Extreme Weather and Low-Income Household Finance: Evidence from Payday Loans ⋆

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Abstract

This paper explores the impact of extreme weather exposures on the financial outcomes of low-income households. Using a novel dataset comprising individual-level payday loan applications and loan-level information, we find that both extreme heat and cold days lead to surges in payday loan demand. Extra extreme heat days result in an increase in delinquency and default rates and a reduction of total credit issued, indicating a contraction in loan supply. The effects are especially noticeable for online payday loans. Our findings highlight the heightened financial vulnerability of low-income households to environmental shocks and underscore the need for targeted policies.

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1. Introduction

Extreme temperature events such as heat waves are significantly increasing in both frequency and length in the United States (EPA, 2022). There are many reasons why low-income households may face additional financial hardship during extreme temperature days due to unequal exposure (Barreca, Park, and Stainier, 2022; Benz and Burney, 2021), resulting in lost wages, health issues with associated medical costs, inadequate emergency funds, outdated infrastructure and appliances, higher energy bills, and limited knowledge of available insurance options. Our paper investigates the financial implications of these challenges on low- to middle-income households using a novel dataset on payday loans, the most popular alternative credit product used for short-term liquidity by these income groups.

We investigate the causal effects of extreme temperatures on payday loan market outcomes. Our individual-level dataset covers both storefront and online payday loan applications. We explore the impact of extreme weather days on a variety of payday loan market outcomes, including the number of inquiries, credit approval, default, and delinquency rates. The results shed light on both how *demand for* and *access to* alternative credit products for low-income households are affected by extreme temperature events. We find that having more extreme temperature days increases the demand for payday loans but decreases the total credit issued. Additionally, we show that the negative impact on vulnerable households can be amplified through potentially disastrous debt cycles, featuring increasing delinquency and default rates.

Our study complements an emerging literature on the impacts of natural disasters on household finance (Del Valle, Scharlemann, and Shore, 2022; Gallagher and Hartley, 2017; Gallagher, Billings, and Ricketts, 2020). Using data from consumer credit panels, student loans, and credit card transactions, these studies find that spikes in credit card borrowing after natural disasters are modest and short-lived, and that households ultimately reduce their total debt due to their use of insurance to repay their debts rather than to rebuild. Our paper makes two significant departures. First, the literature so far has focused on large natural disasters, which are associated with Federal Emergency Management Agency (FEMA) declarations and subsequent aid programs. In contrast, we examine extreme temperature days, which do not lead to any FEMA declaration. Extreme temperature events tend to occur more frequently than major natural disasters like earthquakes and volcanic eruptions and can affect vast areas, impacting large populations and extensive agricultural zones. Repeated extreme weather events can cause incremental damage. As we show below, they also lead to sizable and significant deterioration of household financial health. Second, existing studies on climate change and household finance offer limited evidence on low-income households. This is partly because previous studies use traditional credit sources, such as credit cards, and hence miss the impacts on individuals who lack access to credit card lines.[1] These marginalized, overwhelmingly low-income households are more likely to suffer the most financially from extreme temperature days.

To overcome the data challenges mentioned above, we use two unique payday loan datasets from *Clarity*.[2] Our first applicant-level dataset includes 1 million consumers randomly selected from Clarity's database between 2012 and 2019. It provides comprehensive information on application date, income, age, ZIP code of residence, among other things. For the same group of borrowers, we have a second loan-level dataset that contains rich information on approved loan characteristics, including highest credits, maturation, delinquency, and default dates. To construct daily weather outcomes, we use satellite-based data from ERA5-Land. It contains the daily temperature and precipitation with $0.1^\circ \times 0.1^\circ$ horizontal resolution covering the continental United States from 2012 to 2019. We merge the ERA5-Land climate data with payday lending market outcomes at the Census ZIP Code Tabulation Area (hereafter ZCTA) by month level. The resulting measures of ZCTA-level weather exposure capture variation across both ZCTA and calendar year-month periods.

[1] For example, Miller and Soo (2021) show that low-income households are more likely to use high-interest credit products like payday loans and have limited access to formal credit.

[2] Clarity is an agency that specializes in alternative financial services data as part of the major credit reporting agency, Experian.

We adopt a fixed effects temperature-bin approach, a well-established empirical design in the climate economy literature[3] to causally identify the impact of extreme weather days on payday loan market outcomes. The main independent variable counts the number of days with daytime (between 8am and 8pm) mean temperature falling into different temperature bins.[4] Our empirical design controls for a rich set of fixed effects that may correlate with extreme weather days, allowing us to identify the marginal effects of extreme heat and cold days relative to the local average. We first examine the impact on payday loan demand and credit approval. We then explore how extreme temperature exposure affects the performance of existing payday loan accounts. Finally, we differentiate between the impact of extreme temperature days on online versus storefront payday loan markets.

There are three main transmission mechanisms through which extreme weather days can affect individual demand and repayment for payday loan products. First, extreme weather days may decrease labor income (Colmer, 2021; Graff Zivin and Neidell, 2014; Heal and Park, 2016), potentially increasing payday loan demand and default rate. Second, energy costs, adopting heating or cooling devices, and health expenditure needs rise with extreme weather shocks, which could also increase payday loan demand (Deschenes, 2022; Zivin and Shrader, 2016; Park, Pankratz, and Behrer, 2021).[5] We evaluate the income versus expenditure channels by including borrower income as a control or not. Conversely, the third mechanism suggests that extreme weather might deter individuals from accessing payday loans. For example, extreme weather may affect transportation (Roth Tran, 2023), making it challenging for households to visit a payday loan storefront in person, thereby diminishing

[3]For example, Deschênes and Greenstone (2007); Graff Zivin and Neidell (2014); Barreca et al. (2016); Cohen and Dechezleprêtre (2022).

[4]Figure 1 depicts the average annual distribution of daytime mean temperatures across 16 temperature bins over the 2012–2019 period. We refer to days with daytime mean temperature above 33°C as *extreme heat* days. Around 2.5% ZCTA-day observations in our sample are "extreme heat days" by this definition. Similarly, we refer to days with daytime mean temperature below -9°C as *extreme cold* days. Around 1.0% ZCTA-day observations in our sample are "extreme cold days" by this definition.

[5]According to Woolf et al. (2023), heat event days are responsible for almost 235,000 emergency department visits and more than 56,000 hospital admissions for heat-related or heat-adjacent illness, adding approximately $1 billion in health care costs each summer.

overall applications. We provide empirical evidence on this channel by comparing storefront payday loans with online payday loans.

We find that having more extreme temperature days in a month increases payday loan demand. Total inquiries for payday loans significantly increase with more extreme heat or cold days. One extra extreme heat day (with daytime mean temperature above 33°C) is associated with a 0.009 increase in inquiries, while one extra extreme cold day (with daytime mean temperature below -9°C) is associated with a 0.011 increase in inquiries. In other words, one standard deviation increase in the number of extreme heat days leads to about a 0.4% increase in total inquiries relative to the baseline. This impact is consistent with several potential channels, such as extreme temperature days lowering household income and/or increasing household expenditure on health- or energy-related costs.

Next, we examine the impact of extreme weather on credit issuance and the performance of existing loans in payday loan markets. We find asymmetric effects of extreme heat and cold days. Extreme heat days significantly reduce total credit issued and accounts opened. In particular, one extra extreme heat day is associated with a 0.4% drop in credit issued. Having more extreme heat days in a month also leads to deteriorating performances of existing payday loans, as we observe significant increases in delinquency and default rates. However, extreme cold days do not affect the credit issuance or performance of existing payday loan accounts. Taken together, our results suggest that payday loan lenders reduce credit supply during extreme heat days out of concern for an increase in default and delinquency rates.

Furthermore, we document the asymmetric effects of extreme heat and cold days on labor incomes. We show that extreme heat days negatively affect income, whereas extreme cold days do not. The decline in borrower quality during extreme heat days is consistent with our observations of reducing credit supply and worsening loan performance. Our main results are robust to multiple sensitivity checks. For example, we show that using alternative definitions of temperature bins, including lags of the dependent variables, or using a balanced panel to address selection does not affect our results.

We then explore heterogeneity in payday loan markets over several dimensions. First, we distinguish between the storefront and online payday loan markets. Correia, Han, and Wang (2022) show that online loans are associated with higher default rates and, as a result, higher premiums. We find that the impact of extreme temperature days operates more through changes in online payday loan markets. In particular, for online payday loan borrowers, we observe increases in their inquiries, delinquency, and default rates, with decreases in accounts opened and credit issued with more extreme heat days. In contrast, storefront payday loan outcomes do not respond significantly to extreme temperature days. One potential explanation is that the accessibility and ease of application of the online payday loan market may make it more sensitive to changes in temperature and weather conditions. Finally, we examine the distributional effects across ZCTAs. Our estimates suggest that counties with higher population shares of Hispanics, who are predominantly involved in outdoor work, see larger increases in demand and larger decreases in total credits for payday loans with more extreme heat days.

We extend our analysis to include alternative subprime credit, including rent-to-own, installment, and auto loans. Borrowers of these subprime alternative credits take out larger amounts of credit and bear more negative consequences for their creditworthiness in case of defaults. We show that extreme heat days increase *demand* for subprime alternative credits without negatively impacting credit supply or delinquency rates, suggesting different impacts of extreme weather exposures across loan types.

Our paper makes three contributions. First, we add to the growing literature on alternative credit markets. Payday loans are a controversial source of liquidity for low- to middle-income customers (Allcott et al., 2022; Gathergood, Guttman-Kenney, and Hunt, 2019). Payday loan borrowers pay higher interest rates and often struggle to repay the loan on time, leading to loan renewal and a cycle of accumulating interest and fees, resulting in persistent debt.[6] Mostly based on geographic variation in regulations of and access to payday loans, a large literature finds mixed results on the effects of payday loans on consumers (Bhutta, Skiba, and Tobacman, 2015; Dobridge, 2018; Di Maggio, Ma, and Williams, 2021; Melzer, 2011, 2018; Miller and Soo, 2021; Morse, 2011; Skiba and Tobacman, 2019).[7] Instead of evaluating the impact of payday loan access, our payday application and payday transaction data allow us to directly assess the impact of extreme temperatures on payday loan performance. Our study illustrates that extreme weather exposures, particularly extreme heat days, significantly worsen the performance of existing payday loan accounts. The impact operates through online payday loan markets.

Second, our paper adds to the recent literature that examines the impact of environmental shocks and household finance. Previous work examines how natural disasters and the transition away from fossil fuels affect households in traditional credit markets (Blonz, Tran, and Troland, 2023; Del Valle, Scharlemann, and Shore, 2022; Gallagher and Hartley, 2017; Gallagher, Billings, and Ricketts, 2020). We add to this work by focusing on alternative credit products used by lower-income households. The payday loan applicant- and loan-level datasets we use allow us to distinguish between the *demand for, access to, and performance of* payday loan market products. Although existing work finds that spikes in credit card borrowing after natural disasters are modest and short-lived, we show that payday loan markets may operate differently. With more extreme heat days, lower-income households have a higher demand for payday loan credits while facing tightened credit supply and higher delinquency rates.

