sole lender or a group of lenders. In the case of syndicated loans, we follow Ivashina [2009] in determining the lead lender. We define the lead lender as the one with the role of 'administrative agent'. If a syndicated loan does not have an administrative agent, then the lender that acts as agent, arranger, bookrunner, lead arranger, lead bank, or lead manager is defined as the lead bank. There are syndicated loans for which we identify more than one lead lender. For the majority of such loans, we are unable to decide on lead lenders due to incomplete information on lender shares. Therefore, we do not include such loans in our baseline results.

3 Measuring Temperature Shocks

Due to the changing climate, we observe shifts in temperature distribution due to change in either mean or variance of temperature distribution. Such shifts increase the likelihood of observing temperatures that once were considered extreme. In this section, we propose three measures of temperature shocks and test their validity for our research questions. Starting in 1951, our long-term temperature reference period spans 30 years. For our reference period, we calculate three statistics specific to a location (state) and month. These statistics are:

$$
\begin{aligned}
\mathsf{T}^{99^{th}}_{sm,51-80} &= P_{99}\left(\mathsf{T}_{smt}\right)_{t \in \{1951, \dots, 1980\}} && \forall \text{ s and } \forall \text{ m} \\
\mu_{sm,51-80} &= \frac{1}{30}\sum_{t=1951}^{1980} \mathsf{T}_{smt} && \forall \text{ s and } \forall \text{ m} \\
\sigma_{sm,51-80} &= \left[\frac{1}{29}\sum_{t=1951}^{1980} \left[\mathsf{T}_{smt} - \mu_{sm,51-80}\right]^2\right]^{\frac{1}{2}} && \forall \text{ s and } \forall \text{ m}
\end{aligned}
\tag{1}
$$

where P_{99} denotes an operator selecting the 99^{th} percentile of quantity inside $(\cdot)$, T_{smt} represents the temperature for state *s* in month *m* of year *t*, and $\mu_{sm,51-80}$ and $\sigma_{sm,51-80}$ represent mean and standard deviation, respectively, estimated for a state-month pair. In the following, we describe the construction of temperature shock measures in detail.

3.1 Change in Mean Temperature (CIMT)

One way to measure temperature shocks is to estimate the change of average temperature with respect to the average temperature estimated over the fixed reference period, which in our case is from 1951 to 1980. Specifically, by 'Change in Mean Temperature' (CIMT) for state *s* in year *t*, we mean the following quantity:

$$
\text{CIMT}_{st} = \frac{1}{12}\sum_{m=1}^{12}[\mu_{smt} - \mu_{sm,51-80}]; \ \text{t} \geq 1981 \tag{2}
$$

where μ_{smt} is the rolling window mean (window size = 10) described above, and $\mu_{sm,51-80}$ represents mean temperature for state *s* for month *m* over our reference period. In simple terms, equation (2) corresponds to average change in mean monthly temperature observed at annual frequency.

3.2 Non-Parametric Probability of Observing Extreme Temperature (NPPOET)

In this subsection, we describe the construction of a non-parametric measure of temperature shock. We have $s \times m$ $(= 48 \times 12 = 576)$ estimates of $\mathsf{T}^{99^{th}}$, denoted by $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$, over the reference period from 1951 to 1980. From year 1981 onwards, we generate a dichotomous variable, denoted E^{99th}_{smt}, that equals 1 if T_{smt} exceeds $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$, where T_{smt} denotes the temperature of state *s* for month *m* of year *t*. Finally, we calculate 'Non-Parametric Probability of Extreme Temperature' (NPPOET) for state *s* in year *t* as follows:

$$\mathsf{NPPOET}_{st} = \mathsf{MA}^{36}_{\mathsf{Dec}}[\mathsf{E}^{99th}_{smt}];\ \ \mathsf{t} \geq 1981 \tag{3}$$

where $\mathsf{MA}^{36}_{\mathsf{Dec}}[\cdot]$ represents the 36-month moving average (MA) observed in December of each year.

3.3 Parametric Probability of Observing Extreme Temperature (PPOET)

In climate research, it is common to assume that temperature, in an unchanging climate, is normally distributed, see Hansen et al. [2012] and Ropelewski et al. [1985]. In this subsection, we assume that the temperature in an unchanging climate is normally distributed. From 1981 onwards, we define a dichotomous variable that equals 1 if the observed temperature for state *s* in month *m* of year *t*, denoted T_{smt}, exceeds the state-month specific 99^{th} percentile implied by the parameters $\mu_{sm,51\ \ 80}$ and $\sigma_{sm,51\ \ 80}$ estimated in equation (1). We denote this variable by P_{smt}. Next, we calculate 'Parametric Probability of Extreme Temperature' (PPOET) for state *s* in year t as follows:

$$\text{PPOET}_{st} = \text{MA}^{36}_{\text{Dec}}[\text{P}_{smt}];\ \text{t} \geq 1981 \tag{4}$$

where $\text{MA}^{36}_{\text{Dec}}[\cdot]$ represents the 36-month moving average (MA) observed in December of each year.

3.4 Descriptive Analysis

Table I presents detailed summary statistics of three proposed temperature shock variables. Our first measure, CIMT_{st}, averages to 1.2 degrees Fahrenheit. The within-state and between-states variation of CIMT_{st} accounts for roughly 74 percent and 26 percent, respectively, of the overall variation. CIMT_{st} shows a considerable range (3.2 degree Fahrenheit) with a maximum (minimum) change in mean temperature of 2.9 (-0.3) degrees Fahrenheit. The negative values are confined to lower (than 10^{th}) percentiles, which implies that this variable is non-negative in a majority of instances. Figure 1-(a) shows a time-series plot of the cross-sectional average of CIMT_{st}. Two features are prominent. First, CIMT_{st} averages above zero in all years in our sample period. Second, the decadal averages, starting in 1990, are monotonous and increasing. The CIMT_{st} increased from 0.6 degrees Fahrenheit to 1.6 degrees Fahrenheit. This is equivalent to an annual growth rate of 3.7 percent in CIMT_{st}.

Insert Table I Here

The non-parametric temperature shock measure, NPPOET_{st}, averages to 7.8 percent with an inter-quartile range of 8.3 percent. The decomposition of the variation in NPPOET_{st} suggests that within-state variance explains approximately three-quarters of the overall variance. Our parametric temperature shock measure, PPOET_{st}, averages to 3.5 percent and shows considerable variation with a standard deviation of 3.9 percent, the majority of which is contributed by within-state variation. An interesting pattern is that parameter implied statistics (corresponding to PPOET_{st}) are always lower than their empirical counterparts (corresponding to NPPOET_{st}). One interpretation of this finding is that temperature extremes are more frequent than that implied in an unchanging climate scenario. This finding is in line with the general scientific consensus presented in IPCC [2001] and IPCC [2012].

Figure 1-(b) presents a monthly time-series plot of cross-sectional averages of NPPOET_{st} and PPOET_{st}. The empirical probability of observing extreme temperature always exceeds its parameter implied counterpart, which implicitly assumes an unchanging climate. This plot visually confirms the mean differential between NPPOET_{st} and PPOET_{st}. The NPPOET and PPOET series are increasing in time with an annual growth rate of approximately 2.9 percent and 5 percent, respectively. Overall, these findings show that temperature extremes are more likely now than before.

Before proceeding to validation tests, we want to answer an important question. Is it the change in the mean and/or variance of the temperature distribution that is driving temperature extremes? We proceed by constructing equivalents of NPPOET_{smt} and PPOET_{smt} based on first percentiles denoted by $\widehat{\text{NPPOET}}_{smt}$ and $\widehat{\text{PPOET}}_{smt}$, respectively.[3] The time series plots of cross-sectional means (figure 3-(a)) and standard deviations (figure 3-(b)) of $\widehat{\text{NPPOET}}_{smt}$ and $\widehat{\text{PPOET}}_{smt}$ suggest that the left tail of temperature distribution is shrinking. The correlation between NPPOET_{smt} and $\widehat{\text{NPPOET}}_{smt}$, and PPOET_{smt} and $\widehat{\text{PPOET}}_{smt}$ is negative, implying that temperature extremes are likely to be driven by a change in the mean,

[3] $\text{NPPOET}_{smt} = \text{MA}^{36}[\mathsf{E}^{99th}_{smt}]$, and PPOET_{smt} is defined analogously using P^{99th}_{smt}. For NPPOET_{smt}, the first percentile equivalent is based on a dummy variable $\mathsf{E}^{1^{st}}_{smt}$, which equals 1 if the temperature for state s in month m of year t, denoted T_{smt}, is lower than $\mathsf{T}^{1^{st}}_{sm,51\ \ 80}$, which represents the first percentile observed over the reference period for state s for month m. Similarly, for PPOET_{smt}, the first percentile equivalent is based on a dummy variable $\mathsf{P}^{1^{st}}_{smt}$, which equals 1 if T_{smt} is lower than the first percentile implied by parameters $\mu_{sm,51\ \ 80}$ and $\sigma_{sm,51\ \ 80}$.

rather than the variance, of temperature distribution.[4]

3.5 Validating Temperature Shock Measures

Studies like IPCC [2001] report that climate change via extreme temperature intensifies natural disasters. The increase in intensities is likely to adversely affect borrowers' debt-serviceabilities. Consider an excerpt from 10-K filings of Regions Financial Group (2016) as an anecdote:

"$[\cdots]$ there is no insurance against $[\cdots]$ resulting adverse impact on our borrowers to timely repay their loans and the value of any collateral held by us. The severity and impact of $[\cdots]$ weather-related events are difficult to predict and may be exacerbated by global climate change."

In table II, we formally test the validity of the exacerbation channel using disaster damages data from SHELDUS, which we aggregate to the state-year level. Before aggregating, we convert all variables to 'per capita' levels and inflation adjust all dollar variables to the 2016 level. Our main dependent variable is the log of total monetary damages (the sum of crop and property damages) in column (1). We run this test with other measures of damages, namely injuries and fatalities per $100,000$ people as dependent variables in columns (2) and (3), respectively. All model specifications include state and year fixed effects to control for unobserved state- and year-specific effects. The standard errors are clustered at the state level. The results suggest that the temperature shock variables relate positively in a meaningful manner with intensities of climate events.

Insert Table II Here

In column (1) of table II, the results imply that a one-unit increase in tem-

[4] $\rho(\text{NPPOET}_{smt}, \widehat{\text{NPPOET}}_{smt}) = -0.2067$ and $\rho(\text{PPOET}_{smt}, \widehat{\text{PPOET}}_{smt}) = -0.1149$. Here ρ represents correlation.

perature shock measures significantly increases the total damages. For instance, a one-degree Fahrenheit (a percentage) increase in CIMT$_{st}$ (NPPOET$_{st}$) increases total monetary damages by approximately 33 (2) percent. The total damages remain statistically unresponsive to our third temperature shock measure, PPOET$_{st}$. The sign of the coefficient is positive, which implies that if there were an effect, it would have been in the expected direction. Other damage variables, injuries, and fatalities are unresponsive to the temperature shock variables in the majority of instances. This result is not surprising, as humans can move out of hazard's way or can take shelter if and when hazard strikes.

Table III presents the second validation test for borrowers' serviceability, which is directly affected by a borrower's profitability and its volatility. We measure profitability by return-on-assets (ROA) and its volatility, denoted σ_{ROA}, by a rolling window (window size = 5) standard deviation. In panel A, a firm is classified into the 'high' group (into the low group, otherwise) if X_{st} exceeds its median value, where $X_{st} \in \{$CIMT, NPPOET, PPOET$\}_{st}$. We test for the difference in means (medians) of two groups of firms by *t-test* (*Wilcoxon-Mann-Whitney Test*). The results in panel A suggest that the firms in the high group have lower and more volatile profitability than those in the low group.

Insert Table III Here

We go a step further and find the right counterfactual for a firm in the high group using the Abadie et al. [2004] matching estimator using a treatment variable equalling 1 for firms in the high group and 0 for those in the low group. We match firms on four continuous variables: size, leverage, tangibility, and market-to-book ratio, and two discrete variables: 2-digit SIC industry classification and year. In panel B of table III, the average treatment effect of being located in the high temperature shock state is a decrease (an increase) of 0.8 to 1 percent (0.14 to 0.32

percent) in a firm's return on assets (σ_{ROA}).

4 Baseline Results

4.1 Empirical Estimation Strategy

Our empirical approach is inspired by Khwaja and Mian [2008]. In this study, the authors rely on a one-off exogenous shock and firm borrowing from multiple banks to identify credit supply shocks using firm-year fixed effects to control for credit demand. This approach needs to be modified when one is using Dealscan, in which majority of firms are not multi-bank firms. Moreover, in Dealscan, a loan contact, called a facility, is observed only once at origination. Thus, we cannot see changes over time for a particular facility. We overcome these challenges by resorting to the cohort approach used in contexts similar to ours in Acharya et al. [2018], Berg et al. [2019], and Popov and Horen [2014].

Forming cohorts is a double-edged sword. On the one hand, we do not want the groups to be too small, because then they would lack representativeness. On the other hand, if we make the groups too large, we would construct away the potential impact of inter-group heterogeneity. So, we must proceed carefully. Although the cohort approach is a simple way to ensure the time-series dimension of a bank's lending to a cohort over time, there are no clear guidelines on how to form cohorts of firms. In our baseline results, we start with the least conservative setup, in which cohorts are formed on 9 census regions (9R). We then progress by making the cohorts more sophisticated: cohorts formed on 9 census regions (9R), 5 Fama-French industry classifications (5FF), and 2 leverage groups (2L) based on median value. The two intermediate specifications consider cohorts formed on 9 census regions and 10 Fama-French industry classifications (10FF), and 9 census regions and 2 leverage groups. We control for credit demand by cohort fixed effects interacted with year fixed effects. Depending on the cohort type, the cohort-year fixed effects in our specifications take four forms: region-year, region-industry-year, region-leverage group-year, and region-industry-leverage group-year fixed effects. Degryse et al. [2019] show the validity of these types of fixed effects as controls for credit demand even in tranquil periods, that is in the absence of exogenous shock(s).[5] Acharya et al. [2018], Berg et al. [2019] and Popov and Horen [2014] use similar fixed effects to control for credit demand. Moreover, our cohort-year fixed effects also control for any observed and unobserved characteristics that are shared by firms in the same cohort, and that might influence loan outcome.

Next, we aggregate state-year level temperature shock variables to the cohort(c)-bank(b)-year(t) level in the following manner:

$$\text{X}_{cbt} = \sum_{s} \sum_{i} \frac{\text{L}_{iscbt}}{\text{L}_{bt}} \text{X}_{st} \tag{5}$$

where $X_{st} \in \{\text{CIMT, NPPOET, PPOET}\}_{st}$, and L_{iscbt} is the amount lent by bank *b* in year *t* to firm *i* that is located in state *s* and belongs to cohort *c*. This weighting scheme captures the asymmetric exposures of different banks to the same cohort. With the variables of interest calculated as above, we run the following panel regression to estimate loan outcome variables:

$$\text{Loan Outcome}_{cbt} = \beta_1 \text{X}_{cbt-1} + \text{Cohort}_c \times \text{Year}_t + \text{Cohort}_c \times \text{Bank}_b + u_{cbt} \tag{6}$$

where $X_{cbt} \in \{\text{CIMT, NPPOET, PPOET}\}_{cbt}$, Loan Outcome_{cbt} is either '$\Delta\text{Volume}_{cbt}$' defined as log growth in loan volume, 'Loan Decrease_{cbt}' a dichotomous variable that equals 1 if the bank decreased lending to a cohort and 0 otherwise, or '$\Delta\text{Spread}_{cbt}$' defined as the change in spread over LIBOR.[6] We include cohort-bank fixed effects to control not only for unobserved characteristics shared by firms in the same cohort

[5] The authors advise using firm-year fixed effects whenever possible.

[6] The loan volume (spread) for a cohort-bank pair is the average amount lent (spread charged) by a bank to a cohort in a year.

and bank heterogeneity but also for relationships between firms in a given cohort and the respective bank.

4.2 Baseline Multivariate Results

In table IV, we present our baseline results. In columns (1)-(4), (5)-(8), and (9)-(12), the dependent variables are 'ΔVolume$_{cbt}$', 'Loan Decrease$_{cbt}$', and 'ΔSpread$_{cbt}$', respectively. In columns (1), (5), and (9), the cohorts are formed on 9 census regions. In columns (2), (6), and (10), the cohorts are formed on 9 census regions and 10 Fama-French industry classifications. In columns (3), (7), and (11), the cohorts are formed on 9 census regions and 2 leverage groups. Lastly, in columns (4), (8), and (12), the cohorts are formed on 9 census regions, 5 Fama-French Industry classifications, and 2 leverage groups. All specifications include cohort-year and cohort-bank fixed effects, and standard errors are clustered by bank.

Insert Table IV Here

4.2.1 Loan Volume

The results in the first four columns of table IV suggest that loan volume on average is decreasing in temperature shocks measures. The results are economically meaningful and statistically significant for all specifications. In panel A, the independent variable is CIMT$_{cbt-1}$. A one-degree Fahrenheit change in long-term mean temperature may result in a 34 percent to 77 percent decline in amount lent. This effect is equivalent to 72 million to 164 million dollars given the mean facility amount of 214 million dollars. An increase of 0.043 degree Fahrenheit in CIMT$_{cbt-1}$ leads to a 1.4 percent to 3 percent decline in mean facility size.[7]

[7] In figure 1-(a), the implied annual growth rate of 3.7 percent in CIMT equals 0.043 degree Fahrenheit. Similarly, in figure 1-(b), the implied annual growth rate of 2.9 (5) percent in NPPOET (PPOET) is equivalent to an increase of 22.62 (17.5) basis points in NPPOET (PPOET).