Our paper also contributes to the literature documenting various impacts of extreme temperature exposures in the United States, including health, employment, time use, school learning, and firm sales, among others (Deschênes and Greenstone, 2011; Wilson, 2019;

[6] Burke et al. (2014) find that four out of five payday loans are rolled over or renewed within 14 days. Their study also shows that most payday loans are issued to borrowers who renew their loans so many times that they end up paying more fees than they originally borrowed.

[7] Fonseca (2023) exploits the time-series variation in the state-level debt collection restrictions and finds that restricting collections reduces access to mainstream credit and increases payday borrowing.

Graff Zivin and Neidell, 2014; Park et al., 2020; Addoum, Ng, and Ortiz-Bobea, 2020).[8] Our analysis shows that extreme temperature exposure, particularly heat stress, also has significant implications for the financial well-being of lower-income households who rely on alternative credit products.

The rest of the paper is organized as follows: Section 2 discusses the relevant background and data. Section 3 describes our research design and presents the main results on payday loan market outcomes. Section 4 offers several extensions. Section 5 concludes. The appendix provides further details.

2. Background and data

In this section, we present several unique datasets used in our analysis. Section 2.1 discusses the background of the U.S. payday loan industry and our payday loan dataset. Section 2.2 presents satellite-based climate data we constructed on temperature and precipitation. Section 2.3 introduces the background of the Low-Income Home Energy Assistance Program and its related dataset.

2.1. Payday loan

Payday loans are a short-term source of liquidity used by low- to middle-income individuals. Typically, the lender advances the borrower \$100 to \$500 in return for a postdated check, timed to coincide with the borrower's next paycheck. Loans usually have two- to four-week maturities. While payday loans provide flexibility in smoothing consumption over time, they can also impose a substantial burden. The fees can be as high as \$15 to \$20 per \$100 principal balance, equivalent to a 400 to 600 annual percentage rate (APR).

There are many reasons why individuals might borrow payday loans despite the outrageous interest rates. About 3% of respondents in the Survey of Consumer Finances indicated that they had taken payday loans. The top reasons for choosing payday loans include emer-

[8] See Dell, Jones, and Olken (2014) for a review of the literature.

gency needs, convenience, and to pay other bills or loans. A significant fraction of respondents take payday loans to pay medical bills or utilities.[9]

We use lender-reported payday loans from Clarity, an agency that specializes in alternative financial services data as part of the major credit reporting agency Experian. Two samples are involved in our analysis.[10] The first is an applicant-level dataset, known hereafter as the random *Clarity* sample, consisting of 1 million consumers randomly drawn from Clarity's database from 2012 to 2019. Each individual comes with a unique applicant ID. For each inquiry, we observe self-reported information obtained during the application process, including state and ZIP code of residence, income, pay frequency, age, homeowner indicator, months of residence in current address, and whether this application takes place online or in a storefront. The second is a loan-level dataset known as the *tradeline* sample, which consists of approved loans from 2013 to 2019. For each loan, we observe loan characteristics such as origination, maturation and delinquency dates, loan size, and amount past due. The applicant/borrower IDs from the two datasets are linked one-to-one. However, we do not have a linkage between the application and approval loan at the record level. Though payday loan lending may require identification, a recent bank account statement, or a recent pay stub (or verification of other income), the information reported in inquiries is self-reported by borrowers and may not be verified (Correia, Han, and Wang, 2022).

Out of 1 million unique borrowers who submitted an inquiry for any type of subprime credit, approximately one-third inquired about payday loans and the rest were for other products such as installment loans. We focus on payday loans in this study. We follow the approaches in Correia, Han, and Wang (2022) to clean the data, validate, and construct the panel. We convert ZIP codes to ZCTA using crosswalks from the U.S. Census. Appendix Figure B.1 shows the geographical distribution of online and storefront borrowers across the U.S. by state.

[9] See Appendix A.1 for a more detailed discussion.

[10] The same dataset has been used in Fonseca (2023); Correia, Han, and Wang (2022).

We construct two variables to measure the demand for payday loans at the ZCTA level. The first variable is *total inquiries*. It is calculated as the total inquiries made by all individuals who reside in each ZCTA each month. This includes cases where an applicant submits multiple inquiries per day. We define a second variable called *unique inquiries*. It is calculated as the total number of unique individuals making inquiries residing in each ZCTA for each month. Thus, individuals who make inquiries multiple times in a single day or across multiple days in a single month will be counted as one unique inquiry.

We use two measures to proxy payday loan performance: *delinquency rate* and *default rate*. We identify a loan as delinquent if it has a non-missing delinquency date. We identify a loan as in default if it has a non-zero past due amount. The monthly ZCTA-level delinquency rate and default rate are thus defined as the percent of loans that are delinquent or default, respectively.

Table 1 provides summary statistics for the full sample in Panel A and the online as well as the storefront payday loan subsamples in Panel B and Panel C, respectively. Our sample consists of about 2.4 times total accounts open in the online market relative to the storefront. In our analysis, we winsorize the top and bottom 1% of credit- and income-related variables to reduce the effects of extreme outliers. On average, about 1.7 accounts are opened in one ZCTA each month. The medium loan amount is \$475, with \$500 from storefront lenders and \$400 from online lenders, respectively. The delinquency rate is on average 8.7% and the default rate is 7.3%.

Our study mainly focuses on low- and middle-income borrowers. In our full sample, the median monthly income is \$2,500, with the 75th percentile at \$3,300. In comparison, the 2015 American Community Survey reported a U.S. median household average monthly income of \$4,491 and \$6,663 for married couples. The storefront payday loan applicant data show lower incomes, with a median of only \$1,494 and a 25th percentile of \$921, which is lower than the \$1,000 poverty threshold for a single-person household in 2015.[11]

[11] https://www.census.gov/library/publications/2016/demo/p60-256.html

2.2. Weather Data

Data on temperature and other weather outcomes are from ERA5-Land, which measures atmospheric variables with enhanced spatial resolution based on the ERA5 climate reanalysis data provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). We obtain daytime mean temperature and precipitation with $0.1° \times 0.1°$ horizontal resolution.

To construct monthly weather variables for each ZCTA, we use the ERA5 grid point closest to the ZCTA centroid. Allowing for non-linear effects, $Tempbin_{m,t}^{k}$ counts the number of days in a month in which the daytime (between 8am and 8pm local time) average temperature falls within the specified range k. For our baseline specification, we construct 16 temperature bins: below $-9°$C, above 33°C, and 14 bins for every 3°C in between.[12] We also include monthly average precipitation data as controls, where daily precipitation is measured as depths in meters of cumulative precipitation in a day. In the empirical models presented hereafter, we use the same temperature bins to estimate the relationship between temperature and the payday loan market and use precipitation as a control variable.

Figure 1 highlights that daytime mean temperatures below -9°C or above 33°C represent very extreme temperatures in our sample. The bars in Figure 1 represent the average annual distribution of daytime mean temperatures across 16 temperature bins over the 2012–2019 period. The height of each bar corresponds to the mean number of days of exposure per year for the average person. Using all ZCTAs of the continental U.S. and all the months, the average person is exposed to about 8.7 days annually with daytime temperatures below -9°C, and 4.3 days where daytime temperatures exceed 33°C. One standard deviation in extreme heat days where daytime temperatures exceed 33°C is around 2 days. Our payday sample only covers a portion of all ZCTAs, since not every ZCTA reports payday loans every month. Within the scope of ZCTAs that report payday loans, which comprises 159

[12] As robustness checks, we also use other temperature definitions to construct temperature bins, such as daily maximum temperature or 24-hour mean temperature. Table 2 presents the summary statistics of daily daytime mean, 24-hour mean, and daily maximum temperatures of ZCTAs with payday loan inquiries during 2012–2019. The top and bottom 1 percentile of daytime mean temperatures are 34°C and $-9°$C, respectively.

days annually, the average person in this sample is exposed to about 1.6 days per year with daytime temperatures falling below -9°C, and 3.2 days where the daytime temperature exceeds 33°C.

Figures 2a and 2b illustrate the spatial distribution of extreme weather shocks. For each ZCTA, we average the monthly number of days that had daytime mean temperatures below -9°C and above 33°C. Extreme heat days occur in southern ZCTAs along the sunbelt states. The hottest ZCTA in the 95th percentile experienced on average 2 days per month where the daytime mean temperature was above 33°C. Extreme cold weather concentrates in the northern ZCTAs. The coldest ZCTA in the 95th percentile experienced on average 3 days per month with daytime mean temperatures below -9°C. Lastly, Appendix Figure B.2 presents the spatial distribution of the daytime mean temperatures across ZCTAs, averaged over the sample period. From the years 2012 to 2019, the national average of daytime mean temperature is around 15°C. ZCTAs in the 90th percentile of the temperature distribution have a daytime mean temperature of around 21.5°C, while ZCTAs in the 95th percentile have a daytime mean temperature of 23°C.

2.3. LIHEAP program

During extreme weather conditions, energy costs surge, leading to subsequent increases in utility bills. Low-income households are particularly vulnerable to these price fluctuations, especially in relation to weather-related energy expenses. In fact, one of the reasons that households resort to payday loans is to pay bills.

To address these challenges, the Low Income Home Energy Assistance Program (LIHEAP)[13] plays a crucial role in providing support to eligible low-income households. LIHEAP offers a range of assistance programs, including addressing heating and cooling energy costs, providing bill payment assistance, offering aid during energy crises, facilitating weatherization efforts, and supporting energy-related home repairs.[14] In most cases, approved

[13] See `https://www.liheap.org/`.

[14] See Appendix A.2 for more details on the LIHEAP program.

households won't receive payment directly. LIHEAP almost always pays grants directly to the energy utility.

We assess whether access to LIHEAP can effectively reduce the need for payday loans among eligible households. Eligible households for this program must meet certain criteria under federal guidelines. LIHEAP eligibility criteria vary across states and are subject to annual changes. Specifically, they must have an income less than 150% of the poverty line or less than 60% of the state's median income, whatever is greater.

We obtained the state median household income and poverty line used by each state each year from the Office of Community Services website.[15] Since household size cannot be observed in the payday loan data, we assume a household size of two. We acknowledge that this assumption inevitably introduces measurement errors in our estimates of the program's effect on reducing payday loan borrowing. In our dataset, approximately 38% of payday loan borrowers fall within the eligible income range. Panels (a) and (b) of Appendix Figure B.3 plot the LIHEAP income eligibility cutoff for single-household families across the U.S. states and the median income of payday loan borrowers in the year 2019.

3. Main empirical results

In this section, we present our main empirical results on how temperature exposures affect payday lending. We first introduce our identification strategy in Section 3.1. We next evaluate the demand channel in Section 3.2 and equilibrium outcomes in Section 3.3. We further investigate the performance of existing accounts in Section 3.4 and examine borrower characteristics in Section 3.5. Finally, we provide several additional robustness checks on our results in Section 3.6.

[15]See https://www.acf.hhs.gov/ocs/policy-guidance/liheap-information-memoranda.

3.1. Methodology

Our primary goal is to identify the effects of temperature exposures on the payday loan market at the ZCTA level. We adopt a non-linear temperature-bin approach using the following form:

$$Outcome_{it} = \theta T_{it} + \mu_t + \eta_{cy} + Controls + \varepsilon_{it}, \tag{1}$$

where $Outcome_{it}$ denotes payday loan-related outcome variables of interest at ZCTA i in month t; θ is a vector of parameters; T_{it} is a vector of climatic variables that we discuss below; μ_t is a year-month fixed effect; η_{cy} is a county-year fixed effect; and ε_{it} is the error term. Standard errors are clustered at the ZCTA level, which is the geographic unit of temperature variations.

The climatic variables in T_{it} include location and time-specific temperature and precipitation measures. We use 16 temperature bins: below -9°C, above 33°C, and 14 bins for every 3°C in between. We choose -3°C–27°C as the omitted baseline daytime (between 8am and 8pm) mean temperature bins. We calculate the number of days in a month that the daytime mean temperature falls within each bin. We also include the monthly average of daily cumulative precipitation to control for any confounding effects from precipitation. In what follows, we refer to days with daytime mean temperature below -9°C as *extreme cold* days and days above 33°C as *extreme heat* days.[16]

Our adoption of the non-linear temperature-bin specification follows the recent climate economy literature (Dell, Jones, and Olken, 2014), motivated by facts related to thermal stress. High temperatures beyond certain thresholds cause worker fatigue and lower task performance. For example, a meta-analysis of ergonomics literature documents that task performance losses start to increase in a non-linear manner at high temperature ranges

[16] In Section 3.6, we use alternative cutoffs for temperature bins based on 24-hour daytime mean temperature or daily maximum temperature and show that the patterns are similar.

(Hancock, Ross, and Szalma, 2007). Other studies also indicate that labor productivity drops significantly as temperature increases.[17] Energy use and utility bills, which increase significantly during hot and cold days, are also non-linear functions of temperature.

Our fixed-effect framework allows us to control for confounding shocks that may correlate with weather variables. To causally identify the effect of temperature exposures on payday loan market outcomes, we include a rich set of fixed effects to control for confounders and rule out spurious relationships. First, we consider seasonality, which may correlate within-year payday loan cycles with temperature fluctuations. Second, a general temperature warming trend may be correlated with national business cycles during this period. To address both concerns, we control for year-month fixed effects. Next, payday loan market outcomes may also be associated with regional business cycles, so we include county-year fixed effects. Our identifying variations are therefore interpreted as weather shocks, exploiting ZCTA-month level temperature deviations from the county-year, year-month averages.

3.2. Do temperature exposures drive demand for payday loans?

We first examine whether temperature exposures affect borrowers' demand for payday loans. We adopt two measures of payday loan demand—total inquiries and unique inquiries—as outcome variables in the regression specification outlined in Equation (1). The left panel of Figure 3 as well as the column (2) of Table 3 provide the estimated impact of a day in six extreme daytime temperature bins on the number of total inquiries, relative to a day with daytime mean temperature falling in the -3°C to 27°C bins. We find strong evidence that total inquiries significantly increase with more extreme heat or cold days. In particular, one extra day with daytime mean temperature above 33°C per month is associated with a 0.009 increase in total inquiries, while one extra day below -9°C is associated with a 0.011 increase in total inquiries in an average ZCTA. In other words, one standard deviation increase in

[17] These include, but are not limited to, evidence from assembly lines, laboratories, meta-analyses, and self-reported surveys: Adhvaryu, Kala, and Nyshadham (2020), Graff Zivin and Neidell (2014), Heal and Park (2020), Niemelä et al. (2002).

the number of extreme heat or cold days per month leads to about a 0.4% increase in total inquiries relative to the baseline.[18]

In general, extreme temperatures lead to higher energy consumption demand and expose households to higher health risks. Such increases in energy costs and health expenditures could directly drive up demand for credit, especially for lower-income households. Extreme weather may also reduce borrowers' incomes, contributing to increases in demand for payday loans. We test the income channel in Section 3.5.

Our results on total inquiries could partially be attributed to a rise in borrowers who make multiple inquiries during extreme temperatures, which might be driven by impulsive decisions, the practice of loan stacking, desperation, or loan denials. To separate from the effects of such behavior, we analyze the impact of temperature exposures on unique inquiries, which measure the number of applicants instead of total applications. The estimation results are shown in the right panel of Figure 3 and in column (3) of Table 3. Echoing the findings on total inquiries, we find similar effects. Specifically, the figure shows that one extra day below -9°C is associated with a 0.002 increase in unique inquiries, and one extra day above 33°C is associated with a 0.003 increase in unique inquiries. Taken together, these results indicate that extreme temperature exposures lead to increasing demand for payday loans.

3.3. Do temperature exposures affect amount of credit issued?

Next, we analyze the impact of extreme temperatures on equilibrium outcomes in payday loan markets. Figure 4 presents results using the total number of accounts open (left panel) and (log) total credit issued (right panel) as outcome variables in specification Equation (1). We find a strong negative relationship between extreme heat days and the number of accounts open. In particular, one extra day above 3°C is associated with a 0.006 decrease in the total number of accounts open in an average ZCTA. In other words, a one standard deviation

[18] In our sample, one standard deviation increase in the number of extreme heat days with daytime temperature above 33°C is around 2 days, and the average baseline total inquiries is around 4.66 days. One standard deviation increase in the number of extreme heat days per month therefore leads to a $0.009 \times 2/4.66 = 0.4\%$ increase in total inquiries relative to the baseline.

increase in the number of extreme heat days per month leads to about a 0.7% increase in accounts open relative to the baseline. Similarly, we find a strong negative relationship between extreme heat days and total credit: one extra day above 33°C is associated with a 0.4% drop in credit issued.

The total number of accounts opened and total amounts of credit issued are jointly determined by credit supply and credit demand. Although payday loan inquiries increase significantly on extreme heat days, equilibrium outcomes suggest a decrease in credit supply during such periods. This contraction in credit supply may be because of two reasons. First, payday lenders tend to screen borrowers from very-low-income backgrounds. We specifically test this income channel in Section 3.5 to see if borrowers' incomes decline during extreme heat days. This may lead to increases in default or delinquency rates that induce payday lenders to reduce credit supply. The following section presents evidence in support of this.

In contrast, we found different effects during extreme cold days. The total number of accounts opened increases by 0.005, but it is still smaller than the increase in total inquiries. There is no significant effect of extreme cold days on the total amount of credit granted. These findings offer suggestive evidence that credit supply is responding to some extent to increased demand during such periods. In contrast to extreme heat days, payday lenders may be less concerned about default or delinquency rates during extreme cold days, as borrowers' incomes might be less affected during extreme cold days.

3.4. Do temperature exposures affect the performance of existing accounts?

We next examine delinquency and default rates associated with extreme weather. Figure 5 reveals that a single extra day with a temperature above 33°C is linked to a 0.09 percentage point increase in delinquency rate and a 0.1 percentage point increase in default rate. In other words, a one standard deviation increase in the number of extreme heat days per month leads to about a 3% increase in default rates relative to the baseline. Our analysis indicates that the effects of temperature exposure on the default and delinquency rates are asymmetric between extreme cold and hot days. Specifically, default and delinquency rates rise during hot days but not during cold days. These findings support our hypothesis that payday lenders reduce credit supply during extreme heat days out of concern for increases in default or delinquency but not during extreme cold days. Overall, our findings suggest that credit supply responds differently to extreme temperature days due to asymmetric impacts on applicant incomes. We investigate this next.

3.5. Do temperature exposures affect applicants' income?

Borrower income plays an important role in both the supply and demand of payday loan lending during extreme temperature days. If extreme weather negatively affects borrower income, we would expect an increase in demand for payday loans. Meanwhile, payday loan lenders may screen borrowers from very-low-income backgrounds, resulting in a contraction in payday loan supply. We regress log of monthly ZCTA average income on the weather exposure measures and other control variables as specified in Equation (1). Figure 6 indicates a negative and statistically significant impact of extreme heat temperature shocks on income. In particular, one extra day with daytime mean temperature above 33°C is associated with a 0.14% decrease in monthly income.

In contrast, we find no significant evidence that extreme cold temperature days affect monthly income. Our finding that cold and hot temperatures have asymmetric effects on income is in line with existing findings.[19] For example, Graff Zivin and Neidell (2014) find that time allocated to labor is reduced with more extreme heat days but is non-responsive at the low end of the temperature distribution.

Despite the importance of the income channel, this is not the only channel through which extreme weather impacts the payday loan market. In Table B.1, we include income as a control variable to isolate the direct effects of temperature exposures from the indirect effects through income. Our baseline results hold after controlling for income, suggesting

[19] In many regions, construction is more heavily scheduled during the summer months than winter months. This is because of factors like favorable weather conditions, extended daylight hours, and optimal setting behaviors of materials such as concrete and asphalt.

other channels, such as increasing energy or health expenditures, also matter.

3.6. Robustness

We perform several additional robustness checks in this section. First, in our main analysis, we define temperature bins based on daytime (between 8am and 8pm) mean temperature: below -9°C, above 33°C, and 14 3°C bins in between. We omit the bins with daytime mean temperature between -3°C and 27°C as the baseline. As robustness checks, we use alternative methods to define temperature bins. Table B.2 shows the results where we define temperature bins using daily maximum temperature: below -6°C, above 36°C, and every 3°C bin in between. We see that an additional day with daily maximum temperature above 36°C results in increased demand, decreased credits, and a rise in default and delinquency. Table B.3 presents results where we define temperature bins using the 24-hour daily mean temperature: below -12°C, above 30°C, and every 3°C bin in between. Again, the main results are similar. Having an additional day in a month with 24-hour daily mean temperature above 30°C results in increased demand, decreased credits, and increased default and delinquency rates. Table B.4 presents results where we calculate the number of days that the daytime mean temperatures are above the 95th percentile and above 33°C, the daytime mean temperatures are below the 5th percentile and below -6°C, and the number of days with daytime mean temperature in between. In summary, these robustness checks show that our main results are not sensitive to the specific definitions of "extreme temperature."

Second, to allow for serial correlations in the dependent variables, we add the lags of the dependent variable as an additional control variable in Table B.5 (using daytime mean temperature), Table B.6 (using daily maximum temperature) and Table B.7 (using 24-hour daily mean temperature). The inclusion of the lagged dependent variable as a regressor significantly reduces our sample size. The estimates on delinquency and default rates are sometimes imprecisely measured, although always positive. Our other main findings are not affected.

Third, our primary payday loan dataset consists of an unbalanced panel, which could potentially induce biases in the results since ZCTAs are dropped out of our analysis when they do not have payday loans reported in a particular month. To address this, we first performed a robustness check with a fully balanced panel. This involved filling in zeros for ZCTA-level observations that occasionally do not have any payday loan observations for the entire study period. As reported in Columns (1)–(4) of Table B.8, our results remained consistent, demonstrating that our findings are not a consequence of possible biases in the unbalanced panel data. We have also conducted a robustness check with a partially balanced panel. Here, we fill in zeros for ZCTAs that occasionally do not have any payday loan observations between the first and last period observed in the sample. This test allowed us to maximize our sample size while controlling for potential biases related to unbalanced data. Columns (5)–(8) of Table B.8 show that our key results hold up.