In panel B, the independent variable is NPPOET_{cbt-1}. Qualitatively, the results resonate with those in panel A but have magnified economic significance. A percentage increase in NPPOET_{cbt-1} leads to a decline of 3.8 percent to 10 percent in loan volume. In dollar terms, this effect is equivalent to 8 million to 21 million dollars for a mean facility amount of 214 million dollars. An increase of 22.6 basis points in NPPOET_{cbt-1} may decrease average facility size by approximately 0.9 percent to 2.3 percent.[7]

In panel C, the independent variable is PPOET_{cbt-1}. The results mimic the economic and statistical significance of their counterparts in panels A and B. The economic significance of the coefficients implies a decline in a loan volume equivalent to 5 percent to 11 percent of the mean facility amount. An increase of 17.5 basis points in PPOET_{cbt-1} implies a decline equivalent to a 0.9 percent to 1.9 percent decrease in mean facility amount.[7]

4.2.2 Loan Decrease

In columns (5)-(8) of table IV, the dependent variable is Loan Decrease_{cbt}, which equals 1 if $\Delta\text{Volume}_{cbt}$ is negative and 0 otherwise. The results of the linear probability model suggest that the probability of a decline in loan volume is increasing in the proposed temperature shock measures. In panel A, the economically significant coefficient suggests that a one-degree Fahrenheit increase in CIMT_{cbt-1} leads to an 8 percent to 16 percent increase in the probability of a decline in loan volume. This increase is equivalent to a 17 percent to 36 percent mean probability of a decline in loan volume (47 percent). The probability of decline in loan volume increases by approximately 43 to 70 basis points with 0.043 degree Fahrenheit increase in CIMT_{cbt-1}.

In panel B, the independent variable is NPPOET_{cbt-1}. A percentage change in NPPOET_{cbt-1} may result in an increase of 1 percent to 2 percent in mean probability of decline in loan volume. The impact of an increase equivalent to 22.6 basis points in NPPOET$_{cbt\ \ 1}$ marginally increases the probability (23 to 44 basis points) of decline in loan volume in a region. Lastly, in panel C, the independent variable is PPOET$_{cbt\ \ 1}$. The marginal impact of a percentage increase in PPOET$_{cbt\ \ 1}$ on Loan Decrease$_{cbt}$ is an increase of approximately 1.4 percent to 2.8 percent.

4.2.3 Spread

Next, we test whether temperature shocks affect, in addition to the quantity, the price of credit as well. We measure the price of credit by the spread (over LIBOR) charged on borrowed funds. The results are presented in columns (9)-(12) of table IV. In column (1) of panel A (B), we find that a degree Fahrenheit (a percent) increase in CIMT$_{cbt\ \ 1}$ (NPPOET$_{cbt\ \ 1}$) increases the spread requirement by 0.14 (1.2) percent. Both of these results are sensitive to cohort formation and lack statistical significance, as we account for variables other than location in our cohort formation. We find no statistically significant association between spread requirement and PPOET$_{cbt\ \ 1}$.

The results suggest that the quantity rather than the price of credit is the relevant margin. One plausible reason for the unresponsiveness of the spread is that many large banks maintain insurance coverage for various risks related to climate disaster. The availability of insurance and the risk of losing corporate clients to competitors may deter a bank from raising its raise interest rate.

4.3 Robustness

Note that in our baseline results, we include all facilities without considering the purpose of a loan facility. The 'purpose' in our baseline results ranges from regular activities like working capital and corporate purposes to irregular activities like LBOs, MBOs, Project Finance, and Aircraft Finance. It is possible that the demand for credit for such purposes is declining in temperature shock measures. In such a scenario, our cohort fixed effects interacted with year fixed effects may not be sufficient to control for credit demand, because the demand for credit would be declining even if banks were willing to lend. In the following, we test the robustness of our baseline results to such concerns.

In the Dealscan sample of firms used in our baseline results, approximately 50 percent of the firms are borrowing for '*working capital*' or '*corporate purposes*'. In table V, we form cohorts based on firms specifying loan purposes as either working capital or corporate purposes and repeat all baseline tests. Overall, the results remain economically and statistically robust in a majority of the specifications.[8]

Insert Table V Here

Bank-firm relationships are significant determinants of important aspects of a debt contract. In the relationship lending literature, it is well documented that forward-looking loan agreements like a line of credit are 'relationship-driven', see Berger and Udell [1995] and Brick and Palia [2007]. If banks value such relationships, then availability and price of credit may not be affected by temperature shocks. Next, we proceed by forming cohorts based on firms applying for loan type *'Revolver/Line >= 1 Yr'*. Approximately 43 percent of firms in our Dealscan sample obtained this type of loan facility. The results are reported in table VI. The results for $\triangle$Volume$_{cbt}$ and Loan Decrease$_{cbt}$ remain economically and statistically robust. The results for $\triangle$Spread$_{cbt}$ remain mixed.

Insert Table VI Here

[8] The second main dependent variable, Loan Decrease$_{cbt}$, is statistically unresponsive to CIMT$_{cbt\ \ 1}$ and PPOET$_{cbt\ \ 1}$ when cohorts are formed on three dimensions: location, industry, and leverage group. One possible reason is a lack of power in the test due to drastic reduction in the number of observations used by the high-dimensional fixed effects estimator.

Next, we test the robustness of our baseline results to inherent differences in lenders' beliefs and responses to climate change. We conduct robustness tests by including contemporaneous lender characteristics in our baseline model specification in equation (6). These characteristics include *size* measured by log total assets, *return-on-assets* measured by net income scaled by total assets, and *Equity-to-Assets* measured by common equity as a percentage of total assets. The results in table VII suggest that our baseline results for ΔVolume$_{cbt}$ and Loan Decrease$_{cbt}$ are not driven by differences in the conditions of lending banks. These results do not change if we replace contemporaneous lender characteristics with their respective lagged values.

Insert Table VII Here

5 Additional Results

5.1 Firm Level Analysis

Due to an increase in the frequency of extreme temperatures in one or more regions of its operations, a bank may impose stringent requirements, on borrowers, to access credit. There are two possible reasons. First, the risk of intense disasters in the future could drive a bank's decision to contract credit supply in all regions of its operation. The second reason is rather subtle. In an adverse scenario, such as the conversion of extreme temperature into intense disasters, a large debt is likely to become a problem not only for the borrowing firm but also for the lending bank. In such a scenario, a bank may carefully tread to avoid any damage to the borrower's business into which the loan amount is invested.Admati and Hellwig [2014] make a similar point in relation to sovereign debt. The lending bank may direct more funds to the affected firm to deal with the consequences of an intense disaster. Such action may require contraction in lending or imposition of stringent lending criteria, by the bank, in other regions. In this manner, the temperature shocks may propagate from one geography to borrowing firms in other regions via a bank lending channel. We refer to this kind of exposure as *Global Exposure*. Therefore, we also ask the following question: does global exposure to extreme temperatures have implications for a borrowing firm's financial outcomes?

5.1.1 Estimating Global Exposure

For a firm *i* located in state *s* in year *t*, the global exposure is denoted by GEXP_{ist}. Next, we describe the construction of GEXP_{ist}. First, using the Dealscan sample, we calculate the total exposure of bank b, denoted EXP_{bt}, to a temperature shock measure as follows:

$$\mathsf{EXP}_{bt}^{\mathsf{X}} = \sum_{s}\sum_{i}\frac{\mathsf{L}_{ibst}}{\mathsf{L}_{bt}}\mathsf{X}_{st} \tag{7}$$

where $X_{st} \in \{\text{CIMT, NPPOET, PPOET}\}_{st}$, and L_{ibst} is the amount lent by bank b at time t to firm i located in state s. For a firm i, we define global exposure to climate change via the bank lending channel as follows:

$$\mathsf{GEXP}_{ist}^{\mathsf{X}} = \sum_{b}\theta_{isbt}\mathsf{EXP}_{bt}^{\mathsf{X}} \tag{8}$$

where the weight θ_{isbt} is defined as $\frac{\mathsf{L}_{isbt}}{\sum_b \mathsf{L}_{isbt}}$. Intuitively, the global exposure of a firm, GEXP_{ist}, is the weighted average of its lenders' exposures to temperature shocks in the regions of their operations. Note that the global exposure is non-trivial for a firm *i* in state *s* in year *t* only if it appears in the Dealscan sample with a loan facility starting in year *t*. In the following, we use the notations $\mathsf{GEXP}_{\mathsf{X}}$ and $\mathsf{GEXP}_{ist}^{\mathsf{X}}$ interchangeably. Moreover, the following analysis is conducted on an orthogonalized version of global exposure. An orthogonalized global exposure variable carries the superscript '$\perp$'.[9]

[9] We orthogonalize the global exposure by subtracting the projection of GEXP_X onto X_{ist} from GEXP_X, where $\text{X} \in \{\text{CIMT, NPPOET, PPOET}\}$.

5.1.2 Matching Estimator

To assess the impact of a firm's global exposure on its fundamentals, we follow the matching approach of Abadie et al. [2004]. The main idea is to isolate the treated observations and then, from the population of non-treated observations, look for the control observations that best match the treated ones on chosen observable characteristics. The Abadie-Imbens matching estimator minimizes Mahalanobis distance between the characteristics of treated and matched observations. In this section, we select one matched control for each treated firm. This estimator produces exact matches on categorical variables, close-to-exact matches on continuous variables, and heteroskedasticity-robust standard errors. We match firms on two categorical variables (SIC 2-digit industry categories and year) and six non-categorical lagged variables (size, leverage, tangibility, market-to-book, profitability, and direct exposure). The direct exposure of a firm is simply $\mathsf{X}_{ist} \in \{\mathsf{CIMT}, \mathsf{NPPOET}, \mathsf{PPOET}\}_{ist}$. We divide borrowing firms into two groups based on the median value of global exposure, $\mathsf{GEXP}^{?}_{\mathsf{X}}$, of firms in our Dealscan firms. The treatment variable equals 1 for the *high* ($>$ median) group and equals 0 for the *low* group.

Insert Table VIII Here

In table VIII, we report the differential change in four variables, cash and equivalents, net book leverage, net market leverage, and net equity issuance. The standard errors, for the treatment on the treated (ATT) produced by the Abadie and Imbens estimator, are bias-corrected for less-than-accurate matching on continuous covariates.[10] The dependent variables are cash and equivalents (*che*) as percentage of total assets (*at*) in column (1), net book leverage defined as total long-term debt

[10] In tables A-IV and A-V, we present results for median tests. We test the difference in medians of a firm characteristic across two groups by calculating the continuity corrected Pearson's χ^2 statistic. The p-values are reported in the table. Note that we are unable to match treated and control firms on all matched continuous covariates. Hence, we opt for standard errors corrected for the bias induced by less-than-perfect matching on all continuous covariates.

(*dltt+dlc*) net of cash and equivalents (*che*) scaled by total assets (*at*) in column (2), net market leverage defined as total long-term debt (*dltt+dlc*) net of cash and equivalents (*che*) scaled by market value of assets (*(prcc_f*$\times$*csho)+at-ceq*) in column (3), and net equity issuance defined as sale of common and preferred stock (*sstk*) net of purchases of common and preferred stock (*prstkc*) scaled by total assets (*at*) in column (4).

In panel A, the treated and control firms are sampled from all Dealscan firms. The results in column (1) suggest that firms in the high group hold on average more cash (as a proportion of total assets) than their counterparts in the low group. The difference in the average cash holdings of the two groups of firms ranges between 0.7 and 1.5 percent. While the results are mixed for net book leverage in column (2), the results are statistically and economically significant for net market leverage in column (3). The treated firms, on average, have less leverage (0.8 to 1.2 percent) than their matched counterparts. Lastly, the coefficients for ATT based on $\text{GEXP}^{?}_{\text{CIMT}}$ and $\text{GEXP}^{?}_{\text{NPPOET}}$ suggest that net equity financing for treated firms is relatively lower.

In the climate finance literature, coastal regions are given special consideration. Although the effects of temperature shocks occur everywhere, the coastal regions usually suffer the first-order effects of such shocks. In panel B of table VIII, we repeat our analysis by sampling treated and control firms from all Dealscan firms with headquarters in coastal US states. The coefficients gain economic and statistical significance, while the direction of the effect, relative to that in panel A, remains unchanged.

5.1.3 Global Exposure and Regional Employment

This part of the analysis is based on state-level data with a sample period of 21 years, starting in 1997. The state-level macroeconomic data are sourced from the

Bureau of Economic Analysis. We test whether global exposure affects state-level real quantities. We test the following panel regression to estimate the real outcome variable for state s at time t:

$$\text{Real Outcome}_{st} = \beta_1 \times \text{GEXP}^{?}_{X} + \Gamma \text{X}_{st-1} + \text{State}_s + \text{Year}_t + u_{st} \tag{9}$$

where $\text{GEXP}^{?}_{X} \in \{\text{GEXP}^{?}_{CIMT}, \text{GEXP}^{?}_{NPPOET}, \text{GEXP}^{?}_{PPOET}\}_{st-1}$ and $\text{X}_{st-1} \in \{\text{CIMT, NPPOET, PPOET}\}_{st-1}$.[11] The real outcome variable is related to employment: growth in jobs, and growth in income. Before calculating growth variables, we scale level variables by population. The main rationale for focussing on employment variables is that large firms are a relatively stable source of employment in a region.[12]

The multivariate results are presented in table IX. In panel A, the independent variable is $\text{GEXP}^{?}_{CIMT}$. In column (1), the coefficient is negative but lacks statistical significance. In column (2), the dependent variable is growth in the total number of jobs. The economic significance of the coefficient implies a decline of 0.48 percent in total jobs with a one-degree Fahrenheit increase in global exposure. The majority of this decline is driven by the impact of global exposure on the number of waged jobs. A one-degree Fahrenheit increase in global exposure may lead to a decline of 0.53 percent in waged jobs in the following period. The coefficient for the number of proprietorship jobs is negative and statistically insignificant.

Insert Table IX Here

In panel B, the dependent variable is $\text{GEXP}^{?}_{NPPOET}$. In column (1), the coeffi-

[11] The independent variable $\text{GEXP}^{?}_{X}$ is orthogonalized as described in section 5.1. In this section, $\text{GEXP}_\text{X} \equiv \text{GEXP}^\text{X}_{st} = \sum_b \theta_{sbt} \text{EXP}^\text{X}_{bt}$ and the weight θ_{sbt} is defined as $\frac{\text{L}_{sbt}}{\sum_b \text{L}_{sbt}}$.

[12] For instance, Dayton, Ohio lost more than $10,000$ local jobs (direct and indirect) when General Motors closed its 4.1 million-square-foot Moraine Assembly operation in late 2008. This example shows the impact a large firm can have on regional employment. See 'Manufacturing and Technology News January 12, 2010, Volume 17, No.1'.

cient is statistically and economically significant. A percentage increase in $\text{GEXP}^{?}_{NPPOET}$ results in a decline equivalent to 2 percent (6 basis points) of mean income growth (3.5 percent). The coe□cient in column (2), which is statistically significant at the 10 percent level, implies a 2.8 percent decline in mean growth in the total number of jobs in a state (1.1 percent). The results gain economical and statistical significance for growth in salaried jobs. The coe□cient, now statistically significant at the 5 percent level, implies a decline equivalent to 5 percent of mean growth in salaried jobs (0.8 percent). In panel C, the independent variable is $\text{GEXP}^{?}_{PPOET}$. The coe□cients in the first three columns carry signs in line with our expectations but lack statistical significance.

5.2 Small Firms' Analysis

In section 4, we find that the temperature shocks adversely a□ect the availability of credit in a region. The importance of credit is especially profound for small businesses. Due to their lack of a proven track record or reputation, small businesses lack access to funding sources such as formal equity and debt markets. Banks are therefore an important source of funding for small businesses. Thus, the implications of climate change's impact via the credit channel are more profound for small businesses.

In this sub-section, we explore the implications of extreme temperatures for credit availability from the perspective of small firms. We use gridded monthly temperature data from the University of Delaware to estimate temperature shock measures. We use county-bank-year level small firm lending data submitted to the Federal Deposit Insurance Corporation (FDIC) under the Community Reinvestment Act (CRA). The empirical approach in this sub-section remains similar to that in section 4.1. Appendix B provides complete details. The sample period is from 1997 to 2017.

Insert Table X Here

The results are presented in table X. We find that temperature extremes adversely affect the amount lent by banks to small businesses in a geographical region. The adversity of this effect is monotonically increasing with bank size. The amount lent in a region is most significantly affected for large banks (assets in excess of 10 billion dollars), and this decrease in amount lent is not compensated by the lending of small banks (assets less than or equal to 10 billions dollars) that are likely to operate at a regional level.

6 Conclusion

This study focuses on the implications of temperature shocks, 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 temperature extremes translates into increased credit rationing via an availability channel. We document that the adverse impact of temperature extremes is more profound on credit supplied by relatively larger banks. Additionally, we also find that temperature shocks propagate via a bank lending channel. Therefore, a region with a stable climate may nevertheless bear indirect costs of a changing climate elsewhere. These novel findings are our contribution to the nascent literature exploring links between climate change and finance.

References

Alberto Abadie and Guido W. Imbens. Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1):235–267, 2006.

Alberto Abadie and Guido W. Imbens. Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics*, 29(1):1–11, 2011.

Alberto Abadie, David Drukker, Jane Leber Herr, and Guido W. Imbens. Implementing matching estimators for average treatment effects in stata. *The Stata Journal*, 4(3):290–311, 2004.