4. Further discussions

We extend our discussion of extreme weather exposure and credit demand over several dimensions. Section 4.1 discusses heterogeneities between online and storefront markets. Section 4.2 conducts heterogeneity analysis to examine the distributional effects of extreme temperature shocks based on education. Section 4.3 compares our findings on the payday loan market with other types of subprime credit. Section 4.4 evaluates the impact of the LIHEAP on payday loan markets.

4.1. Storefront versus online payday loans

To this point, we have not differentiated between the storefront and online payday loan markets. However, as these two markets have unique characteristics, we might anticipate heterogeneous effects of temperature exposures. For instance, storefront loan borrowers must apply in person, which can be challenging during days with extreme weather. To explore the heterogeneities between the two markets, we repeat our earlier analysis separately for storefront (Figure 7 and Table B.9) and online (Figure 8 and Table B.10) payday loan markets.

For online payday loans, we observe increases in unique inquiries, delinquency, and default rates, with decreases in accounts opened and credit issued under more extreme heat days. Online payday loan inquiries also increase when there are more extreme cold days. Compared to online borrowing, storefront loan borrowers' unique inquiries and accounts open are less responsive to extreme temperatures. We also observe a less significant response in storefront payday loan default and delinquency rates compared to online loans. It is interesting to note that higher levels of precipitation decrease inquiries for storefront loans but increase inquiries for online loans. One potential explanation is that extreme weather discourages or makes it more difficult for individuals to make in-person trips.

Taken together, our results suggest that the effects of temperature exposures on the payday loan market operate predominantly through changes in online payday loan markets. The distinctive characteristics of the online payday loan market, such as its accessibility and ease of application, may make it more sensitive to changes in temperature and weather conditions.

4.2. Heterogeneous effects

In this section, we conduct heterogeneity analysis to examine potential distributional effects. To do so, we link ZCTA-level payday loan application data with neighborhood demographic compositions. In particular, we use the share of the Hispanic population, given their dominant employment in the construction sector, and outdoor work in general, with greater exposure to temperatures. Among all occupation groups, construction workers are most likely to be affected by extreme heat due to the outdoor nature of their work. As a result, they are more likely to suffer from income loss and health-related issues due to direct exposure, and they often lack sufficient protective measures against extreme temperatures.

In the following analysis, we include the interaction of temperature bins and county-level demographic measures as additional variables to test whether disadvantaged neighborhoods are disproportionally affected by extreme weather. We consider the following specification:

$$Outcome_{it} = \theta T_{it} + \gamma T_{it} \times Hispanic_c + \mu_t + \eta_{cy} + Controls + \varepsilon_{it}, \tag{2}$$

where $Hispanic_c$ is a dummy variable that takes the value 1 if county c in which ZCTA i belongs falls within the top 5th percentile in the share of Hispanics among all counties in the year 2012, and is 0 otherwise. We use the same set of fixed effects and control variables as in our baseline specification. Our primary interest is in the coefficient γ, which measures the differential impacts based on county characteristics.

Table B.11 reports the estimates of γ's for seven dependent variables. The results indicate that counties with a larger share of the Hispanic population see a more significant increase in demand for payday loans with an increased number of extreme heat days, along with decreases in total credit. Extreme weather imposes a more considerable impact on households in more disadvantaged neighborhoods, and as a consequence it drives up their demand for payday loans more. The results also suggest a contraction in payday loan supply leading to a decrease in total credits.

4.3. Other subprime alternative credits

While our main focus is on the payday loan industry, our dataset contains information on other types of subprime credit products from Clarity. This section briefly describes findings for alternative subprime credit, including rent-to-own, installment, auto, and auto title loans. Compared to payday loans, these alternative subprime credit products are more broadly available in the U.S., and borrowers usually take out larger amounts of credit through each application. Interest rates on these loans could be very high if the borrower has bad credit records. Unlike payday loans, defaults on these loans negatively affect borrowers' creditworthiness.

Table B.12 reports the impact of temperature shocks on borrower income, the total number of inquiries, accounts opened, and default rates. Similar to our findings on payday loans, borrower income decreases while demand for credit increases during extreme heat days. However, in contrast to payday loan lending, the number of accounts opened increases and there is no impact on total credits approved, because the increases in extreme heat days are not associated with greater delinquency. Figure 9 illustrates these results. This evidence suggests that lenders are more willing to extend credit like installment loans when demand increases due to extreme temperatures. To summarize, our results show that the impact of weather exposures differs significantly according to the type of loan products.

4.4. Low-Income Home Energy Assistance Program

One major policy initiative aimed at helping households with energy needs during extreme weather conditions is the Low-Income Home Energy Assistance Program (LIHEAP). As discussed previously, one potential factor contributing to the rising demand for payday loans during extreme temperatures is the increase in heating or cooling costs. Given the negative impacts of extreme weather days on household payday loan market outcomes, we now investigate whether LIHEAP helps improve payday loan market performance.

Our research design exploits the eligibility thresholds of LIHEAP, which vary across states and are proportional to the state-level median income, as detailed in Section 2.3. Our specification resembles a fuzzy regression discontinuity design, in that we compare payday loan market outcomes for households slightly above versus below the eligibility thresholds within a narrow bandwidth.[20] We use the following specification to offer evidence of the impact of LIHEAP on payday loan borrowing:

$$\text{Outcome}_{it} = \theta \text{T}_{it} + \beta \text{Treat}_{it} + \mu_t + \eta_{cy} + \text{Controls} + \varepsilon_{it}, \tag{3}$$

where Treat_{it} is a dummy variable that equals 1 if the payday loan applicant/borrower i is *eligible* for the LIHEAP program in month t and equals 0 otherwise. In addition to

[20] However, it is worth noting that we do not have information on the household-level LIHEAP enrollment status, which prevents us from executing a full RDD design.

precipitation, year-month fixed effects, and county-year fixed effects, we also control renter fixed effects and age group fixed effects. Standard errors are clustered at the ZCTA level.

We restrict our sample to payday loan borrowers whose incomes are within a narrow range of the LIHEAP income eligibility cutoff. The eligibility cutoff varies based on household size, with larger households having lower cutoffs per person. However, household size is not available for payday loan borrowers in our data. We assume a household size of two to define Treat_{it}, and acknowledge that this assumption could introduce measurement errors in our analysis.

In our main analysis, we adopt a bandwidth of $1,000 around the eligibility income threshold in each state. We end up with a sample of 32,555 inquiry records and about 2,200 records of loans. As reported in Table 4, we found no significant evidence that eligibility for LIHEAP changes most payday loan market outcomes, such as credits, default, or delinquency rates. We have two measures of inquiries at the individual level, *total inquiries* and *days inquired*, which measure the total number of inquiries an individual made and the number of days an individual made inquiries within each month, respectively. The estimates on inquiries are significant and negative, suggesting that access to LIHEAP could lower household demand for payday loans by offering an additional source of income subsidy when extreme weather occurs.

There are many reasons why we may not see a significant impact of LIHEAP on other payday loan market outcomes that are related to the program's design and accessibility across different states. For instance, in states like Arizona and California, LIHEAP is available only once a year or 12-month period but accessible throughout the year; in Wisconsin, it is a once-a-year benefit available only between October and May; in Ohio, there is a 12-week application processing time. Households may choose to apply or receive the LIHEAP benefits during a period without extreme weather conditions or fail to use LIHEAP to smooth their credit demand over the course of the year. Targeting the accessibility and availability of LIHEAP during extreme weather days may help alleviate the negative impacts on payday loan markets. As mentioned previously, the lack of information on the number of household members could also bias our results toward zero in the case of classical measurement errors. Evidence in this section is merely suggestive and should be taken with caution.

5. Conclusion

Payday loans are a controversial short-term source of liquidity for low- to middle-income customers. In this paper, we study how extreme temperatures affect household credit markets. We build a panel of monthly ZCTA-level temperature exposure and a panel of monthly credit market measures. Our findings indicate that extreme heat days lead to more payday loan inquiries, higher delinquency rates, and higher default rates. However, we do not see a corresponding increase in the number of accounts open or credit issued. This indicates that extreme heat increases demand for payday loan borrowing but reduces supply, presumably because of the increased risk of delinquency and default.

Our study sheds light on the relationship between environmental shocks and household finance, particularly regarding the use of non-traditional credit products by lower-income households under extreme temperature shocks. Our findings highlight the heightened financial vulnerability of low-income households during extreme weather events and underscore the urgent need for targeted interventions and policies. Developing strategies to mitigate the adverse impacts of climate change on vulnerable individuals and assisting low-income households in building resilience against these challenges is essential. Our research contributes to the ongoing discourse on climate change adaptation and the financial well-being of low-income households.

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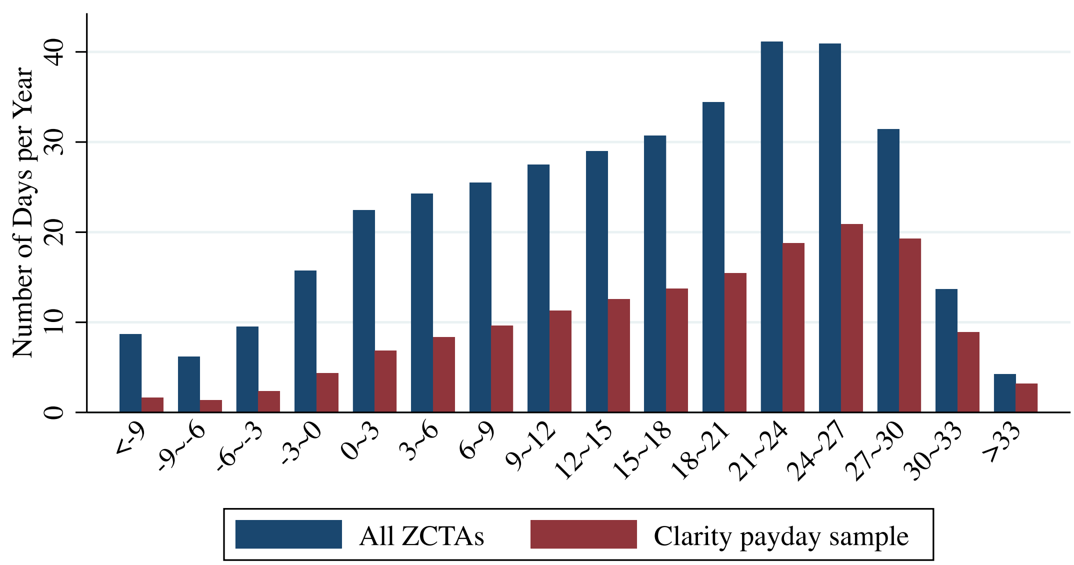
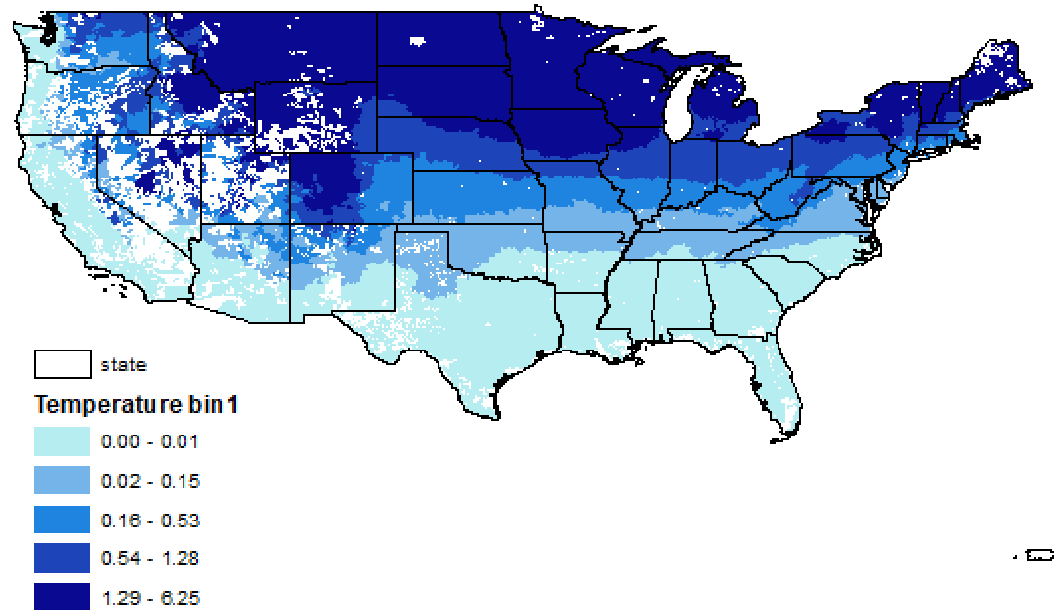
Figure 1: Distribution of daytime mean temperatures, 2012–2019