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.

Jawad M Addoum, David T Ng, and Ariel Ortiz-Bobea. Temperature shocks and establishment sales. *Available at SSRN 3411225*, 2019.

Anat Admati and Martin Hellwig. *The Bankers' New Clothes: What's Wrong with Banking and What to Do about It*. Princeton University Press, 2014.

Malcolm Baker, Daniel Bergstresser, George Serafeim, and Jeffrey Wurgler. Financing the response to climate change: The pricing and ownership of us green bonds. 2018.

Markus Baldauf, Lorenzo Garlappi, and Constantine Yannelis. Does climate change affect real estate prices? only if you believe in it. 2018. Available at SSRN: https://ssrn.com/abstract=3240200.

Tobias Berg, Anthony Saunders, Larissa Schäfer, and Sascha Steffen. "brexit" and the contraction of syndicated lending. *Available at SSRN 2874724*, 2019.

Allen N. Berger and Gregory F. Udell. Relationship lending and lines of credit in small firm finance. *The Journal of Business*, 68(3):351–381, 1995.

Ivan E. Brick and Darius Palia. Evidence of jointness in the terms of relationship lending. *Journal of Financial Intermediation*, 16(3):452 – 476, 2007.

Sudheer Chava and Michael R. Roberts. How does financing impact investment? the role of debt covenants. *The Journal of Finance*, 63(5):2085–2121, 2008.

Matthieu Chavaz. Riders of the storm: Economic shock & bank lending in a natural experiment. Technical report, Working Paper, 2014.

Kristle Romero Cortés. Rebuilding after disaster strikes: How local lenders aid in the recovery. 2014. Mimeo, Available at SSRN: https://ssrn.com/abstract=2523411.

Hans Degryse, Olivier De Jonghe, Snaja Jakovljecić, Klass Mulier, and Glenn Schepens. Identifying credit supply shocks with bank-firm data: Methods and applications. *Journal of Financial Intermediation*, 2019.

Manthos D Delis, Kathrin De Greiff, and Steven Ongena. Being stranded on the carbon bubble? climate policy risk and the pricing of bank loans. 2018. Available at SSRN: https://ssrn.com/abstract=3125017.

James Hansen, Makiko Sato, and Reto Ruedy. Perception of climate change. *Proceedings of the National Academy of Sciences*, 109(37):E2415–E2423, 2012.

IPCC. Climate change 2001: The scientific basis. *Cambridge University Press, Cambridge.*, pages 101–165, 2001.

IPCC. Managing the risks of extreme events and disasters to advance climate change adaptation: Special report of the intergovernmental panel on climate change. 2012.

Victoria Ivashina. Asymmetric information effects on loan spreads. *Journal of Financial Economics*, 92(2):300 – 319, 2009.

Asim Ijaz Khwaja and Atif Mian. Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review*, 98(4):1413–42, 2008.

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.

C.F. Ropelewski, J.E. Janowiak, and M.S. Halpert. The analysis and display of real time surface climate data. *Monthly weather review*, 113(6):1101–1106, 1985.

Michael Schwert. Municipal bond liquidity and default risk. *The Journal of Finance*, 72(4):1683–1722, 2017.

Appendix A: Additional Results

This appendix contains additional estimates that are described in our paper but are not reported to save space:

- **Table A-I** presents summary statistics for state-level temperature shocks data matched with SHELDUS data aggregated to the state level.
- **Table A-II** presents summary statistics for variables used in baseline results presented in table IV in the main text of this study. This table corresponds to the cohorts based on 9 census regions (9R).
- **Table A-III** presents summary statistics for the firm-level analysis.
- **Table A-IV** presents median tests in panel A and average treatment effect on treated (ATT) estimated for all Dealscan firms.
- **Table A-V** presents median tests in panel A and average treatment effect on treated (ATT) estimated for all Dealscan firms located in coastal states.

Appendix B: Small Businesses

In this section, we study the implications of temperature shocks for small businesses. The main reason is that small businesses, unlike corporations, do not have access to formal debt markets, so they rely solely on banks for credit. Below we describe the data and construction of our temperature shock measures in detail, followed by empirical findings.

B.1. Data Description

B.1.1. Temperature Data

The temperature data come from the Terrestrial Air Temperature dataset from the University of Delaware. The data are publicly available on the website of the Physical Sciences Division of NOAA. This dataset is a time-series of monthly average air temperature for grids with a spatial resolution of 0.5×0.5 degrees. The data are monthly and are available from 1900 to 2017. One advantage of this gridded dataset is that it provides a balanced panel that potentially adjusts for issues like missing station data in a reasonable way.

B.1.2. Small Business Lending Data

From our baseline analysis in section 4 of this study, we find that temperature shocks have robust implications for the availability of credit in a region. In this section, our main aim is to study the impacts of temperature shocks for credit availability from small businesses' perspective. In this section, we use data made available to the Federal Financial Institutions Examination Council (FFIEC) under the Community Reinvestment Act (CRA). The Community Reinvestment Act is intended to encourage depository institutions to help meet the credit needs of the communities in which they operate, including low- and moderate-income neighborhoods, consistent with safe and sound banking operations. We focus on table 'D1-1 - Small Business Loans by County - Originations' of the dataset. This table provides detailed information on aggregate number and amount of loans by a bank to small businesses in a county. Additionally, the CRA dataset reports loans in three categories: loans of $100,000$ dollars or less, loans of more than $100,000$ and less than or equal to $250,000$ dollars, and loans of more than $250,000$ dollars. In this part of the analysis, we examine three loan categories in aggregate as well as in isolation.

B.2 Temperature Shock Measures

In this section, we estimate temperature shock measures using a base reference period of 30 years starting in 1951. The overall technique we use to calculate temperature shock measures remains similar to that in section 3. For our reference period, we calculate three statistics specific to a location (grids located in the contiguous US) and a month. These statistics are as follows:

$$
\begin{aligned}
\mathsf{T}^{99^{th}}_{gm,51-80} &= P_{99}\big(\mathsf{T}_{gmt}\big)_{t\in\{1951,\ldots,1980\}} && \forall \text{ g and } \forall \text{ m}\\
\mu_{gm,51-80} &= \frac{1}{30}\sum_{t=1951}^{1980}\mathsf{T}_{gmt} && \forall \text{ g and } \forall \text{ m}\\
\sigma_{gm,51-80} &= \left[\frac{1}{29}\sum_{t=1951}^{1980}\big[\mathsf{T}_{gmt}-\mu_{gm,51-80}\big]^2\right]^{\frac{1}{2}} && \forall \text{ g and } \forall \text{ m}
\end{aligned}
\tag{10}
$$

where P_{99} denotes an operator selecting the 99^{th} percentile of a quantity inside $(\cdot)$; T_{gmt} represents the temperature for grid g in month m of year t; and $\mu_{gm,51-80}$ and $\sigma_{gm,51-80}$ represent mean and standard deviation, respectively, estimated for grid-month pair. There are a total of $4,398$ grids located in the contiguous US. Next, we obtain representative longitudes and latitudes of all US counties from the U.S. Gazetteer Files. We calculate the distance between a county and the grid, and we allocate a county to the closest grid. This yields a balanced panel containing county($\tilde{c}$)-grid(g) pairs. The average distance between a county and its matched grid is 12 miles.

For a county, denoted by $\tilde{c}$, we calculate NPPOET and PPOET as in equations (3) and (4). In figure B1, we present a monthly time-series of cross-sectional means (figure B1-(a)) and standard deviations (figure B1-(b)), respectively, of NPPOET and PPOET. In figure B2, we present the monthly time-series cross-sectional means (figure B2-(a)) and standard deviation (figure B2-(b)), respectively, for $\widehat{NPPOET}$ and $\widehat{PPOET}$. The overall findings of section 3.4 carry over. Moreover, the correlation between NPPOET and $\widehat{NPPOET}$ (PPOET and $\widehat{PPOET}$) of -19 (-9) percent implies that temperature distribution is shifting to the right and temperature extremes are driven mainly by change in the mean temperature.

B.3. Multivariate Analysis

In rest of the analysis, we use subscript b for lending bank, $\tilde{c}$ for county, c for cohort ($\equiv$ state in this section) in which county is located, and t for year. '$\mathsf{L}_{\tilde{c}cbt}$' represents the amount lent by a bank b to county $\tilde{c}$ located in cohort c at time t. In this part of the analysis, by cohort we mean state. To be consistent with the notation and terminology used in section 3, we prefer to use term cohort.

B.3.1. Methodology

The basic approach to multivariate analysis in this section remains similar to that presented in section 4.1. The cohorts are formed by states, and the observation is at the cohort-bank-year level. We aggregate county-year level temperature shock variables to the cohort(c)-bank(b)-year(t) level as follows:

$$
\mathrm{X}_{cbt} = \sum_{\tilde{c}} \frac{\mathsf{L}_{\tilde{c}cbt}}{\mathsf{L}_{bt}}\mathrm{X}_{\tilde{c}t} \tag{11}
$$

where $X_{\tilde{c}t} \in \{\text{CIMT, NPPOET, PPOET}\}_{\tilde{c}t}$. With the variables of interest calculated as above, we run the following panel regression to estimate loan outcome variables:

$$
\text{Loan Outcome}_{cbt} = \beta_1 \mathrm{X}_{cbt-1} + \text{Cohort}_c \times \text{Year}_t + \text{Cohort}_c \times \text{Bank}_b + u_{cbt} \tag{12}
$$

where $X_{cbt\ 1} \in \{\text{CIMT, NPPOET, PPOET}\}_{cbt\ 1}$, and Loan Outcome$_{cbt}$ is either 'ΔVolume$_{cbt}$', defined as log growth in loan volume, or 'Loan Decrease$_{cbt}$', a dichotomous variable that equals 1 if the bank decreased lending to a cohort and 0 otherwise. We include cohort-bank fixed effects to control not only for unobserved characteristics shared by firms in the same cohort and bank heterogeneity, but also for relationships between the firms in a given cohort and the respective bank. We assume that credit demand operates at the cohort level and control for credit demand in our regression specification by including state-year fixed effects.

B.3.2. Analysis

The baseline results under equation (12) are presented in table B-I. In panels A and B, the independent variables are NPPOET$_{cbt\ 1}$ and PPOET$_{cbt\ 1}$, respectively. In columns (1) − (5), the dependent variable is ΔVolume$_{cbt}$, defined as log growth in loan volume. In columns (6) − (10), the dependent variable is Loan Decrease$_{cbt}$, a dichotomous variable that equals 1 if the bank decreased lending to a state and 0 otherwise. All specifications include cohort-year and cohort-bank fixed effects. The standard errors are clustered by bank.

In table B-I, we present the first set of results that are blind to loan types (based on amount). In column (1), the coefficients on two proposed temperature shock measures are statistically significant. Economically, a percentage increase in NPPOET$_{cbt\ 1}$ (PPOET$_{cbt\ 1}$) implies a 2.3 (2.2) percent decline in loan volume, and a 0.98 (1.2) percent increase in the likelihood of decline in loan volume.

The granularity and comprehensiveness of the CRA data allow us to conduct analysis conditioning on bank type (by size). In columns (2) and (6) of table B-I, we include banks with assets less than or equal to 1 billion dollars. We call these banks *'small-sized banks'*. In columns (3) and (7), we include banks with assets greater than 1 billion dollars and less than or equal to 10 billion dollars. We refer to these banks as *'medium-sized banks'*. In columns (4) and (8), we include banks with assets greater than 10 billion dollars and less than or equal to 100 billion dollars. We refer to these banks as *'large banks'*. In columns (5) and (10), we include banks with assets higher than 100 billion dollars. We refer to these banks as *'ultra-large banks'*.

The results in columns (2)-(5) suggest that loan volume declines in temperature shock measures for all bank types. Interestingly, the severity of the decline in loan volume is monotonically increasing with bank size. For instance, a percentage increase in NPPOET$_{cbt\ 1}$ implies a 1.3 percent decline in loan volume by small banks, and a 22 percent decline in loan volume by ultra-large banks. In column (7), the likelihood of a decline in loan volume is statistically unresponsive to temperature shock measures for small banks. In columns (8)-(10), the results suggest that the likelihood of a decline in loan volume worsens in bank size with a percentage increase in temperature shock measures.

In tables B-II, B-III, and B-IV, we repeat all specifications using data for small-sized loans ($\leq 100,000$ dollars), medium-sized loans (more than $100,000$ and less than or equal to $250,000$ dollars), and large-sized loans (more than $250,000$ dollars), respectively. The results in all but one specification remain similar to their counterparts in table B-I. The dependents are statistically unresponsive to temperature shock measures for small banks, although the signs of coefficients are consistent with our expectations.

In the CRA dataset, the counties are classified into four income groups based on median household income. The ***low-income group*** includes counties with income less than 50 percent of median household income. The ***moderate-income group*** includes counties with income greater than 50 percent and less than or equal to 80 percent of median household income. The ***middle-income group*** includes counties with income greater than 80 percent and less than or equal to 120 percent of median household income. Lastly, the ***upper-income group*** includes counties with income greater than 120 percent of median household income.

In table B-V, we focus on low-income regions. On average, the temperature shocks adversely impact loan volume in a region. A percentage increase in $\text{NPPOET}_{cbt\ \ 1}$ ($\text{PPOET}_{cbt\ \ 1}$) implies a decrease of loan volume by 3.7 (3) percent, and an increase of 1.2 (1.1) percent in the likelihood of a decline in loan volume. These findings are more profound for large-sized banks. Overall, the results in tables B-VI - B-VIII gain significance economically and statistically.

To conclude, we summarize the findings of tables B-II - B-VIII as follows:

- Loan volume is adversely impacted by temperature shocks. This impact is more profound for relatively larger banks. On average, we find that regional characteristics are less likely to play any role in credit made available by banks.
- The likelihood of a decline in loan volume is increasing in the temperature shock measures proposed in this study. The economic significance of this increase is higher for larger banks.

This appendix includes the following:

- FIGURES
  - **Figure B1** presents monthly time-series plots of cross-sectional a) means and b) standard deviations of NPPOET and PPOET (based on the 99^{th} percentile) using gridded temperature data sourced from the University of Delaware. The base reference period is $1951 - 1980$.
  - **Figure B2** presents monthly time-series plots of cross-sectional a) means and b) standard deviations of NPP$\hat{\text{O}}$ET and PP$\hat{\text{O}}$ET (based on the 1^{st} percentile) using gridded temperature data sourced from the University of Delaware. The base reference period is $1951 - 1980$.
- TABLES:
  - **Table B-I** presents summary statistics of the temperature shock measures constructed using the temperature data from the University of Delaware. The sample period is $1997 - 2017$.
  - **Table B-II** presents regression results for small businesses borrowing funds less than or equal to $100,000$ dollars.
  - **Table B-III** presents regression results for small businesses borrowing funds greater than $100,000$ dollars and less than or equal to $250,000$ dollars.
  - **Table B-IV** presents regression results for small businesses borrowing funds greater than or equal to $250,000$ dollars.
  - **Table B-V** presents regression results for small businesses located in low-income counties.
  - **Table B-VI** presents regression results for small businesses located in moderate-income counties.
  - **Table B-VII** presents regression results for small businesses located in middle-income counties.
  - **Table B-VIII** presents regression results for small businesses located in upper-income counties.

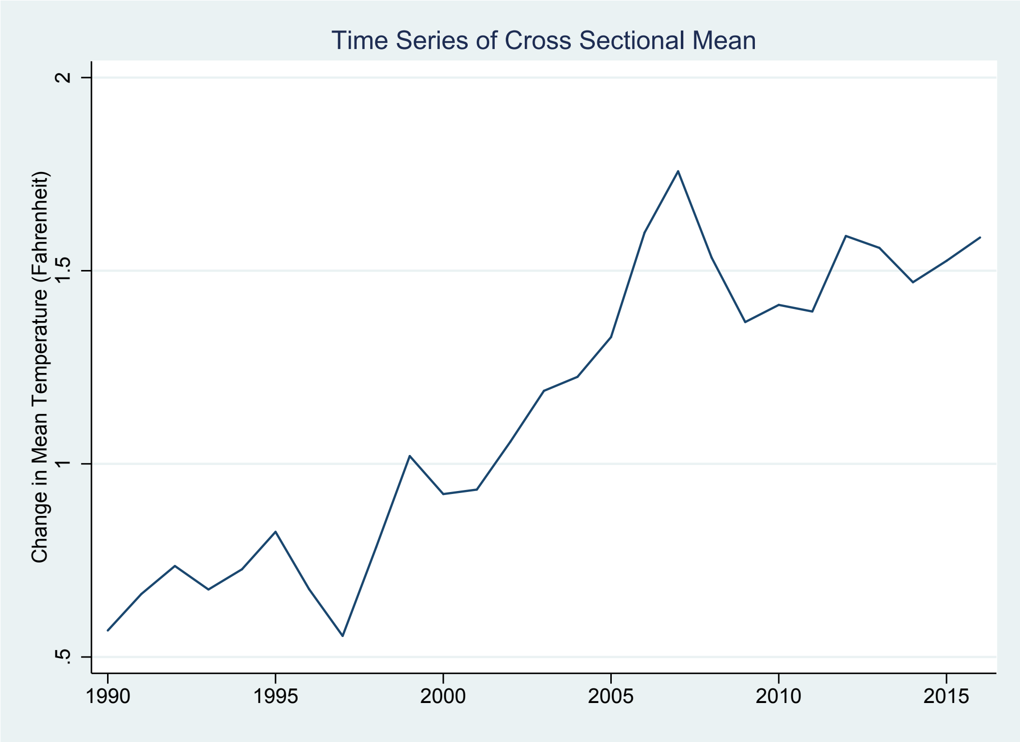
Appendix C: An Additional Validation Test

This appendix presents details of an additional validation test of temperature shock measures proposed in this study.

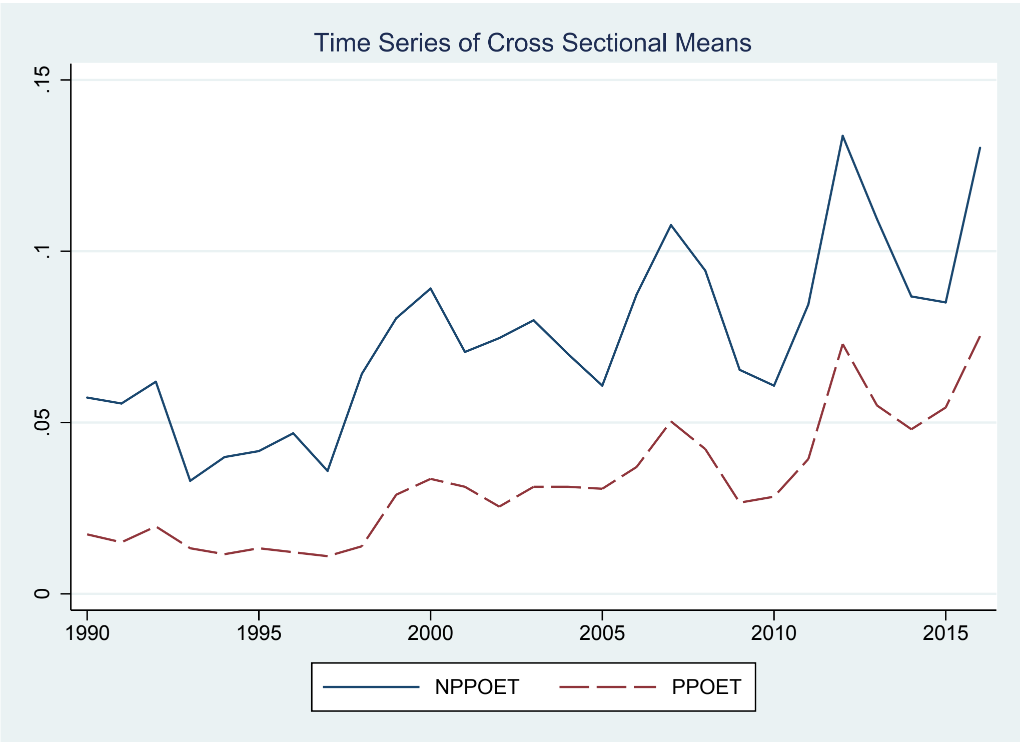
We perform textual analysis on 10-K filings submitted by US firms the SEC. Specifically, we search for the phrases: 'climate change', 'greenhouse gases', 'global average temperature' 'global warming', 'intense weather', 'intergovernmental panel on climate change', 'IPCC', 'Kyoto Protocol', 'the Paris Accord', and 'rising sea level'. Next, we define a variable ***Mention***, which is a dichotomous variable that equals 1 if a firm mentions at least one the searched phrases and equals 0 otherwise. The sample period is 1993 - 2017.

In figure C1, we present the proportion of firms mentioning at least one of the searched phrases in its 10-K filings. The industry classification follows the Fama-French 48 industry classification scheme. In line with our expectations, the majority of the firms with industry classification of ***Coal***, ***Petroleum, and Natural Gas***, and ***Utilities*** are mentioning climate change (or related phrases) in their 10-K filings. Overall, all industries, to some definite extent, are reflecting upon climate change in their 10-K filings.

In table C-I, we present OLS regression results where the dependent variable is ***mention***. We expect a significant correlation between a firm's propensity to pay attention to climate change or its related effects and the temperature shock measures. In column (1)-(3), we run our tests for the sample of all firms without considering their industry types. We find that there is a significant positive correlation between the Change in Mean Temperature (CIMT) and mention. The coefficients for the non-parametric probability of extreme temperature (NPPOET) and the parametric probability of extreme temperature (PPOET) are positive but lacks statistical significance. In columns (4)-(6), we repeat OLS regression tests for all industries but ***Coal***, ***Petroleum and Natural Gas***, and ***Utilities***. The results overall gain economic and statistical significance.

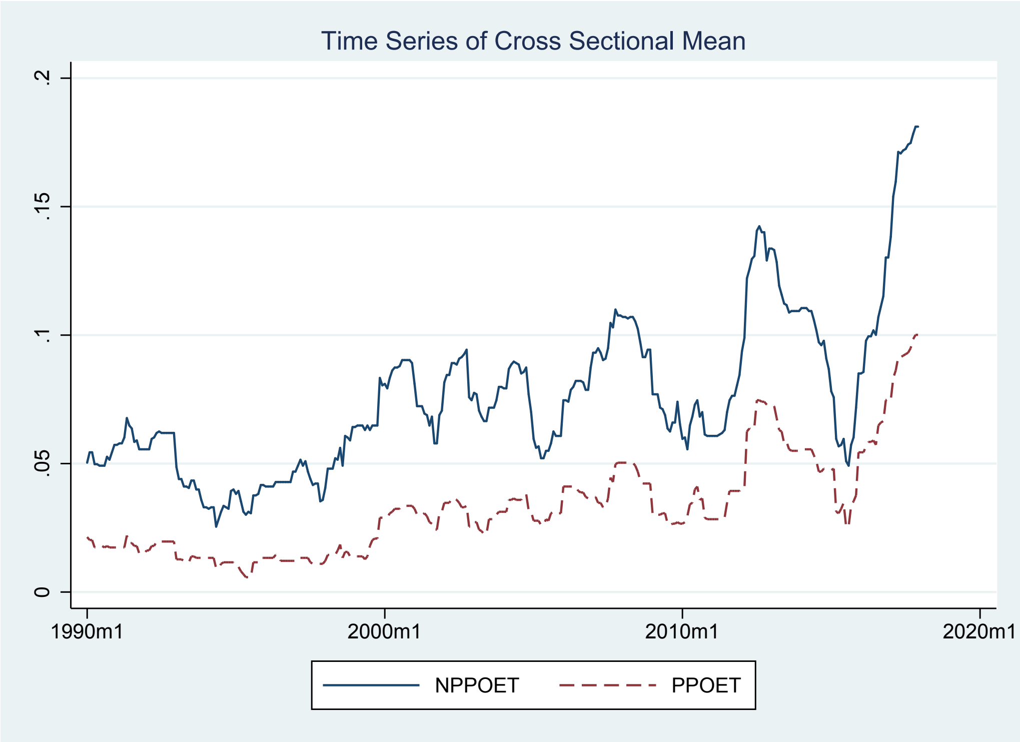


(a)

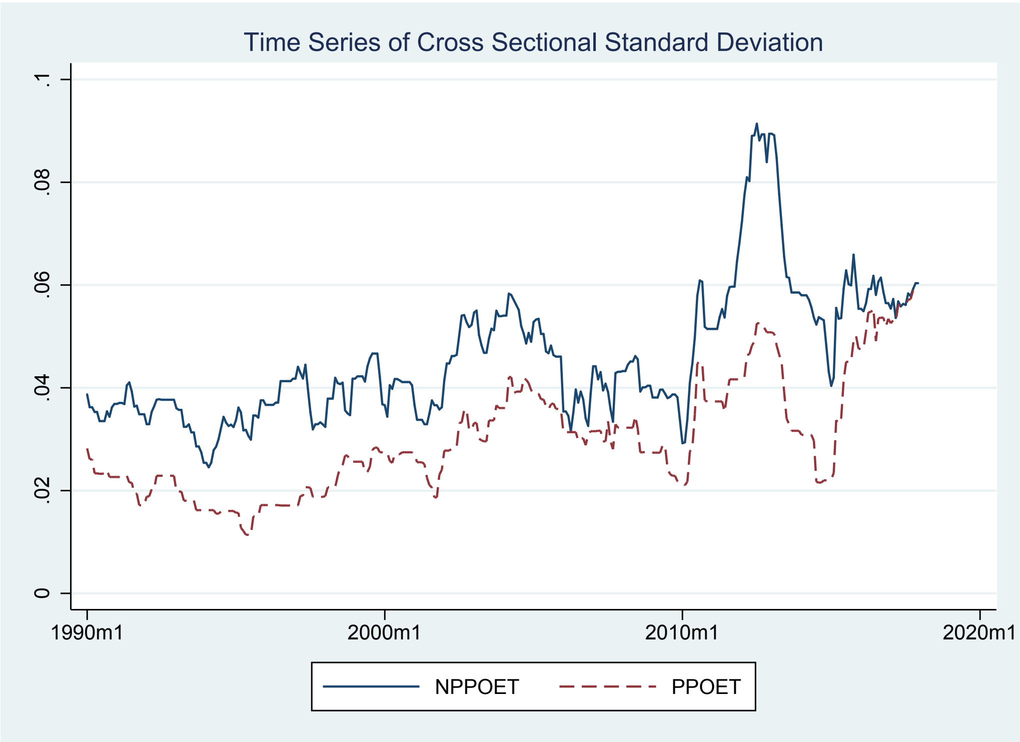


(b)

Figure 1: The figure represents time series plot of the cross-sectional mean of Change in Mean Temperature (CIMT) in panel (a), and Non-Parametric Probability of Extreme Temperature (NPPOET), and Parametric Probability of Extreme Temperature (PPOET) based on 99^{th} percentile of temperature distribution in panel (b). The sample period is 1990-2017.

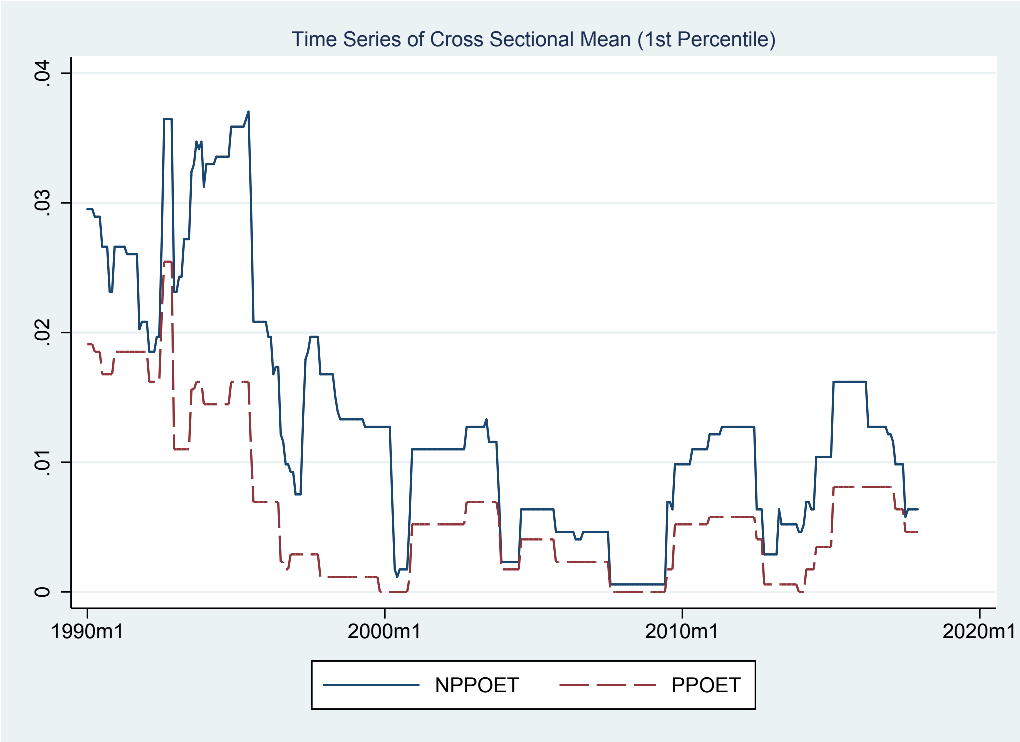


(a)

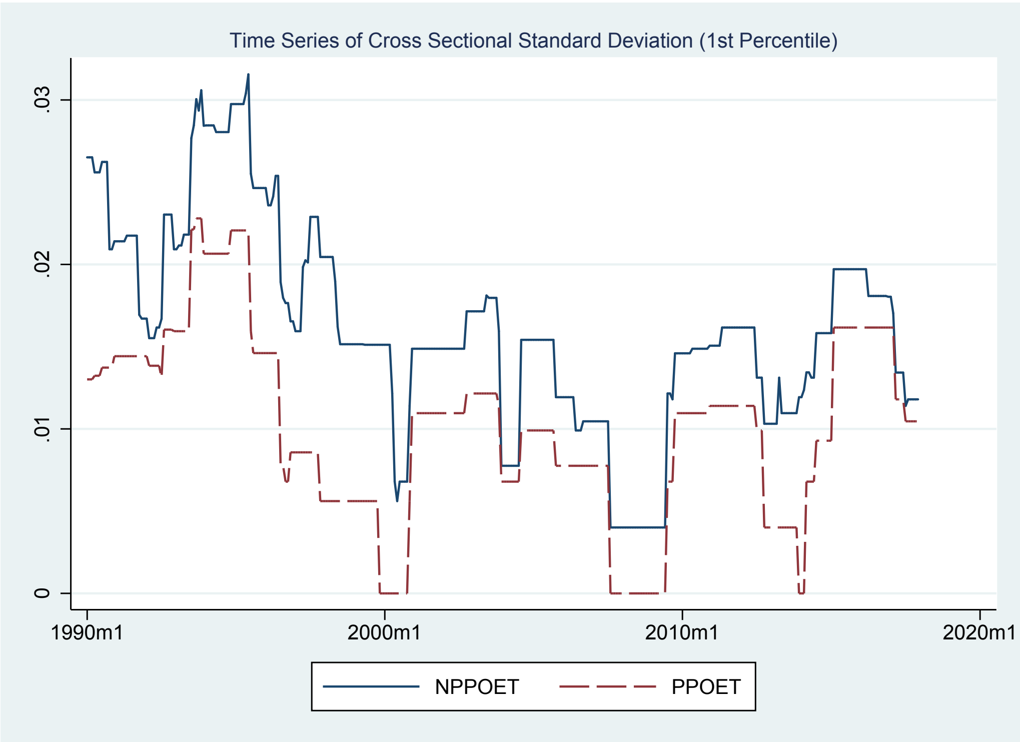


(b)

Figure 2: The figure represents time series plot of cross-sectional means (a) and standard deviation (b) of Non-Parametric Probability of Extreme Temperature (NPPOET), and Parametric Probability of Extreme Temperature (PPOET) based on 99^{th} percentile of temperature distribution. The sample period is 1990:M1 – 2017:M12.

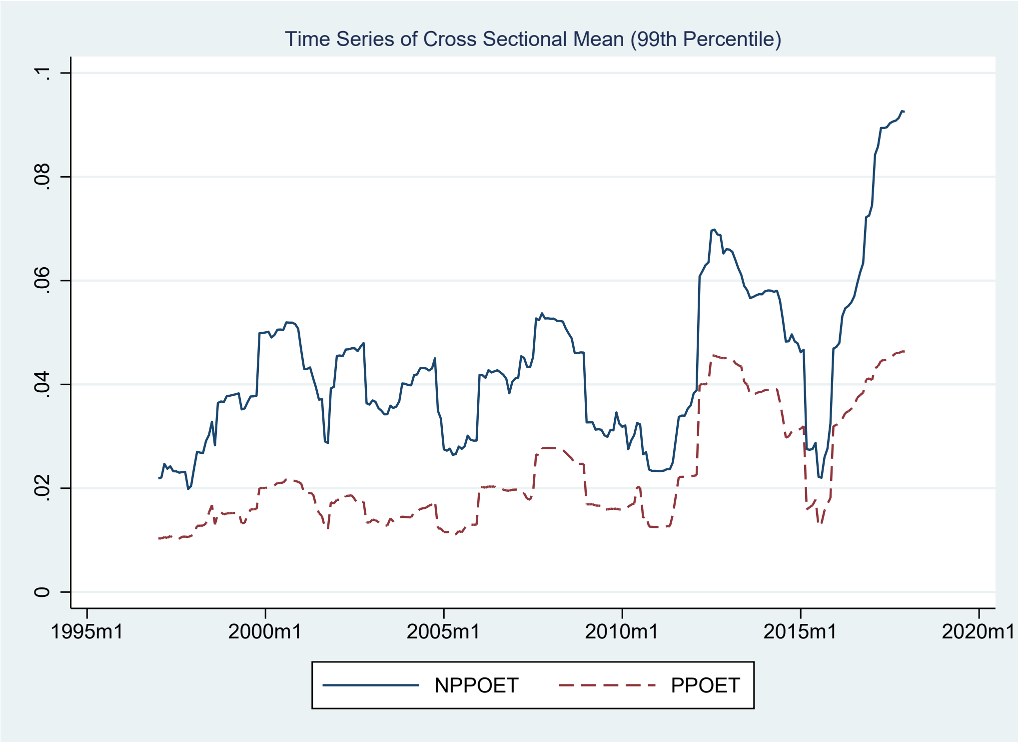


(a)

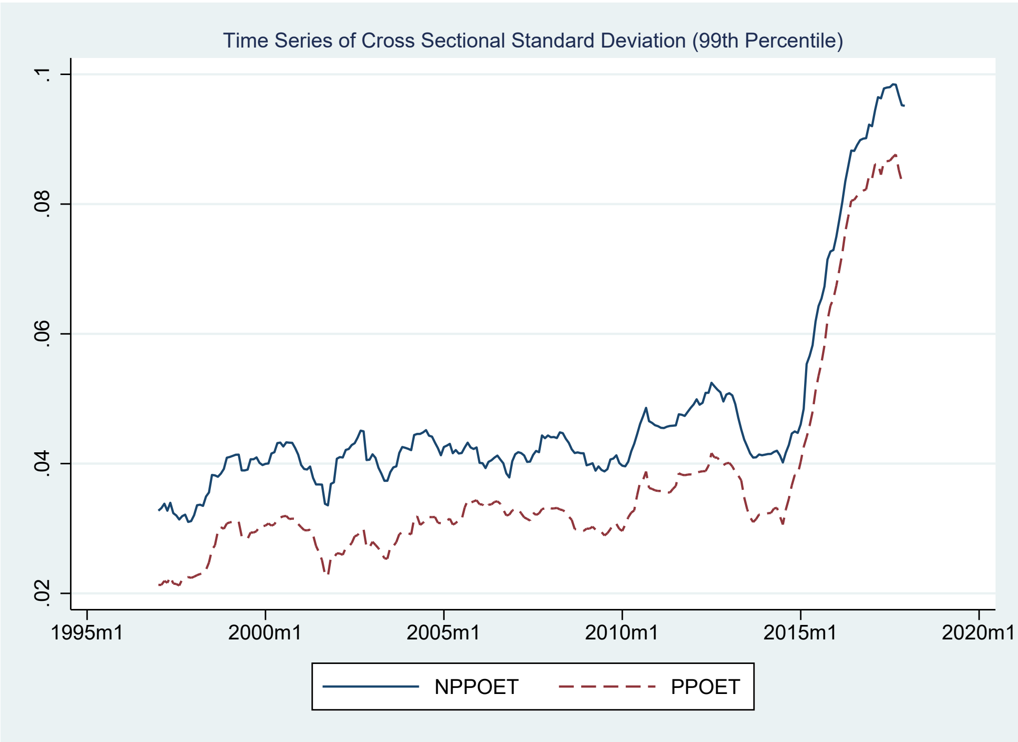


(b)

Figure 3: The figure represents time series plot of cross-sectional means (a) and standard deviation (b) of Non-Parametric Probability of Extreme Temperature (NPPOET), and Parametric Probability of Extreme Temperature (PPOET) based on 1^{st} percentile of temperature distribution. The sample period is 1990:M1 – 2017:M12.