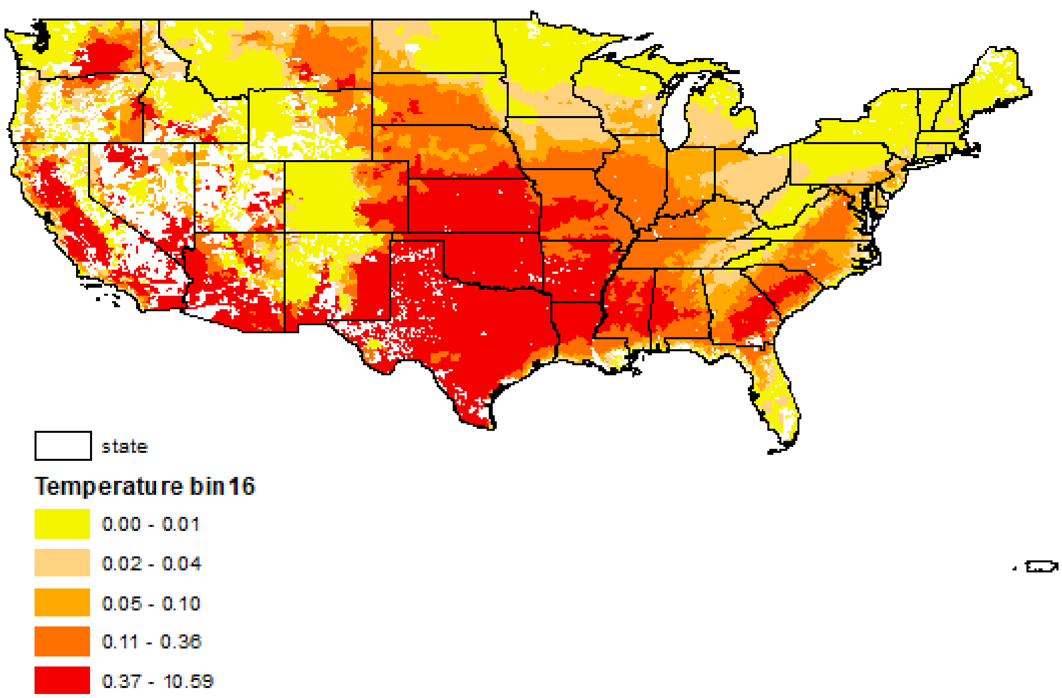
Notes: The figure shows the historical average distribution of daytime mean temperatures across 16 temperature-day bins. Each bar represents the average number of days per year in each temperature bin from 2012–2019. The "All ZCTAs" dataset represents ZCTAs of the continental U.S., summing to 365 days across all bins. The "Clarity payday sample" covers a subset of all ZCTAs, since not every ZCTA reports payday loans every month. In total, there are 159 days across the bins.

Figure 2: Geographical distribution of daytime temperature bins

(a) Average monthly number of days with daytime mean temperature below -9°C

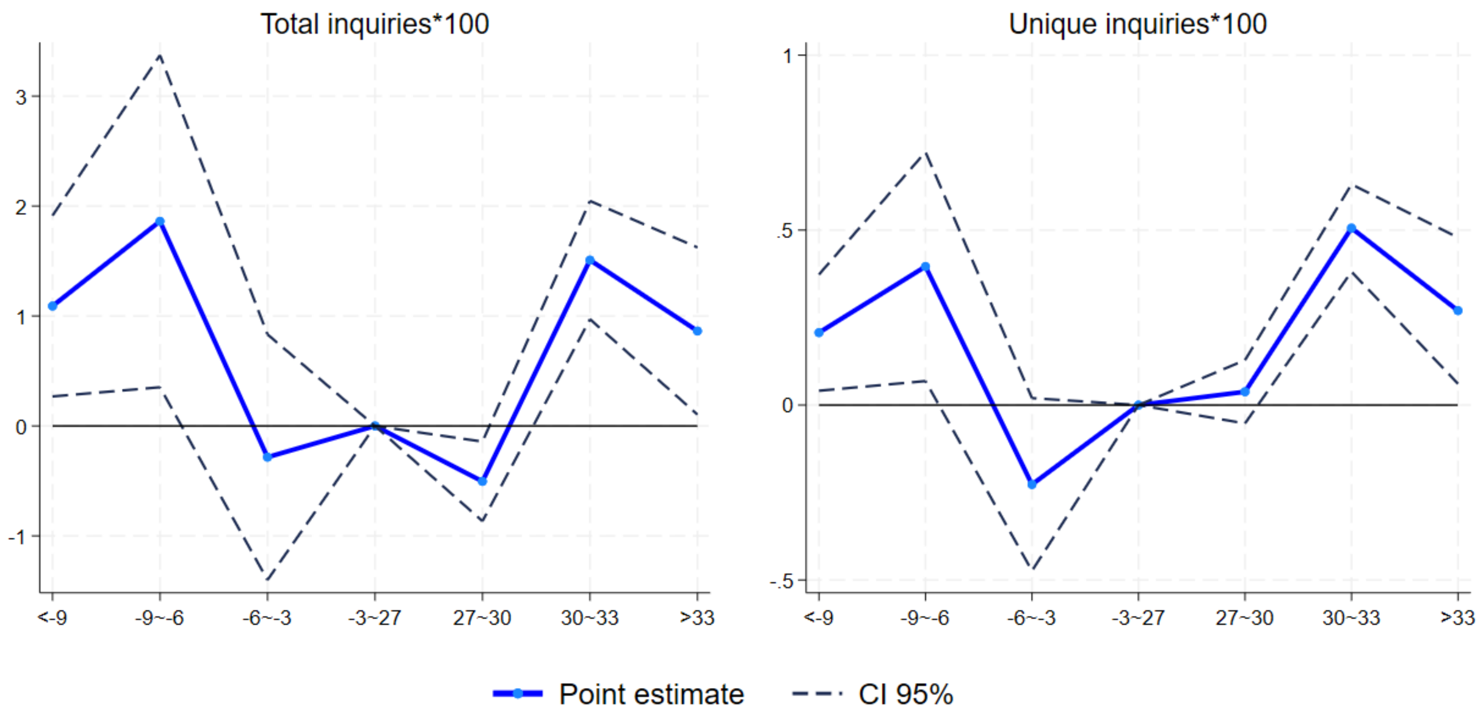


(b) Average monthly number of days with daytime mean temperature above 33°C



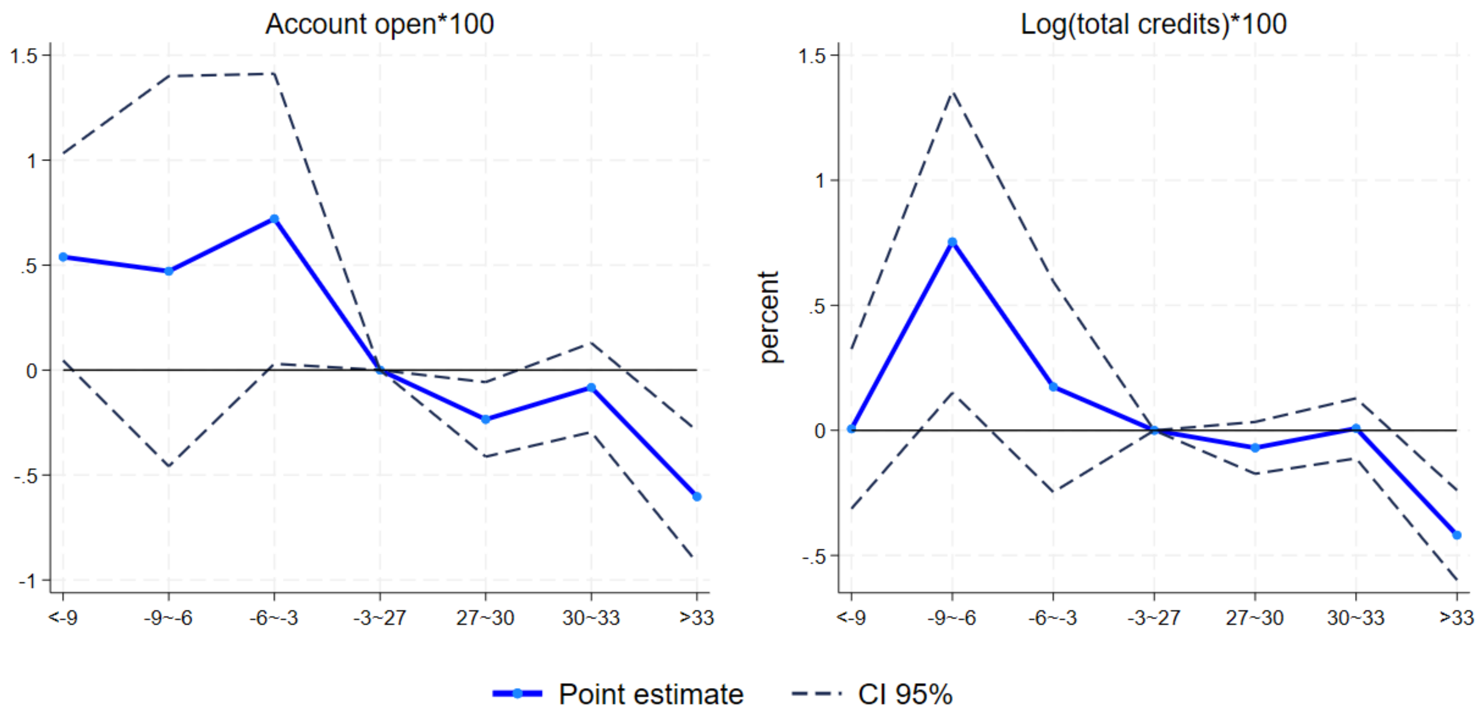
Notes: The figure shows the spatial distribution across ZCTAs of the monthly number of days that had daytime (between 8am and 8pm) mean temperatures below -9°C in panel (a) and above 33°C in panel (b).

Figure 3: Impact on total inquiries and unique inquiries



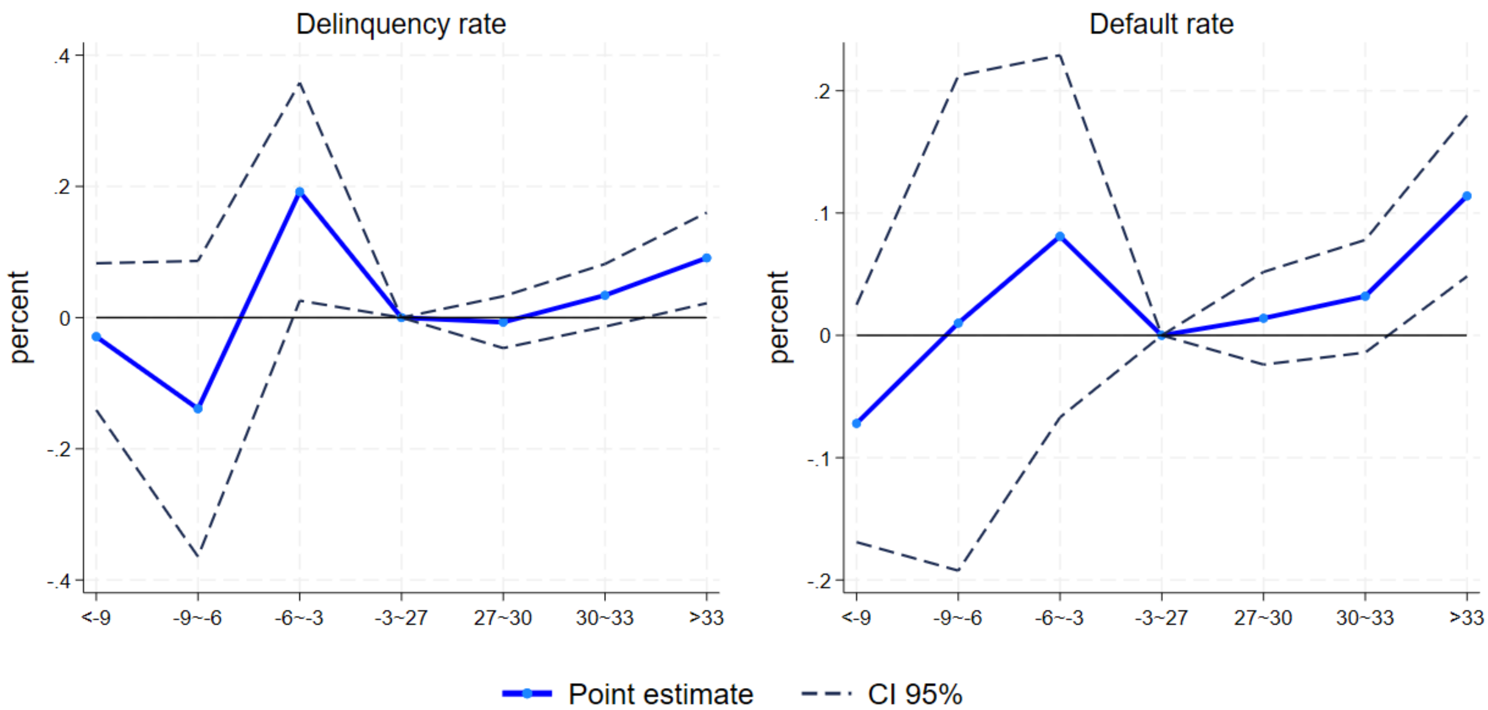
Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins on number of total inquiries (left) and unique inquiries (right), relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95% confidence intervals are based on standard errors clustered at the ZCTA level.

Figure 4: Impact on account open and total credits



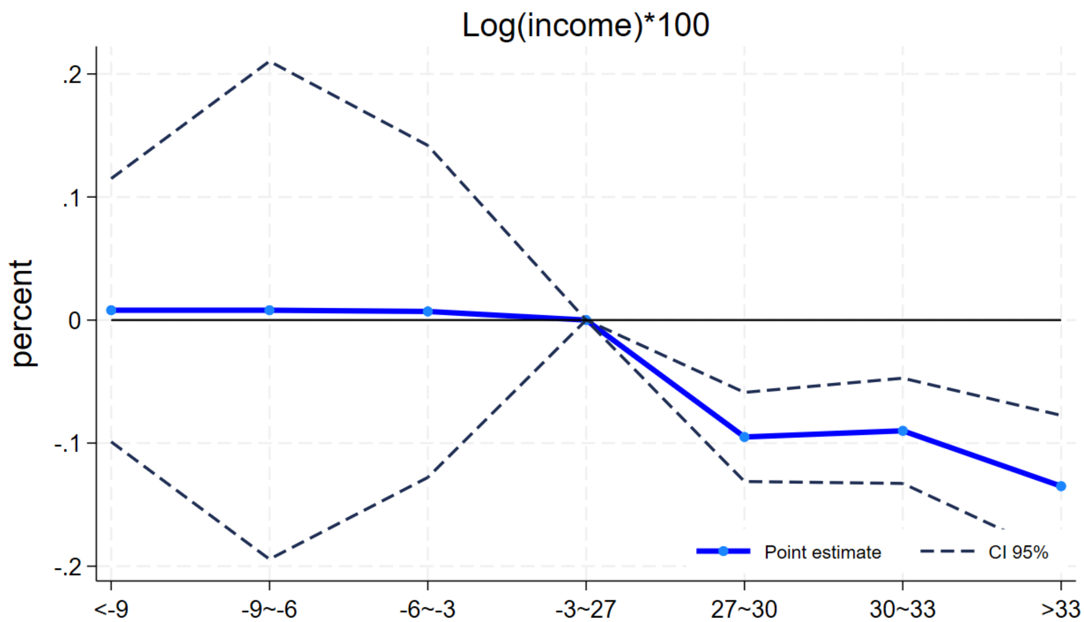
Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins on number of accounts open (left) and log of total credits (right), relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95% confidence intervals are based on standard errors clustered at the ZCTA level.

Figure 5: Impact on delinquency rate and default rate



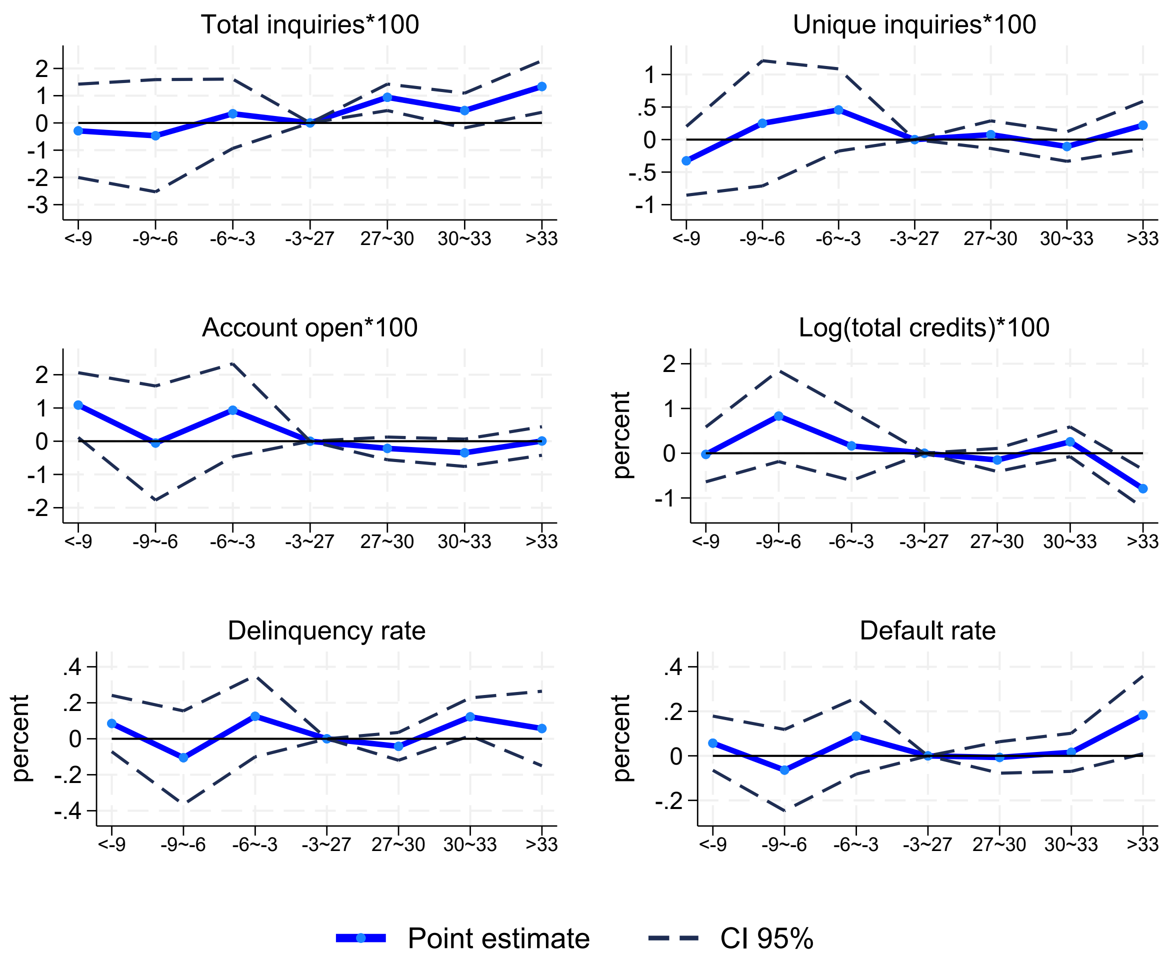
Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins on delinquency rate (left) and default rate (right), relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95% confidence intervals are based on standard errors clustered at the ZCTA level.