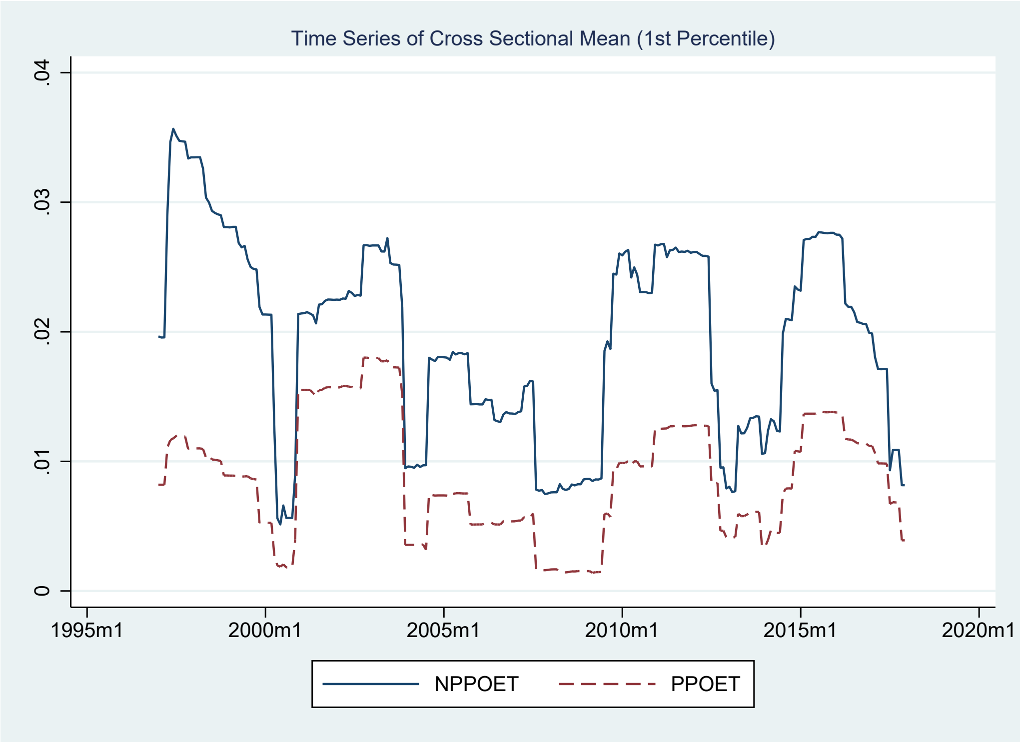


(a)

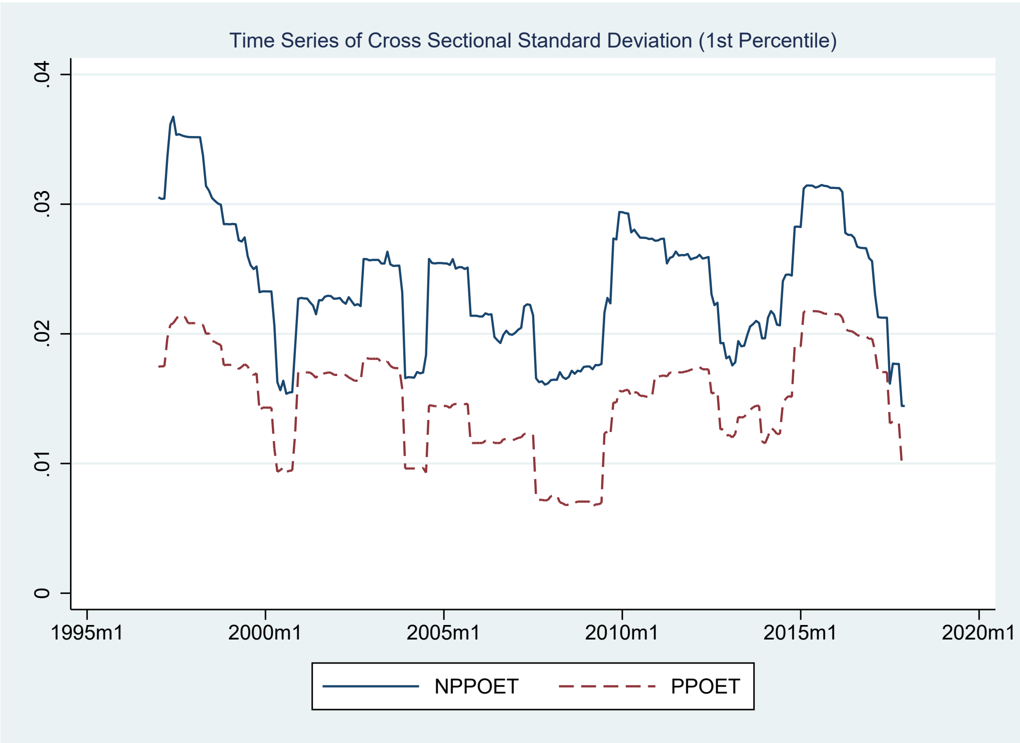


(b)

Figure B1: presents monthly time-series plots of cross-sectional means (a) and standard deviations (b) of NPPOET and PPOET (based on 99^{th} percentile) using gridded temperature data sourced from the University of Delaware. The base reference period is 1951−1980. The sample period is 1997:M1 – 2017:M12.



(a)



(b)

Figure B2: presents monthly time-series plots of cross-sectional means (a) and standard deviations (b) of $\widehat{\text{NPPOET}}$ and $\widehat{\text{PPOET}}$ (based on 1^{st} percentile) using gridded temperature data sourced from the University of Delaware. The base reference period is 1951−1980. The sample period is 1997:M1 − 2017:M12.

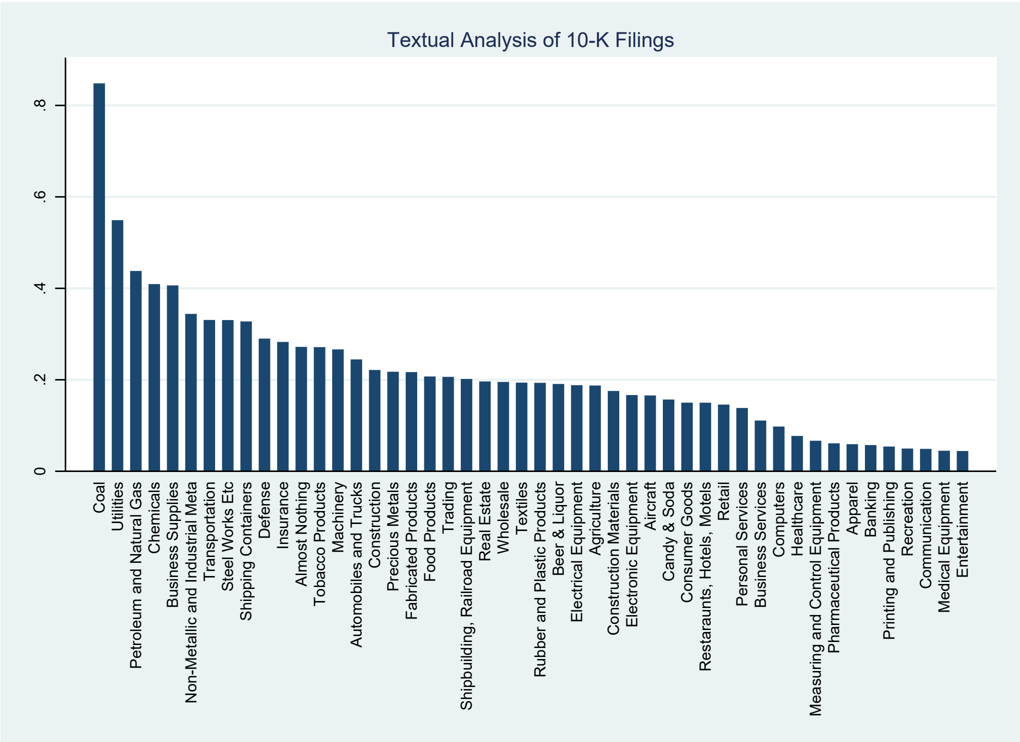


Figure C1: presents the proportion of firms in mentioning 'climate change' and related words and phrases in 10-K filings submitted to the SEC. The sample period is $1993 - 2017$.

Table I: Summary Statistics

The table presents summary statistics for key temperature shock measures estimated using state level temperature data from the National Oceanic and Atmospheric Administration (NOAA). The sample period spans 28 years starting in 1990 and ending in 2017. To calculate temperature shock measures in this study, we follow Goddard Institute of Space Studies (GISS) at NASA and choose 1951-1980 as the temperature reference period. Let T_{smt} denote observed temperature for state *s* in month *m* of year *t*, μ_{smt} denote state-month specific rolling window (window size = 10) mean temperature in year t, $\mu_{sm,51\ \ 80}$ represents state-month specific mean temperature estimated over chosen reference period and $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$ denotes state-month specific 99^{th} percentile of temperature distribution observed over reference period.*Change in Mean Temperature* is a measure of shift in mean of temperature distribution and equals $\frac{1}{12}\sum_{m=1}^{12}[\mu_{smt} - \mu_{sm,51\ \ 80}]$. *'NPPOET'* is 36-month moving average (observed in December each year) of dichotomous variable that equals 1 (0 otherwise) if T_{smt} exceeds $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$. *'PPOET'* is 36-month moving average (observed in December each year) of a dichotomous variables that equals 1 (0 otherwise) if T_{smt} exceeds the 99^{th} percentile implied by normal distribution with mean $\mu_{sm,51\ \ 80}$ and standard deviation $\sigma_{sm,51\ \ 80}$. Note that the calculations of means and standard deviations are state-month specific to minimize the effects of seasonalities and geography.

	N	Mean	Standard Deviation			Minimum	p10	p25	p50	p75	p90	Maximum
			Overall	Between	Within							
CIMT_{st} (°F)	1,344	1.155	0.504	0.257	0.435	-0.282	0.522	0.815	1.126	1.506	1.823	2.877
NPPOET_{st}	1,344	0.078	0.057	0.029	0.049	0.000	0.000	0.028	0.083	0.111	0.139	0.361
PPOET_{st}	1,344	0.035	0.039	0.017	0.035	0.000	0.000	0.000	0.028	0.056	0.083	0.250

Table II: Validation Test - Exacerbation

In this table, we present results assessing the validity of temperature shock measures proposed in this study. Specifically, we assess whether the intensity of disasters is increasing in temperature shock measure. We measure of the intensity of disasters by the log of per capita total damages (crop and property) (column 1), total injuries (column 2) and fatalities (column 3) per $100,000$ people. The dollar variables are adjusted to the 2016 level. The sample period is from 1990 to 2016. The independent variables are *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The reference period spans 30 years starting 1951. The independent variables are defined as following. Let T_{smt} denote observed temperature for state s in month m of year t, μ_{smt} denote state-month specific rolling window (window size = 10) mean temperature in year t, $\mu_{sm,51\ \ 80}$ represents state-month specific mean temperature estimated over chosen reference period and $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$ denotes state-month specific 99^{th} percentile of temperature distribution observed over reference period.*CIMT* is a measure of shift in mean of temperature distribution and equals $\frac{1}{12}\sum_{m=1}^{12}[\mu_{smt} - \mu_{sm,51\ \ 80}]$. *'NPPOET'* is 36-month moving average (observed in December each year) of dichotomous variable that equals 1 (0 otherwise) if T_{smt} exceeds $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$. *'PPOET'* is 36-month moving average (observed in December each year) of a dichotomous variables that equals 1 (0 otherwise) if T_{smt} exceeds the 99^{th} percentile implied by normal distribution with mean $\mu_{sm,51\ \ 80}$ and standard deviation $\sigma_{sm,51\ \ 80}$. The standard errors are clustered by state, and t-statistics are presented in square brackets. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Variables	(1) Total Damages	(2) Injuries	(3) Fatalities
Panel A			
CIMT_{st}	0.335**	0.283	0.000
	[2.123]	[0.720]	[0.005]
R^2	0.476	0.151	0.120
Panel B			
NPPOET_{st}	1.960**	2.646	0.436
	[2.360]	[1.045]	[1.649]
R^2	0.476	0.151	0.121
Panel C			
PPOET_{st}	1.040	5.515	0.565**
	[0.689]	[1.522]	[2.089]
R^2	0.475	0.152	0.121
N	1,296	1,296	1,296
State FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
SE Clustered by	State	State	State

Table III: Validation Test - Serviceability

This table presents the results for the second validation test for the temperature shock measures. The variables of interest are 'Return on Assets (ROA), defined as operating profit before depreciation and amortization (oibdp) as the fraction of total assets (at) and 'Volatility$_{ROA}$' is rolling window (window size = 5) standard deviation of a firm's ROA. In panel A, the results correspond to ***t-test*** (in parentheses $(\cdot)$) and ***Wilcoxon-Mann-Whitney Test*** (in brackets $[\cdot]$) for two groups of Compustat firms. The division of firms, into the high and low group, is based on the median value of temperature shock measure: ***Change in Mean Temperature*** (Panel A1), ***NPPOET*** (Panel A2) and ***PPOET*** (Panel A3). This division is performed on a yearly basis. In panel B, we present the average treatment effect for the treated (ATT) estimated using Abadie and Imbens [2011] estimator. The firms are matched on four continuous variables, namely 'Total Assets' defined as logarithm of total assets (at), 'Book Leverage' defined as ratio of total liabilities (lt) as ratio of total assets (at), and 'Tangibility' defined as ratio of net property, plant and equipment (ppent) and total assets (at), 'Market-to-Book', defined as ratio of market value of assets ((prcc$_f$×csho)+at-ceq) scaled by book value of assets (at) and two discrete variables namely 2-digit SIC industry classification and year. The treatment variable is based on median values (> median = 1) of temperature shock measures: Change in Mean Temperature in Panel B1, NPPOET in Panel B2 and PPOET in Panel B3. The estimator is bias-corrected for continuous variables. Each treated firm is matched with one control firm. In panel B, the z-statistic is presented in square brackets, $[\cdot]$. The sample period is 1990 - 2017. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Median Tests

Panel A1: Change in Mean Temperature (CIMT)			
	Return on Assets	Volatility$_{ROA}$	N
High	(2.824), [10.162]	(9.912), [4.550]	44,010
Low	(5.141), [10.657]	(8.815), [4.177]	50,824
Difference	(-2.317***), [-0.495***]	(1.097***), [0.374***]	
Panel A2: NPPOET			
	Return on Assets	Volatility$_{ROA}$	N
High	(2.710), [10.007]	(9.789), [4.574]	34,044
Low	(4.825), [10.666]	(9.064), [4.224]	60,790
Difference	(-2.115***), [-0.659***]	(0.725***), [0.349***]	
Panel A3: PPOET			
	Return on Assets	Volatility$_{ROA}$	N
High	(2.471), [9.942]	(10.032), [4.713]	32,203
Low	(4.886), [10.686]	(8.960), [4.175]	62,631
Difference	(-2.414***), [-0.744***]	(1.071***), [0.538***]	