Figure 6: Impact on average income



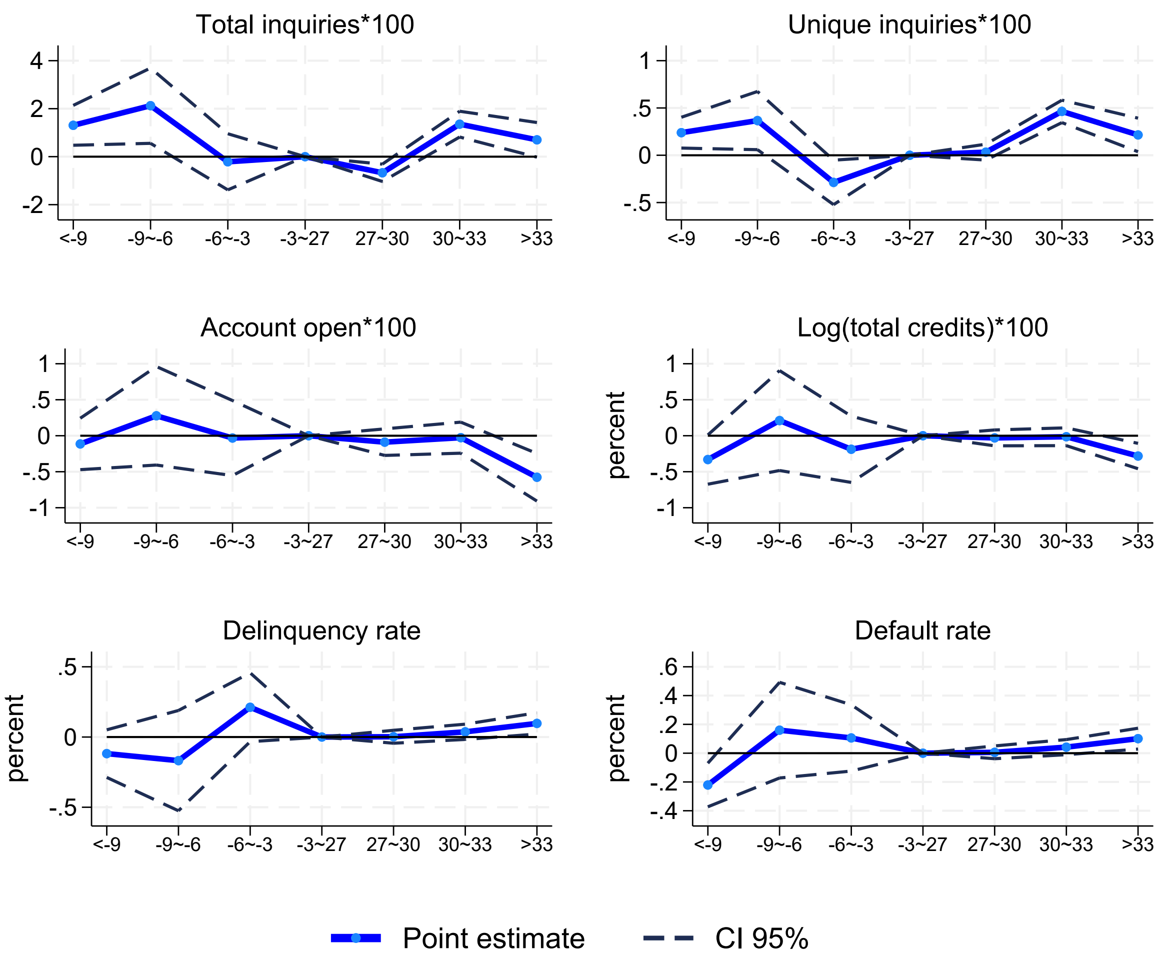
Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins on log of average income, relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95% confidence interval is based on standard errors clustered at the ZCTA level.

Figure 7: Storefront payday loans



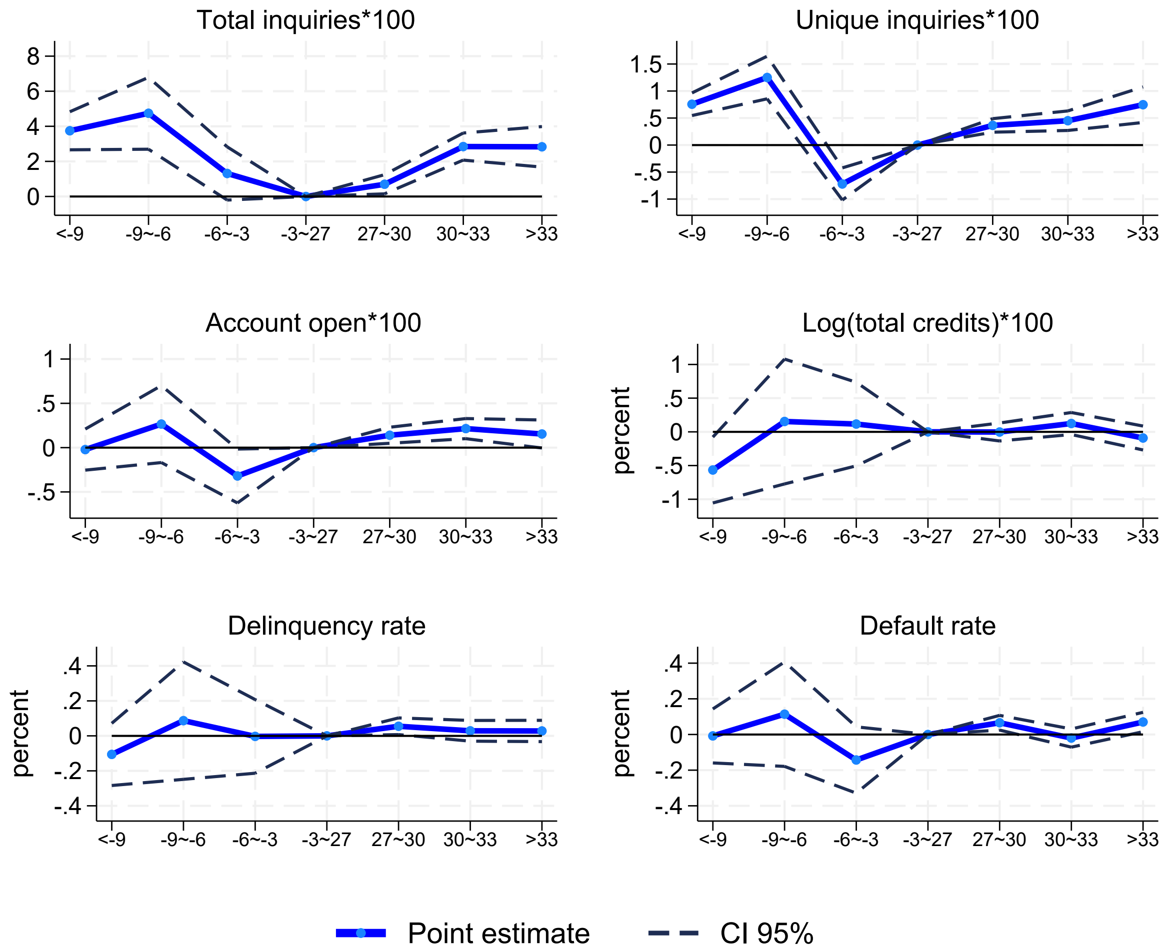
Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins relative to a day in the -3°C to 27°C bins on the storefront payday loan market. Dependent variables considered are number of total inquiries (top left), unique inquiries (top right), number of accounts open (middle left), log of total credits (middle right), delinquency rate (bottom left), and default rate (bottom right). Responses are estimated using specification (1). The 95% confidence interval is based on standard errors clustered at the ZCTA level.

Figure 8: Online payday loans



Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins relative to a day in the -3°C to 27°C bins on the online payday loan market. Dependent variables considered are number of total inquiries (top left), unique inquiries (top right), number of accounts open (middle left), log of total credits (middle right), delinquency rate (bottom left), and default rate (bottom right). Responses are estimated using specification (1). The 95% confidence interval is based on standard errors clustered at the ZCTA level.

Figure 9: Alternative subprime credit: installment loans



Notes: The figure provides the estimated impact of a day in six different daytime mean temperature bins relative to a day in the -3°C to 27°C bins on installment loans. Dependent variables considered are number of total inquiries (top left), unique inquiries (top right), number of accounts open (middle left), log of total credits (middle right), delinquency rate (bottom left), and default rate (bottom right). Responses are estimated using specification (1). The 95% confidence interval is based on standard errors clustered at the ZCTA level.

Table 1: Summary statistics of the payday loan dataset

	mean	sd	p25	p50	p75	N
Full sample						
account open	1.73	1.38	1	1	2	115925
total highest credit	637.10	703.90	255	475	765	115925
delinquency rate	8.69	26.51	0	0	0	115925
default rate	7.33	24.57	0	0	0	115925
inquiry made	4.66	5.43	1	3	6	476928
unique inquiry	1.76	1.37	1	1	2	476928
average monthly income	2661	1343	1742	2500	3261	456435
Storefront sample						
	mean	sd	p25	p50	p75	N
account open	1.94	1.62	1	1	2	30853
total highest credit	882.90	1075.00	300	500	1000	30853
delinquency rate	6.38	23.00	0	0	0	30853
default rate	4.42	19.44	0	0	0	30853
inquiry made	2.05	2.22	1	1	2	54497
unique inquiry	1.46	0.98	1	1	2	54497
average monthly income	1758	1193	921	1494	2272	33230
Online sample						
	mean	sd	p25	p50	p75	N
account open	1.57	1.15	1	1	2	89921
total highest credit	518.4	421.3	255	400	605	89921
delinquency rate	9.62	28.1	0	0	0	89921
default rate	8.42	26.46	0	0	0	89921
inquiry made	4.64	5.36	1	3	6	454759
unique inquiry	1.69	1.26	1	1	2	454759
average monthly income	2706	1345	1751	2500	3333	443623

Notes: This table provides the summary statistics for the full payday loan sample, the storefront payday loan, and the online payday loan subsamples.

Table 2: Summary statistics of ZCTA daily temperatures

	All ZCTAs								
	mean	sd	p99	p95	p90	p50	p10	p5	p1
Daytime mean	14.80	11.18	33.28	29.95	28.07	16.39	-0.56	-4.79	-13.38
24-hour mean	12.92	10.72	30.59	27.56	25.78	14.34	-1.61	-5.79	-14.49
Maximum	18.19	11.02	36.90	33.14	31.11	19.95	2.40	-1.23	-9.07
	ZCTAs with payday loan inquiries								
	mean	sd	p99	p95	p90	p50	p10	p5	p1
Daytime mean	17.55	10.32	34.38	31.04	29.28	19.45	2.72	-1.04	-9.18
24-hour mean	15.65	9.91	31.64	28.58	27.08	17.34	1.50	-2.01	-10.19
Maximum	20.90	10.20	38.17	34.36	32.34	22.89	5.92	1.81	-5.34

Notes: This table provides the summary statistics for daily temperatures of all ZCTAs (upper panel) and ZCTAs that have payday loan inquiries in that month (lower panel) during 2012–2019. Daytime mean refers to the average temperature between 8am and 8pm local time.