Panel B: Abadie-Imbens Matching Estimator

Panel B1: Change in Mean Temperature (CIMT)			
	Return on Assets	Volatility$_{ROA}$	Matches
ATT$_{CIMT}$	-0.008***	0.285***	43,193
	[-8.072]	[4.675]	
Panel B2: NPPOET			
	Return on Assets	Volatility$_{ROA}$	Matches
ATT$_{NPPOET}$	-0.010***	0.143**	33,470
	[-8.943]	[2.028]	
Panel B3: PPOET			
	Return on Assets	Volatility$_{ROA}$	Matches
ATT$_{PPOET}$	-0.010***	0.322***	31,675
	[-8.433]	[4.440]	

Table IV: Baseline Results

The table presents baseline regression results where the dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. ΔSpread is the change in interest rate over $LIBOR$ charged by a bank. The observation is at cohort(c)-bank(b)-year(t) level. In columns (1), (5), and (9), cohorts are formed by 9-Census regions (9R). In columns (2), (6) and (10), the cohorts are formed on 9-Census Regions (9R) and 10 Fama-French Industries (10FF). In columns (3), (7) and (11), the cohorts are formed on 9-Census Regions (9R), 2 ratings groups ($2L$) based on median value of debt-to-EBITDA defined as ratio of long-term debt (dlc+dltt) as fraction of a firms earnings before interest, tax, depreciation and amortization (ebitda). Lastly, in columns (4), (8) and (12), the cohorts are formed on 9-Census Regions (9R) and 5 Fama-French Industries (5FF) and 2 ratings groups ($2L$) based on median value of debt-to-EBITDA. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The state level independent variable, say X, is aggregated to cohort-bank-year level as following: $X_{cbt} = \sum_s \sum_i \frac{L_{iscbt}}{L_{bt}} X_{st}$ where L_{iscbt} represent loan amount to firm *i* located in state *s* of cohort *c* from bank *b* in year *t*. The sample period is 1990 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable											
	ΔVolume$_{cbt}$				Loan Decrease$_{cbt}$				ΔSpread$_{cbt}$			
Panel A												
CIMT$_{cbt-1}$	-0.336***	-0.450***	-0.547***	-0.727***	0.086***	0.100***	0.151***	0.164**	0.140***	0.100	0.055	0.357
	[-9.006]	[-4.504]	[-7.336]	[-3.097]	[4.695]	[3.621]	[5.043]	[2.355]	[3.357]	[1.013]	[0.593]	[1.394]
R^2	0.186	0.402	0.346	0.490	0.184	0.381	0.318	0.486	0.176	0.376	0.308	0.431
Panel B												
NPPOET$_{cbt-1}$	-3.824***	-4.911***	-6.103***	-10.067***	1.035***	1.102***	1.578***	1.952**	1.205***	2.162**	0.421	3.719
	[-6.971]	[-3.629]	[-7.084]	[-3.409]	[4.430]	[3.050]	[4.606]	[2.163]	[2.761]	[2.153]	[0.399]	[1.195]
R^2	0.181	0.400	0.343	0.491	0.183	0.380	0.314	0.484	0.175	0.377	0.308	0.429
Panel C												
PPOET$_{cbt-1}$	-4.967***	-5.326***	-8.138***	-10.605**	1.469***	1.425**	1.957***	2.821**	0.679	1.858	0.454	2.409
	[-5.892]	[-2.807]	[-4.797]	[-2.246]	[4.512]	[2.453]	[3.578]	[2.170]	[0.844]	[0.925]	[0.289]	[0.597]
R^2	0.173	0.393	0.333	0.481	0.180	0.378	0.308	0.482	0.173	0.376	0.307	0.427
N	2,989	2,728	1,778	1,053	2,989	2,728	1,778	1,053	2,989	2,728	1,778	1,053
Cohorts by	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L
Cohort x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table V: Robustness - Loan Purpose

The table presents robustness of our baseline results to inclusion of certain loan purposes. In this table, the cohorts are formed using firms that specify loan purpose are 'Corporate Purposes' and 'Working Capital Purposes'. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. ΔSpread is the change in interest rate over $LIBOR$ charged by a bank. The observation is at cohort(c)-bank(b)-year(t) level. In columns (1), (5), and (9), cohorts are formed by 9-Census regions (9R). In columns (2), (6) and (10), the cohorts are formed on 9-Census Regions (9R) and 10 Fama-French Industries (10FF). In columns (3), (7) and (11), the cohorts are formed on 9-Census Regions (9R), 2 ratings groups ($2L$) based on median value of debt-to-EBITDA defined as ratio of long-term debt (dlc+dltt) as fraction of a firms earnings before interest, tax, depreciation and amortization (ebitda). Lastly, in columns (4), (8) and (12), the cohorts are formed on 9-Census Regions (9R) and 5 Fama-French Industries (5FF) and 2 ratings groups ($2L$) based on median value of debt-to-EBITDA. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The state level independent variable, say X, is aggregated to cohort-bank-year level as following: $X_{cbt} = \sum_s \sum_i \frac{L_{iscbt}}{L_{bt}} X_{st}$ where L_{iscbt} represent loan amount to firm *i* located in state *s* of cohort *c* from bank *b* in year *t*. The sample period is 1990 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable											
	ΔVolume$_{cbt}$				Loan Decrease$_{cbt}$				ΔSpread$_{cbt}$			
Panel A												
CIMT$_{cbt-1}$	-0.334***	-0.625***	-0.464***	-0.829**	0.101***	0.175***	0.121***	0.165	0.160***	0.202	-0.034	-0.003
	[-7.259]	[-4.710]	[-5.761]	[-2.160]	[5.411]	[4.720]	[3.436]	[1.693]	[2.710]	[1.502]	[-0.278]	[-0.008]
R-squared	0.271	0.438	0.477	0.523	0.265	0.473	0.422	0.523	0.250	0.496	0.337	0.511
Panel B												
NPPOET$_{cbt-1}$	-3.811***	-7.747***	-5.646***	-11.897**	1.346***	2.004***	1.606***	3.060***	1.420***	2.902*	-1.431	-0.401
	[-6.689]	[-5.009]	[-5.122]	[-2.568]	[5.994]	[4.931]	[3.619]	[2.867]	[2.645]	[1.747]	[-0.988]	[-0.150]
R-squared	0.268	0.440	0.477	0.531	0.267	0.472	0.423	0.532	0.248	0.496	0.338	0.511
Panel C												
PPOET$_{cbt-1}$	-4.491***	-10.193***	-5.547**	-15.810**	1.441***	2.570***	1.310*	4.006	1.642*	1.593	-2.141	-5.752
	[-5.236]	[-4.266]	[-2.025]	[-2.332]	[4.173]	[3.559]	[1.697]	[1.546]	[1.906]	[0.827]	[-0.737]	[-0.980]
R-squared	0.259	0.435	0.468	0.519	0.257	0.468	0.416	0.524	0.247	0.494	0.338	0.513
N	1,755	1,144	953	380	1,755	1,144	953	380	1,755	1,144	953	380
Cohorts by	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L
Cohort x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table VI: Robustness - Loan Type

The table presents robustness of our baseline results to inclusion of certain loan types. In this table, the the cohorts are formed using firms obtaining 'Revolver/Line >= 1 Yr' type of loans. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. ΔSpread is the change in interest rate over $LIBOR$ charged by a bank. The observation is at cohort(c)-bank(b)-year(t) level. In columns (1), (5), and (9), cohorts are formed by 9-Census regions (9R). In columns (2), (6) and (10), the cohorts are formed on 9-Census Regions (9R) and 10 Fama-French Industries (10FF). In columns (3), (7) and (11), the cohorts are formed on 9-Census Regions (9R), 2 ratings groups ($2L$) based on median value of debt-to-EBITDA defined as ratio of long-term debt (dlc+dltt) as fraction of a firms earnings before interest, tax, depreciation and amortization (ebitda). Lastly, in columns (4), (8) and (12), the cohorts are formed on 9-Census Regions (9R) and 5 Fama-French Industries (5FF) and 2 ratings groups ($2L$) based on median value of debt-to-EBITDA. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The state level independent variable, say X, is aggregated to cohort-bank-year level as following: $X_{cbt} = \sum_s \sum_i \frac{L_{iscbt}}{L_{bt}} X_{st}$ where L_{iscbt} represent loan amount to firm *i* located in state *s* of cohort *c* from bank *b* in year *t*. The sample period is 1990 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable											
	ΔVolume$_{cbt}$				Loan Decrease$_{cbt}$				ΔSpread$_{cbt}$			
Panel A												
CIMT$_{cbt-1}$	-0.447***	-1.176***	-0.858***	-1.114**	0.124***	0.296***	0.260***	0.416***	0.121*	0.568***	0.190*	0.030
	[-7.186]	[-8.202]	[-5.288]	[-2.660]	[6.645]	[5.495]	[5.352]	[4.162]	[1.780]	[5.007]	[1.835]	[0.153]
R-squared	0.271	0.464	0.423	0.511	0.269	0.488	0.397	0.565	0.202	0.449	0.380	0.412
Panel B												
NPPOET$_{cbt-1}$	-4.561***	-11.477***	-11.566***	-17.050***	1.387***	3.110***	3.417***	5.886***	1.111	4.424**	2.545*	-0.544
	[-6.503]	[-5.184]	[-5.131]	[-3.397]	[7.055]	[5.184]	[5.987]	[4.482]	[1.416]	[2.592]	[1.796]	[-0.182]
R-squared	0.264	0.449	0.423	0.515	0.267	0.483	0.396	0.563	0.201	0.441	0.380	0.412
Panel C												
PPOET$_{cbt-1}$	-6.728***	-15.694***	-15.602***	-17.466*	2.440***	4.327***	4.986***	5.974*	1.213	7.156**	3.139	-4.473
	[-4.506]	[-4.583]	[-5.935]	[-2.024]	[6.307]	[4.032]	[4.705]	[1.955]	[1.011]	[2.096]	[1.362]	[-0.774]
R-squared	0.258	0.438	0.409	0.493	0.267	0.476	0.389	0.539	0.200	0.440	0.379	0.413
N	1,756	1,146	985	552	1,756	1,146	985	552	1,756	1,146	985	552
Cohorts by	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L
Cohort x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table VII: Robustness - Bank Controls

The table presents robustness of our baseline results to inclusion of bank level controls. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. ΔSpread is the change in interest rate over $LIBOR$ charged by a bank. The observation is at cohort(c)-bank(b)-year(t) level. In columns (1), (5), and (9), cohorts are formed by 9-Census regions (9R). In columns (2), (6) and (10), the cohorts are formed on 9-Census Regions (9R) and 10 Fama-French Industries (10FF). In columns (3), (7) and (11), the cohorts are formed on 9-Census Regions (9R), 2 ratings groups ($2L$) based on median value of debt-to-EBITDA defined as ratio of long-term debt (dlc+dltt) as fraction of a firms earnings before interest, tax, depreciation and amortization (ebitda). Lastly, in columns (4), (8) and (12), the cohorts are formed on 9-Census Regions (9R) and 5 Fama-French Industries (5FF) and 2 ratings groups ($2L$) based on median value of debt-to-EBITDA. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The state level independent variable, say X, is aggregated to cohort-bank-year level as following: $X_{cbt} = \sum_s \sum_i \frac{L_{iscbt}}{L_{bt}} X_{st}$ where L_{iscbt} represent loan amount to firm *i* located in state *s* of cohort *c* from bank *b* in year *t*. The sample period is 1990 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Dependent Variable											
	ΔVolume$_{cbt}$				Loan Decrease$_{cbt}$				ΔSpread$_{cbt}$			
Panel A												
CIMT$_{cbt-1}$	-0.312***	-0.449***	-0.565***	-0.638**	0.074***	0.133**	0.201***	0.209**	0.093	0.060	-0.043	0.203
	[-7.237]	[-3.827]	[-4.511]	[-2.800]	[3.847]	[2.462]	[5.692]	[2.626]	[1.554]	[0.551]	[-0.397]	[1.225]
R-squared	0.272	0.504	0.411	0.539	0.248	0.480	0.394	0.539	0.252	0.488	0.424	0.499
Panel B												
NPPOET$_{cbt-1}$	-3.847***	-4.799***	-5.872***	-7.672**	0.995***	1.399**	2.065***	2.652**	1.543*	0.956	-1.030	1.050
	[-6.743]	[-3.785]	[-3.724]	[-2.160]	[3.826]	[2.658]	[4.370]	[2.223]	[1.969]	[0.849]	[-1.041]	[0.661]
R-squared	0.270	0.503	0.404	0.537	0.249	0.479	0.388	0.538	0.252	0.488	0.425	0.497
Panel C												
PPOET$_{cbt-1}$	-5.252***	-7.245***	-8.758***	-18.778**	1.257***	2.361***	3.001***	5.779**	1.679	0.306	-2.562	3.066
	[-5.890]	[-3.327]	[-3.538]	[-2.308]	[3.007]	[3.321]	[3.835]	[2.407]	[1.277]	[0.173]	[-1.196]	[0.672]
R-squared	0.264	0.501	0.397	0.538	0.245	0.478	0.380	0.538	0.251	0.488	0.425	0.498
N	1,537	1,403	1,029	641	1,537	1,403	1,029	641	1,537	1,403	1,029	641
Cohorts by	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L	9R	9R-10FF	9R-2L	9R-5FF-2L
Cohort x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort x Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table VIII: Borrowing Firm Level Analysis

The table presents average treatment effect for the treated (ATT) estimated using Abadie and Imbens [2011] estimator. The dependent variables are 'Cash and Equivalents' (column 1), defined as cash and equivalents (che) scaled by total assets (at), 'Net Book Leverage' (column 2), defined long-term debt (dlc+dltt) net of cash and equivalents (che) scaled by total assets (at), 'Net Market Leverage' (column 3), defined long-term debt (dlc+dltt) net of cash and equivalents (che) scaled by market value of assets ((prcc_f×csho)+at-ceq) and 'Equity Issuance' (column 4), defined as sale of common and preferred stock (sstk) net of purchases of common and preferred stock (prstkc) scaled by previous period's total assets (at). For a borrowing firm i in state s the global exposure is calculated as $\sum_b \theta_{isbt}\, EXP_{bt}$ where $\text{EXP}_{bt} = \sum_c \sum_i \frac{\mathsf{L}_{isbt}}{\mathsf{L}_{bt}} X_{st}$ where the weight θ_{isbt} is defined as $\frac{\mathsf{L}_{isbt}}{\sum_b \mathsf{L}_{isbt}}$ and $\text{X} \in \{\text{CIMT}, \text{NPPOET}, \text{PPOET}\}$. In these tests, the treated group is a set of firms whose orthogonalized global exposure exceeds the median value. Rest of the firms are defined as non-treated group. Panel A is based on all Dealscan firms. In panel B, the treated and control sample is obtained from Dealscan firms with headquarters in coastal states of mainland USA. The firms are matched on six continuous variables, namely 'Total Assets' defined as logarithm of total assets (at), 'ROA' defined as ratio of operating income (oibdp) and total assets (at),'Book Leverage' defined as ratio of total liabilities (lt) as ratio of total assets (at), and 'Tangibility' defined as ratio of net property, plant and equipment (ppent) and total assets (at), 'Market-to-Book', defined as ratio of market value of assets ((prcc_f×csho)+at-ceq) scaled by book value of assets (at), one of the three temperature shock variables, and two discrete variables namely 2-digit SIC industry classification and year. All matching is implemented on lagged values of continuous covariates. The estimator is bias corrected for continuous variables. Each treated firm is matched with one control firm. The z-statistic is presented in square brackets, [·]. The sample period is 1990 - 2017. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: All Dealscan Firms

	(1)	(2)	(3)	(4)	
	Cash and Equivalents	Net Book Leverage	Net Market Leverage	Net Equity Issuance	Matches
$\text{ATT}_{\text{GEXP}^{\perp}_{\mathsf{CIMT}}}$	0.012***	-0.010*	-0.012***	-0.007*	2,139
	[4.826]	[-1.814]	[-2.992]	[-1.718]	
$\text{ATT}_{\text{GEXP}^{\perp}_{\mathsf{NPPOET}}}$	0.015***	-0.009	-0.011**	-0.012***	2,101
	[5.904]	[-1.552]	[-2.608]	[-3.302]	
$\text{ATT}_{\text{GEXP}^{\perp}_{\mathsf{PPOET}}}$	0.007**	-0.008	-0.008**	-0.0003	2,107
	[2.429]	[-1.351]	[-1.992]	[-0.068]	

Panel B: All Dealscan Firms in Coastal States

	(1)	(2)	(3)	(4)	
	Cash and Equivalents	Net Book Leverage	Net Market Leverage	Net Equity Issuance	Matches
$\text{ATT}_{\text{GEXP}^{\perp}_{\mathsf{CIMT}}}$	0.009**	-0.012	-0.016***	-0.013**	1,210
	[2.238]	[-1.502]	[-2.771]	[-2.129]	
$\text{ATT}_{\text{GEXP}^{\perp}_{\mathsf{NPPOET}}}$	0.017***	-0.028***	-0.024***	-0.015***	1,187
	[4.308]	[-3.607]	[-4.008]	[-2.750]	
$\text{ATT}_{\text{GEXP}^{\perp}_{\mathsf{PPOET}}}$	0.011**	-0.013*	-0.008	-0.017***	1,166
	[2.584]	[-1.652]	[-1.303]	[-2.920]	

Table IX: Global Exposure and Real Quantities

The table presents the dependent variables are macro-economic employment variables. All dependent variables are year-on-year growth variables calculated using relevant level variables scaled by state population. All dollar variables are deflated to 2016 level using deflator for personal consumption expenditure (series: DPCERD3A086NBEA). In these tests, the independent variable is lagged orthogonalized global exposure denoted $\text{GEXP}^{?}_{\text{X},st\ 1}$ for state s and $X \in \{\text{CIMT}, \text{NPPOET}, \text{PPOET}\}$. The global exposure is calculated as $\sum_b \theta_{sbt}\ \ EXP_{bt}$ where $\text{EXP}_{bt} = \sum_s \frac{L_{sbt}}{L_{bt}} X_{st}$ where the weight θ_{sbt} is defined as $\frac{L_{sbt}}{\sum_b L_{sbt}}$ and $X \in \{\text{Change in Mean Temperature}, \text{NPPOET}, \text{PPOET}\}$. The sample period is 1997 - 2017. All regression specifications include state and year fixed effects. For brevity reasons, the coefficients are scaled by $\times 100$. The standard errors are robust to heteroskedasticity and t-statistics are presented in square brackets, $[\cdot]$. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1)	(2)	(3)	(4)
		Jobs		
	Income	Total	Salaried	Propreitorship
Panel A: Change in Mean Temperature				
$\text{GEXP}^{?}_{\text{CIMT}}$	-0.750	-0.480*	-0.525*	-0.132
	[-1.238]	[-1.706]	[-1.657]	[-0.312]
R^2	0.705	0.779	0.787	0.685
Panel A: NPPOET				
$\text{GEXP}^{?}_{\text{NPPOET}}$	-6.197*	-3.085*	-4.045**	0.746
	[-1.775]	[-1.754]	[-2.055]	[0.262]
R^2	0.706	0.780	0.788	0.686
Panel A: PPOET				
$\text{GEXP}^{?}_{\text{PPOET}}$	-1.469	-2.674	-3.744	1.880
	[-0.312]	[-1.063]	[-1.382]	[0.464]
R^2	0.704	0.779	0.787	0.685
N	796	796	796	796
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes

Table X: Small Businesses

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $\mathrm{X}_{cbt} = \sum_{\tilde{c}} \frac{\mathrm{L}_{\tilde{c}cbt}}{\mathrm{L}_{bt}} \mathrm{X}_{\tilde{c}t}$ where $\mathrm{L}_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.529***	-0.491***	-0.843***	-1.566***	-3.886***	0.256***	0.189***	0.406***	0.741***	1.648***
	[-9.837]	[-5.388]	[-8.195]	[-3.624]	[-5.160]	[9.538]	[4.725]	[8.513]	[3.491]	[3.810]
R^2	0.112	0.177	0.162	0.170	0.197	0.139	0.203	0.188	0.194	0.227
Panel B										
NPPOET$_{cbt-1}$	-2.783***	-2.331***	-2.936***	-8.670***	-16.034***	1.210***	0.694***	1.603***	3.517***	7.844***
	[-9.335]	[-5.042]	[-6.222]	[-5.362]	[-5.064]	[8.383]	[3.238]	[6.551]	[3.667]	[4.311]
R^2	0.112	0.177	0.161	0.170	0.196	0.138	0.202	0.187	0.193	0.227
Panel C										
PPOET$_{cbt-1}$	-2.383***	-1.849***	-2.701***	-7.774***	-29.452***	1.152***	0.548*	1.605***	3.150**	17.100***
	[-6.274]	[-2.913]	[-4.436]	[-3.558]	[-4.197]	[5.991]	[1.824]	[5.034]	[2.305]	[5.219]
R^2	0.111	0.176	0.160	0.169	0.196	0.138	0.202	0.187	0.193	0.228
N	80,935	19,593	30,019	21,052	8,482	80,935	19,593	30,019	21,052	8,482
Bank Size Class (billons)	All	< =1	(1, 10]	(10, 100]	> 100	All	< =1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table A-I: Summary Statistics I

The table presents summary statistics for state level temperature shocks data matched with state level SHELDUS dataset. 'Total Damages' are sum of crop and property damages per capita. 'Total Injuries' and 'Total Fatalities' per 100,000 people. The dollar variables are adjusted to 2016 level. The sample period is from 1990 to 2016. The temperature shock variables are defined as following. Let T_{smt} denote observed temperature for state *s* in month *m* of year *t*, μ_{smt} denote state-month specific rolling window (window size = 10) mean temperature in year t, $\mu_{sm,51\ \ 80}$ represents state-month specific mean temperature estimated over chosen reference period and $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$ denotes state-month specific 99^{th} percentile of temperature distribution observed over reference period.*Change in Mean Temperature* is a measure of shift in mean of temperature distribution and equals $\frac{1}{12}\sum_{m=1}^{12}[\mu_{smt} - \mu_{sm,51\ \ 80}]$. *'NPPOET'* is 36-month moving average (observed in December each year) of dichotomous variable that equals 1 (0 otherwise) if T_{smt} exceeds $\mathsf{T}^{99^{th}}_{sm,51\ \ 80}$. *'PPOET'* is 36-month moving average (observed in December each year) of a dichotomous variables that equals 1 (0 otherwise) if T_{smt} exceeds the 99^{th} percentile implied by normal distribution with mean $\mu_{sm,51\ \ 80}$ and standard deviation $\sigma_{sm,51\ \ 80}$.

variable	N	Mean	SD	p10	p25	p50	p75	p90
Total Damages	1,296	2.614	1.710	0.399	1.361	2.448	3.689	4.992
Injuries	1,296	1.517	3.809	0.026	0.177	0.541	1.352	3.331
Fatalities	1,296	0.229	0.560	0.000	0.043	0.121	0.263	0.496
CIMT (°F)	1,296	1.136	0.498	0.516	0.807	1.096	1.484	1.802
NPPOET	1,296	0.074	0.053	0.000	0.028	0.056	0.111	0.139
PPOET	1,296	0.032	0.036	0.000	0.000	0.028	0.056	0.083

Table A-II: Summary Statistics II

The table presents summary statistics for relevant variables used in baseline results. This table is based on cohorts of firms formed on 9 Census regions (9R). 'Facility Amount' is the average amount lent by a bank to a cohort. 'Spread' measures cost of credit and equals percentage points above LIBOR charged on a loan facility. 'ΔVolume' is defined as the log growth in amount lent to a cohort by a bank. 'Loan Decrease' is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. 'ΔSpread is first differenced spread charged over LIBOR. Our temperature shock variables are loan weighted and aggregated to cohort(c)-bank(b)-year(t) level in the following manner. The state level independent variable, say X, is aggregated to cohort-bank-year level as following: $\mathrm{X}_{cbt} = \sum_s \sum_i \frac{\mathsf{L}_{iscbt}}{\mathsf{L}_{bt}} \mathrm{X}_{st}$ where L_{iscbt} represent loan amount to firm i located in state s of cohort c from bank b in year t, and X $\in$ {CIMT, NPPOET, PPOET}. The sample period is from 1990 to 2017.

Variable	N	Mean	SD	p10	p25	p50	p75	p90
Facility Amount ($b)	6,251	0.214	0.455	0.005	0.018	0.063	0.233	0.561
Spread (%)	6,251	3.113	1.701	1.165	2.000	2.883	4.050	5.155
ΔVolume	3,273	0.072	1.294	-1.495	-0.659	0.075	0.809	1.629
Loan Decrease	3,273	0.466	0.499	0.000	0.000	0.000	1.000	1.000
ΔSpread (%)	3,273	0.005	1.585	-1.689	-0.808	0.000	0.750	1.725
CIMT (°F)	6,251	0.890	0.816	0.064	0.217	0.710	1.301	1.979
NPPOET	6,251	0.065	0.076	0.000	0.009	0.041	0.094	0.160
PPOET	6,251	0.031	0.048	0.000	0.000	0.012	0.040	0.083

Table A-III: Summary Statistics

The table presents summary statistics for the main variables used in firm level analysis. *Cash and Equivalents* represents the ratio of cash and equivalents (che) and total assets (at). *Net Book Leverage* is defined as the ration of long-term debt (dltt+dlc) net of cash and equivalents (che) as percentage of total assets (at). For firm *i* in year *t*, the global exposure based on PPOET is estimated as:

$$\text{GEXP}_{st}^{PPOET} = \sum_{b} \theta_{ibt}\, EXP_{bt} \text{ where } \text{EXP}_{bt} = \sum_{s}\sum_{i} \frac{\mathsf{L}_{isbt}}{\mathsf{L}_{bt}} \text{PPOET}_{st}$$

where the weight θ_{ibt} is defined as $\frac{\mathsf{L}_{ibt}}{\sum_b \mathsf{L}_{ibt}}$. Here L_{isbt} represents loan amount to firm i located in state *s* from bank *b* in year *t*. Other independent variables, based on NPPOET, Change in Mean Temperature, and Temperature Anomaly, are defined analogously. The observation is at firm-year level. The sample period is 1990 - 2017.

Variable	N	Mean	SD	p10	p25	p50	p75	p90
Cash and Equivalents	5,563	0.098	0.131	0.004	0.013	0.043	0.129	0.272
Net Book Leverage	5,563	0.209	0.306	-0.196	0.024	0.231	0.398	0.554
Net Market Leverage	5,563	0.169	0.219	-0.096	0.011	0.159	0.311	0.462
Equity Issuance	5,563	0.044	0.189	-0.023	0.000	0.001	0.011	0.111
Total Assets	5,563	5.568	2.008	3.211	4.087	5.256	6.857	8.533
Leverage	5,563	0.572	0.256	0.249	0.401	0.566	0.710	0.859
Market-to-Book	5,563	1.798	1.145	0.932	1.110	1.428	2.028	3.088
Tangibility	5,563	0.313	0.237	0.057	0.117	0.248	0.462	0.692
ROA	5,563	0.107	0.130	-0.006	0.070	0.118	0.169	0.232
$\text{GEXP}^{?}_{\text{CIMT}}$	5,563	0.000	0.218	-0.241	-0.150	-0.024	0.135	0.298
$\text{GEXP}^{?}_{\text{NPPOET}}$	5,563	0.000	0.027	-0.031	-0.019	-0.004	0.014	0.036
$\text{GEXP}^{?}_{\text{PPOET}}$	5,563	0.000	0.018	-0.015	-0.012	-0.003	0.007	0.023

Table A-IV: Borrowing Firm Level Analysis I

The table presents results for Abadie and Imbens [2011] estimator in which the treated group is a set of firms whose orthogonalized global exposure exceeds its median value. For a borrowing firm i in state s the global exposure is calculated as $\sum_b \theta_{isbt}\ EXP_{bt}$ where $\text{EXP}_{bt} = \sum_s \sum_i \frac{\text{L}_{isbt}}{\text{L}_{bt}} X_{st}$ where the weight θ_{isbt} is defined as $\frac{\text{L}_{isbt}}{\sum_b \text{L}_{isbt}}$ and $X \in \{$Change in Mean Temperature, NPPOET, PPOET$\}$. All Dealscan sample firms are split into treated and non-treated groups. The control firms are subset of the non-treated firms selected as the closest match to the treated firms based on a set of firm characteristics: 'Total Assets' defined as logarithm of total assets (at), 'ROA' defined as ratio of operating income (oibdp) and total assets (at),'Book Leverage' defined as ratio of total liabilities (lt) as ratio of total assets (at), and 'Tangibility' defined as ratio of net property, plant and equipment (ppent) and total assets (at), 'Market-to-Book', defined as ratio of market value of assets ((prcc$_f$ csho)+at-ceq) scaled by book value of assets (at), one of the three temperature shock variables, and two discrete variables namely 2-digit SIC industry classification and year. In panel A, we compare the properties of treated and control firms (median comparisons). The medians of size, leverage, the market-to-book value of assets, tangibility, return-on-assets are displayed for the two samples of firms (treated and control). The test for a difference in the medians of a firm characteristic across two groups is conducted by calculating the continuity corrected Pearson's χ^2 statistic, with the p-values of this test reported at the bottom rows of panels A1, A2, and A3. The average treatment effect on treated in shown in pane B. The estimator is bias-corrected for continuous variables. Each treated firm is matched with one control firm. In panel B, the z-statistic is presented in square brackets, [ ]. The sample period is 1990 - 2017. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Median Tests all firms

Panel A1: Change in Mean Temperature						
	Size	Leverage	Tangibility	Market-to-Book	ROA	Direct Exposure
Control	5.158	0.559	0.246	1.385	0.121	0.852
Treated	5.159	0.563	0.250	1.423	0.118	0.744
p-value	1.000	0.482	0.541	0.076	0.199	0.000
Panel A2: NPPOET						
	Size	Leverage	Tangibility	Market-to-Book	ROA	Direct Exposure
Control	5.204	0.556	0.250	1.385	0.119	0.056
Treated	5.200	0.568	0.248	1.451	0.120	0.028
p-value	0.951	0.031	0.805	0.002	1.000	0.000
Panel A3: PPOET						
	Size	Leverage	Tangibility	Market-to-Book	ROA	Direct Exposure
Control	5.213	0.559	0.233	1.385	0.121	0.028
Treated	5.183	0.567	0.245	1.419	0.118	0.000
p-value	0.852	0.092	0.236	0.105	0.212	0.000

Panel B: Abadie-Imbens Matching Estimator

Panel B1: Change in Mean Temperature				
	Cash	NBL	NML	EI
$\text{ATT}_{\text{GEXP}^{\perp}_{\text{CIMT}}}$	0.012***	-0.010*	-0.012***	-0.007*
z-stat	[4.826]	[-1.814]	[-2.992]	[-1.718]
Matches	2,139	2,139	2,139	2,139
Panel B2: NPPOET				
	Cash	NBL	NML	EI
$\text{ATT}_{\text{GEXP}^{\perp}_{\text{NPPOET}}}$	0.015***	-0.009	-0.011**	-0.012***
z-stat	[5.904]	[-1.552]	[-2.608]	[-3.302]
Matches	2,101	2,101	2,101	2,101
Panel B3: PPOET				
	Cash	NBL	NML	EI
$\text{ATT}_{\text{GEXP}^{\perp}_{\text{PPOET}}}$	0.007**	-0.008	-0.008**	-0.0003
z-stat	[2.429]	[-1.351]	[-1.992]	[-0.068]
Matches	2,107	2,107	2,107	2,107

Table A-V: Borrowing Firm Level Analysis II

The table presents results for Abadie and Imbens [2011] estimator in which the treated group is a set of firms whose orthogonalized global exposure exceeds its median value. For a borrowing firm *i* in state *s* the global exposure is calculated as $\sum_b \theta_{isbt}\ EXP_{bt}$ where $\text{EXP}_{bt} = \sum_s \sum_i \frac{\text{L}_{isbt}}{\text{L}_{bt}} X_{st}$ where the weight θ_{isbt} is defined as $\frac{\text{L}_{isbt}}{\sum_b \text{L}_{isbt}}$ and X 2 *f*Change in Mean Temperature, NPPOET, PPOET*g*. All Dealscan sample firms with headquarters in coastal states are split into treated and non-treated groups. The control firms are subset of the non-treated firms selected as the closest match to the treated firms based on a set of firm characteristics: 'Total Assets' defined as logarithm of total assets (at), 'ROA' defined as ratio of operating income (oibdp) and total assets (at),'Book Leverage' defined as ratio of total liabilities (lt) as ratio of total assets (at), and 'Tangibility' defined as ratio of net property, plant and equipment (ppent) and total assets (at), 'Market-to-Book', defined as ratio of market value of assets ((prcc$_f$ csho)+at-ceq) scaled by book value of assets (at), one of the three temperature shock variables, and two discrete variables namely 2-digit SIC industry classification and year. In panel A, we compare the properties of treated and control firms (median comparisons). The medians of size, leverage, the market-to-book value of assets, tangibility, return-on-assets are displayed for the two samples of firms (treated and control). The test for a di erence in the medians of a firm characteristic across two groups is conducted by calculating the continuity corrected Pearson's χ^2 statistic, with the p-values of this test reported at the bottom rows of panels A1, A2, and A3. The average treatment e ect on treated is shown in panel B. The estimator is bias-corrected for continuous variables. Each treated firm is matched with one control firm. In panel B, the z-statistic is presented in square brackets, [ ]. The sample period is 1990 - 2017. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Median Tests all-coastal

Panel A1: Change in Mean Temperature						
	Size	Leverage	Tangibility	Market-to-Book	ROA	Direct Exposure
Control	4.990	0.533	0.212	1.386	0.113	0.854
Treated	5.087	0.557	0.220	1.432	0.113	0.734
p-value	0.350	0.013	0.393	0.113	0.968	0.000
Panel A2: NPPOET						
	Size	Leverage	Tangibility	Market-to-Book	ROA	Direct Exposure
Control	4.896	0.523	0.219	1.401	0.116	0.056
Treated	5.032	0.552	0.218	1.496	0.115	0.028
p-value	0.049	0.027	0.935	0.001	0.935	0.000
Panel A3: PPOET						
	Size	Leverage	Tangibility	Market-to-Book	ROA	Direct Exposure
Control	5.072	0.534	0.203	1.437	0.117	0.028
Treated	4.933	0.552	0.209	1.467	0.111	0.000
p-value	0.341	0.075	0.772	0.59	0.062	0.000

Panel B: Abadie-Imbens Matching Estimator

Panel B1: Change in Mean Temperature				
	Cash	NBL	NML	EI
$\text{ATT}_{\text{GEXP}^{\perp}_{\text{CIMT}}}$	0.009**	-0.012	-0.016***	-0.013**
z-stat	[2.238]	[-1.502]	[-2.771]	[-2.129]
Matches	1,210	1,210	1,210	1,210
Panel B2: NPPOET				
	Cash	NBL	NML	EI
$\text{ATT}_{\text{GEXP}^{\perp}_{\text{NPPOET}}}$	0.017***	-0.028***	-0.024***	-0.015***
z-stat	[4.308]	[-3.607]	[-4.008[	[-2.750]
Matches	1,187	1,187	1,187	1,187
Panel B3: PPOET				
	Cash	NBL	NML	EI
$\text{ATT}_{\text{GEXP}^{\perp}_{\text{PPOET}}}$	0.011**	-0.013*	-0.008	-0.0167***
z-stat	[2.584]	[-1.652]	[-1.303]	[-2.920]
Matches	1,166	1,166	1,166	1,166

Table B-I: Summary Statistics

The table presents summary statistics for key temperature shock measures estimated using temperature data from the University of Delaware. The sample period spans 21 years starting in 1997 and ending in 2017. To calculate temperature shock measures in our analysis of CRA data for small firms, we follow Goddard Institute of Space Studies (GISS) at NASA and choose 1951-1980 as the temperature reference period. Let $\mathsf{T}_{\tilde{c}mt}$ denote observed temperature for county in month *m* of year *t*, $\mu_{\tilde{c}mt}$ denote county-month specific rolling window (window size = 10) mean temperature in year t, $\mu_{\tilde{c}m,51\ \ 80}$ represents county-month specific mean temperature estimated over chosen reference period and $\mathsf{T}^{99^{th}}_{\tilde{c}m,51\ \ 80}$ denotes county-month specific 99^{th} percentile of temperature distribution observed over reference period.*Change in Mean Temperature* is a measure of shift in mean of temperature distribution and equals $\frac{1}{12}\sum_{m=1}^{12}[\mu_{smt} - \mu_{\tilde{c}m,51\ \ 80}]$. *'NPPOET'* is 36-month moving average (observed in December each year) of dichotomous variable that equals 1 (0 otherwise) if $\mathsf{T}_{\tilde{c}mt}$ exceeds $\mathsf{T}^{99^{th}}_{\tilde{c}m,51\ \ 80}$. *'PPOET'* is 36-month moving average (observed in December each year) of a dichotomous variables that equals 1 (0 otherwise) if $\mathsf{T}_{\tilde{c}mt}$ exceeds the 99^{th} percentile implied by normal distribution with mean $\mu_{\tilde{c}m,51\ \ 80}$ and standard deviation $\sigma_{\tilde{c}m,51\ \ 80}$. Note that the calculations of means and standard deviations are state-month specific to minimize the effects of seasonalities and geography.

Variable	N	Mean	SD			Min	p10	p25	p50	p75	p90	Max
			Overall	Between	Within							
Distance	67,011	11.917	4.862	4.862	0.000	0.393	5.344	8.506	12.101	15.409	17.926	29.744
$\mathrm{CIMT}_{\tilde{c}t}$ (°C)	67,011	0.238	0.365	0.299	0.209	-1.587	-0.195	0.014	0.227	0.451	0.675	3.300
$\mathrm{NPPOET}_{\tilde{c}t}$	67,011	0.045	0.054	0.032	0.043	0.000	0.000	0.000	0.028	0.056	0.083	0.944
$\mathrm{PPOET}_{\tilde{c}t}$	67,011	0.024	0.043	0.024	0.036	0.000	0.000	0.000	0.000	0.028	0.056	0.889

Table B-II: Small Businesses and Small Loan Size

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. This table is based on all loans of amount less than or equal to $100,000$ dollars. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{cbt}$					Loan Decrease$_{cbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.286***	-0.196**	-0.397***	-1.372***	-2.354**	0.143***	0.074	0.210***	0.638***	1.351***
	[-5.754]	[-2.123]	[-4.191]	[-4.069]	[-2.769]	[4.905]	[1.610]	[4.229]	[3.892]	[3.228]
R^2	0.123	0.183	0.177	0.209	0.251	0.147	0.201	0.198	0.221	0.262
Panel B										
NPPOET$_{cbt-1}$	-1.648***	-1.411***	-1.832***	-6.211***	-9.838***	0.679***	0.371	1.029***	2.441***	6.388***
	[-6.738]	[-3.446]	[-4.784]	[-4.568]	[-3.066]	[4.662]	[1.489]	[4.502]	[3.236]	[3.115]
R^2	0.123	0.184	0.177	0.209	0.251	0.147	0.201	0.198	0.220	0.262
Panel C										
PPOET$_{cbt-1}$	-1.405***	-1.319**	-1.256***	-6.204***	-18.008***	0.701***	0.520	0.955***	2.539**	8.717**
	[-4.347]	[-2.028]	[-2.902]	[-3.163]	[-3.287]	[3.445]	[1.430]	[3.344]	[2.203]	[2.703]
R^2	0.123	0.183	0.177	0.208	0.251	0.146	0.201	0.198	0.220	0.261
N	63,716	16,125	22,314	16,315	7,597	63,716	16,125	22,314	16,315	7,597
Bank Size Class (billons)	All	< =1	(1, 10]	(10, 100]	> 100	All	< =1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table B-III: Small Businesses and Medium Loan Size

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. This table is based on all loans of amount greater than $100,000$ dollars and less than or equal to $250,000$ dollars. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.333***	-0.142*	-0.608***	-1.102***	-2.578***	0.192***	0.059	0.331***	0.630***	1.765***
	[-6.960]	[-1.655]	[-6.923]	[-3.753]	[-3.299]	[6.531]	[1.124]	[6.233]	[3.514]	[3.743]
R^2	0.121	0.193	0.175	0.229	0.267	0.144	0.214	0.199	0.261	0.267
Panel B										
NPPOET$_{cbt-1}$	-1.483***	-0.860**	-2.205***	-3.878***	-9.968***	0.796***	0.254	0.936***	2.316***	8.698***
	[-6.136]	[-2.102]	[-4.999]	[-3.131]	[-4.014]	[5.204]	[0.932]	[3.283]	[2.686]	[4.941]
R^2	0.120	0.193	0.173	0.226	0.265	0.143	0.214	0.197	0.260	0.266
Panel C										
PPOET$_{cbt-1}$	-0.858***	0.407	-1.856***	-4.178**	-18.546***	0.498**	-0.487	0.564	3.056**	15.923***
	[-2.751]	[0.769]	[-3.334]	[-2.200]	[-2.937]	[2.448]	[-1.301]	[1.596]	[2.097]	[3.609]
R^2	0.119	0.193	0.172	0.225	0.266	0.143	0.214	0.197	0.260	0.266
N	41,106	11,972	14,373	8,822	4,898	41,106	11,972	14,373	8,822	4,898
Bank Size Class (billons)	All	< =1	(1, 10]	(10, 100]	> 100	All	< =1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table B-IV: Small Businesses and Large Loan Size

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. This table is based on all loans of amount greater than $250,000$ dollars. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.510***	-0.258***	-0.858***	-1.586***	-3.678***	0.269***	0.163***	0.425***	0.733***	1.479**
	[-10.890]	[-3.494]	[-10.327]	[-4.045]	[-4.625]	[9.486]	[3.415]	[8.563]	[2.950]	[2.128]
R^2	0.121	0.187	0.186	0.206	0.259	0.143	0.206	0.210	0.239	0.266
Panel B										
NPPOET$_{cbt-1}$	-2.472***	-1.564***	-3.071***	-8.664***	-18.324***	1.257***	0.793***	1.506***	3.463***	9.009***
	[-9.767]	[-3.733]	[-7.417]	[-5.231]	[-4.320]	[8.110]	[2.801]	[5.923]	[3.561]	[3.096]
R^2	0.120	0.187	0.182	0.206	0.258	0.143	0.206	0.208	0.239	0.266
Panel C										
PPOET$_{cbt-1}$	-2.045***	-1.063*	-2.959***	-8.101***	-29.067***	1.155***	0.778**	1.390***	3.603**	17.814***
	[-6.296]	[-1.741]	[-5.546]	[-3.769]	[-3.207]	[5.556]	[1.993]	[4.108]	[2.403]	[4.487]
R^2	0.118	0.186	0.180	0.203	0.258	0.142	0.206	0.207	0.238	0.268
N	44,187	12,162	15,652	10,044	5,170	44,187	12,162	15,652	10,044	5,170
Bank Size Class (billons)	All	<=1	(1, 10]	(10, 100]	> 100	All	<=1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table B-V: Small Businesses in Low Income Regions

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. In this table, we form cohorts using counties with income less than or equal of 50 percent of median household income in the US. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort c from bank b in year t. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.669***	-0.025	-0.669***	-3.011***	-3.611***	0.216***	-0.038	0.244***	0.974***	1.499**
	[-6.474]	[-0.098]	[-3.487]	[-6.277]	[-3.486]	[5.307]	[-0.436]	[3.341]	[5.230]	[2.386]
R^2	0.161	0.257	0.248	0.284	0.310	0.163	0.269	0.248	0.299	0.289
Panel B										
NPPOET$_{cbt-1}$	-3.952***	-2.007	-2.919***	-12.079***	-18.466***	1.154***	0.413	0.741*	3.447***	8.456***
	[-6.717]	[-1.484]	[-2.894]	[-5.758]	[-5.180]	[5.059]	[0.827]	[1.910]	[4.074]	[3.821]
R^2	0.161	0.258	0.247	0.278	0.309	0.163	0.270	0.247	0.295	0.289
Panel C										
PPOET$_{cbt-1}$	-4.411***	-0.572	-5.218***	-11.972***	-27.433**	1.319***	1.044	1.291**	3.284***	12.537*
	[-5.286]	[-0.288]	[-3.257]	[-3.693]	[-2.570]	[4.001]	[1.360]	[1.992]	[2.730]	[1.926]
R^2	0.160	0.257	0.248	0.274	0.308	0.162	0.270	0.248	0.293	0.288
N	24,631	4,061	8,308	7,264	4,226	24,631	4,061	8,308	7,264	4,226
Bank Size Class (billons)	All	<=1	(1, 10]	(10, 100]	> 100	All	<=1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table B-VI: Small Businesses in Moderate Income Regions

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. In this table, we form cohorts using counties with income greater than 50 or less than or equal of 80 percent of median household income in the US. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.625***	-0.402***	-1.134***	-1.553***	-4.328***	0.182***	0.082*	0.378***	0.757***	2.249***
	[-7.679]	[-2.749]	[-7.722]	[-3.572]	[-4.905]	[5.662]	[1.837]	[6.680]	[4.214]	[4.255]
R^2	0.126	0.196	0.185	0.217	0.250	0.146	0.206	0.211	0.250	0.275
Panel B										
NPPOET$_{cbt-1}$	-3.770***	-2.548***	-5.046***	-9.277***	-15.711***	1.019***	0.296	1.695***	4.025***	8.310***
	[-7.986]	[-3.535]	[-6.087]	[-4.375]	[-4.093]	[5.885]	[1.152]	[6.163]	[4.638]	[4.192]
R^2	0.126	0.196	0.183	0.217	0.248	0.146	0.206	0.210	0.250	0.273
Panel C										
PPOET$_{cbt-1}$	-3.547***	-2.968***	-4.523***	-6.813***	-20.824***	0.860***	0.540	1.546***	3.224***	11.286***
	[-6.036]	[-3.402]	[-4.063]	[-2.723]	[-2.800]	[3.688]	[1.323]	[4.147]	[2.771]	[3.132]
R^2	0.125	0.195	0.180	0.214	0.248	0.145	0.206	0.208	0.248	0.273
N	44,158	10,219	15,083	11,816	6,118	44,158	10,219	15,083	11,816	6,118
Bank Size Class (billons)	All	< =1	(1, 10]	(10, 100]	> 100	All	< =1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table B-VII: Small Businesses in Middle Income regions

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. In this table, we form cohorts using counties with income greater than 80 or less than or equal of 120 percent of median household income in the US. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.561***	-0.344***	-0.898***	-2.080***	-4.445***	0.247***	0.146***	0.368***	0.713***	2.078***
	[-8.217]	[-3.234]	[-7.081]	[-3.545]	[-3.987]	[8.697]	[3.450]	[6.749]	[5.054]	[4.092]
R^2	0.111	0.180	0.157	0.184	0.212	0.139	0.193	0.192	0.207	0.245
Panel B										
NPPOET$_{cbt-1}$	-2.941***	-2.224***	-3.301***	-10.750***	-19.775***	1.122***	0.797***	1.218***	3.327***	8.703***
	[-8.537]	[-4.293]	[-5.659]	[-3.944]	[-4.405]	[7.273]	[3.305]	[4.583]	[4.795]	[4.407]
R^2	0.111	0.180	0.155	0.183	0.211	0.138	0.193	0.191	0.207	0.244
Panel C										
PPOET$_{cbt-1}$	-2.691***	-1.663**	-3.017***	-11.493***	-41.349***	1.138***	0.598*	1.104***	3.728***	19.183***
	[-5.821]	[-2.220]	[-4.053]	[-2.824]	[-3.901]	[5.577]	[1.858]	[3.179]	[4.021]	[3.623]
R^2	0.110	0.179	0.154	0.182	0.212	0.138	0.192	0.190	0.206	0.245
N	65,490	16,089	23,308	17,000	7,657	65,490	16,089	23,308	17,000	7,657
Bank Size Class (billons)	All	<=1	(1, 10]	(10, 100]	> 100	All	<=1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table B-VIII: Small Businesses in Upper Income Regions

The table presents results of baseline specification extended to the Community Reinvestment Act (CRA) dataset. In this table, we form cohorts using counties with income greater than 120 percent of median household income in the US. The dependent variables are 'ΔVolume' in columns (1) - (4), 'Loan Decrease' in column (5)-(8) and 'ΔSpread' in column (9) - (12). ΔVolume is defined as the log growth in amount lent by a bank to a cohort. Loan Decrease is a dichotomous variable that equals 1 if ΔVolume < 0, and 0 otherwise. The observation is at the cohort(c)-bank(b)-year(t) level. The independent variables are lagged values of *CIMT* (Panel A), *NPPOET* (Panel B) and *PPOET* (Panel C). The county level independent variable, say X, is aggregated to the cohort-bank-year level as following: $X_{cbt} = \sum_{\tilde{c}} \frac{L_{\tilde{c}cbt}}{L_{bt}} X_{\tilde{c}t}$ where $L_{\tilde{c}cbt}$ represent loan amount to county $\tilde{c}$ in cohort *c* from bank *b* in year *t*. The sample period is 1997 - 2017. All regression specifications include Cohort Bank and Cohort Year fixed e□ects. The standard errors are clustered by bank, and t-statistics are presented in square brackets, [ ]. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Dependent Variable									
	ΔVolume$_{sbt}$					Loan Decrease$_{sbt}$				
Panel A										
CIMT$_{cbt-1}$	-0.596***	-0.639***	-0.845***	-2.143***	-3.382***	0.239***	0.231***	0.349***	0.921***	1.944***
	[-9.195]	[-5.079]	[-7.404]	[-4.058]	[-4.804]	[8.842]	[5.087]	[6.852]	[4.400]	[5.059]
R^2	0.116	0.184	0.169	0.185	0.222	0.141	0.210	0.202	0.213	0.249
Panel B										
NPPOET$_{cbt-1}$	-3.318***	-4.158***	-3.051***	-10.498***	-16.246***	1.279***	1.193***	1.338***	4.505***	9.751***
	[-9.195]	[-6.293]	[-5.535]	[-5.888]	[-5.200]	[8.562]	[4.682]	[5.305]	[5.262]	[6.532]
R^2	0.116	0.185	0.167	0.185	0.222	0.141	0.210	0.201	0.212	0.249
Panel C										
PPOET$_{cbt-1}$	-2.827***	-3.961***	-2.607***	-10.362***	-26.373***	1.167***	1.217***	1.190***	4.407***	16.044***
	[-6.311]	[-4.517]	[-3.584]	[-3.729]	[-4.748]	[5.890]	[3.617]	[3.497]	[3.409]	[6.006]
R^2	0.114	0.183	0.166	0.183	0.222	0.140	0.209	0.200	0.211	0.249
N	54,386	12,441	18,910	14,873	6,947	54,386	12,441	18,910	14,873	6,947
Bank Size Class (billons)	All	< =1	(1, 10]	(10, 100]	> 100	All	< =1	(1, 10]	(10, 100]	> 100
Cohort Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE Clustered by	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

Table C-I: Additional Validation Test

In this table we present an additional validation test of temperature shock measures used in this study. We perform a textual analysis of firms' 10-K filings submitted to the SEC. Specifically, we search for the phrases: 'climate change', 'green house gases', 'global average temperature' 'global warming', 'intense weather', 'intergovernmental panel on climate change', 'IPCC', 'Kyoto Protocol', 'the Paris Accord', and 'rising sea level'. We perform simple OLS regressions in which the dependent variable called *Mention* is a dichotomous variable that equals 1 if a firm mentions at least one the searched phrases, and equals 0 otherwise. In columns (1)-(3), we include all firms. In columns (4)-(6), we exclude firms that below to three industry classifications: Coal, Petroleum and Natural Gas, and Utilities. The nature of operations of these industries will make firms in these industries more likely to mention searched phrases. The standard errors are clustered by state. Significance levels: * p < 0.10, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Mention (1 = Yes, 0 = No)					
Variables	All Industries			All Industries (excluding Coal, Utilities, and Petroleum)		
CIMT_{st}	0.199***			0.164***		
	[4.750]			[6.631]		
NPPOET_{st}		0.250			0.510**	
		[0.907]			[2.414]	
PPOET_{st}			0.345			0.641*
			[0.686]			[1.803]
N	21,120	21,120	21,120	16,982	16,982	16,982
R^2	0.041	0.001	0.001	0.033	0.008	0.006
SE Clustered by	State	State	State	State	State	State