Table 3: Impacts of extreme temperatures on payday loan markets

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -9C	0.008	1.091**	0.207**	0.539*	0.006	-0.029	-0.072
	(0.065)	(0.500)	(0.101)	(0.300)	(0.194)	(0.068)	(0.059)
Days between -9C and -6C	0.008	1.862**	0.396**	0.471	0.754**	-0.139	0.010
	(0.123)	(0.918)	(0.199)	(0.565)	(0.367)	(0.137)	(0.123)
Days between -6C and -3C	0.007	-0.284	-0.227	0.721*	0.174	0.192*	0.081
	(0.082)	(0.679)	(0.150)	(0.420)	(0.256)	(0.101)	(0.090)
Days between 27C and 30C	-0.095***	-0.504**	0.038	-0.235**	-0.070	-0.007	0.014
	(0.022)	(0.220)	(0.055)	(0.108)	(0.063)	(0.024)	(0.023)
Days between 30C and 33C	-0.090***	1.509***	0.506***	-0.083	0.008	0.034	0.032
	(0.026)	(0.327)	(0.076)	(0.129)	(0.073)	(0.029)	(0.028)
Days above 33C	-0.135***	0.864*	0.270**	-0.603***	-0.419***	0.091**	0.114***
	(0.035)	(0.462)	(0.127)	(0.191)	(0.109)	(0.042)	(0.040)
Precipitation	-53.220	1,294.401***	195.912*	-97.662	-84.979	163.910***	126.838***
	(47.473)	(439.052)	(103.660)	(182.022)	(119.894)	(46.061)	(43.275)
Observations	439,568	461,993	461,993	110,246	109,424	110,246	110,246
R-squared	0.156	0.195	0.241	0.225	0.283	0.179	0.159
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4: The effects of LIHEAP on payday loan credits

	(1) total inquiries*100	(2) days inquired*100	(3) log(credits)*100	(4) delinquency rate	(5) default rate
Treat	-17.49***	-3.235**	-5.749	1.171	2.789
	(5.564)	1.477	(4.208)	(1.940)	(1.838)
Observations	32,555	32,555	2,156	2,170	2,170
R-squared	0.221	0.178	0.5	0.402	0.351
Year-month FE	X	X	X	X	X
County*Year FE	X	X	X	X	X
Renter FE	X	X	X	X	X
Age group FE	X	X	X	X	X

Notes: The estimation results for Equation (3) are presented for five different outcome variables. Treat is equal to 1 if an individual's income is within the $1,000 bandwidth and below the LIHEAP eligibility cutoff. We also include the temperature bins and the precipitation variables as controls. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix

Appendix A. Background information

Appendix A.1. Reasons for taking payday loans

In 2013, 2016, and 2019 waves of Survey of Consumer Finances[21] respondents were asked two specific questions related to their use of payday loans and the reasons behind their decision to use them. A total of 2,745 participants answered "YES" to the first question, indicating that they had indeed taken out payday loans. That is about 3% of all survey participants. Among these individuals who had used payday loans, Figure A.1 illustrates the distribution of various reasons for taking them. The most prevalent reason reported was for "Emergency" needs, with covering bills and utilities being other commonly mentioned reasons. Additionally, nearly 13% of the respondents stated that they perceived payday loans as their only available option.

Question: During the past year, have you (or anyone in your family living here) taken out a "payday loan," that is, borrowed money that was supposed to be repaid in full out of your next paycheck?

IF YES: Please do not include personal loans from family members or friends.

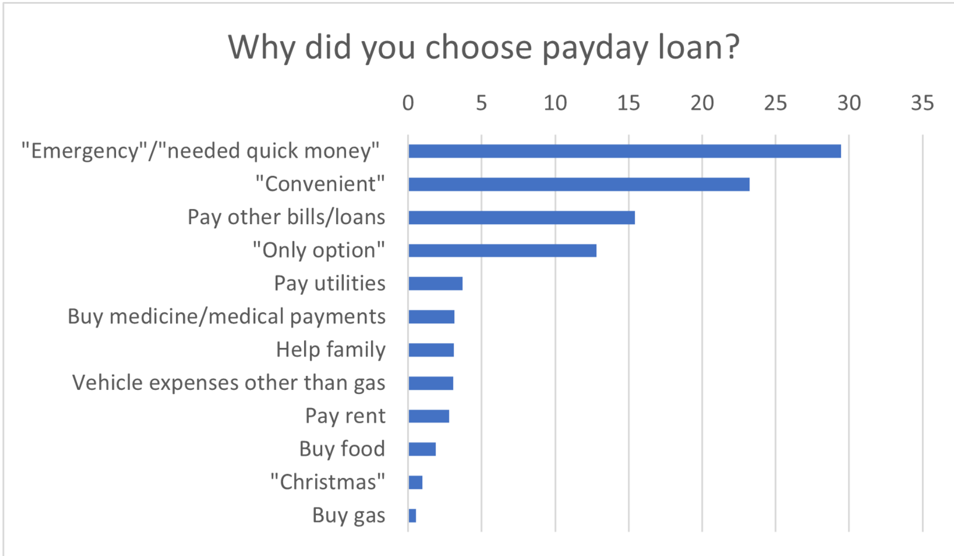
1. YES
2. NO

Question: Why did you choose this type of loan?

1. Buy food
2. Buy gas
3. Buy medicine/medical payments
4. Pay utilities
5. Pay rent
6. Vehicle expenses other than gas
7. Pay other bills/loans

[21] https://www.federalreserve.gov/econres/aboutscf.htm

Appendix Figure A.1: Reasons for taking payday loans



Notes: The figure presents the percentages representing individual reasons for taking a payday loan, calculated based on responses from the Survey of Consumer Finances for the years 2013, 2016, and 2019. The reasons are ordered and plotted in descending order from top to bottom. The percentage indicates how many respondents, out of the total responses, selected each specific reason. The percentages add up to 100.

8. "Christmas"
9. Help family
10. "Emergency"/"needed quick money"
11. "Convenient"
12. "Only option"

Appendix A.2. LIHEAP program

Since its inception in 1981, LIHEAP[22] has been playing a crucial role in providing vital support to eligible low-income households. LIHEAP offers a range of assistance programs, including addressing heating and cooling energy costs, providing bill payment assistance, offering aid during energy crises, facilitating weatherization efforts, and supporting energy-related home repairs. By helping these households manage their utility bills during the crucial cold or hot months of the year, LIHEAP ensures that their energy needs are met. Furthermore, the program offers "crisis" funds to promptly restore utility services for eligible households that have experienced service interruption or are at risk of it. In addition,

[22]See https://www.liheap.org/.

LIHEAP extends support to eligible households by allocating funds for weatherization measures and energy-related home repairs. Notably, the heating and cooling payment assistance program stands as the largest component of LIHEAP. Each year, nearly two-thirds of funding was used for heating and cooling assistance.

The implementation of LIHEAP also differs across states, resulting in varying program structures and offerings. For example, in Arizona and California, LIHEAP provides one-time financial assistance to help eligible households manage their utility bills. In Wisconsin, it is a once-a-year benefit available only between October 1 and May 15. Meanwhile, Delaware offers bills and/or energy assistance twice a year. Florida allows applications up to three times a year. The processing time of applications varies across states as well. For example, in Ohio there is a 12-week application processing time. Oklahoma's non-emergency cooling and winter heating assistance may take up to 60 days for processing.

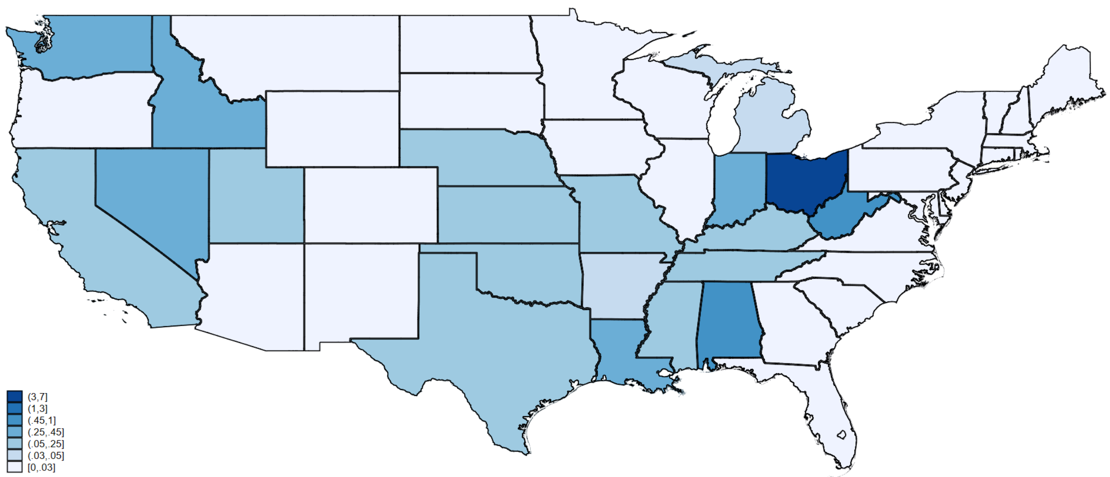
In most cases, approved households won't receive payment directly. LIHEAP almost always pays grants directly to the energy utility. In Minnesota, initial benefits average $500 per household and can be up to $1,400.

According to the latest White paper, cold weather states traditionally spend more than 70% of the LIHEAP funds during the first two quarters of the federal fiscal year.

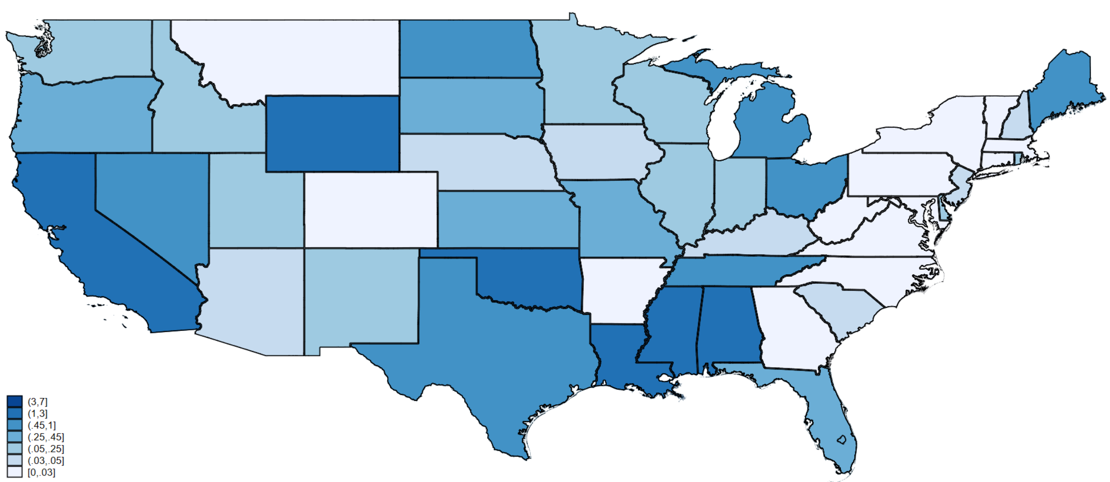
Appendix B. Additional Figures and Tables

Appendix Figure B.1: Geographic Distribution of loans per capita

(a) Storefront

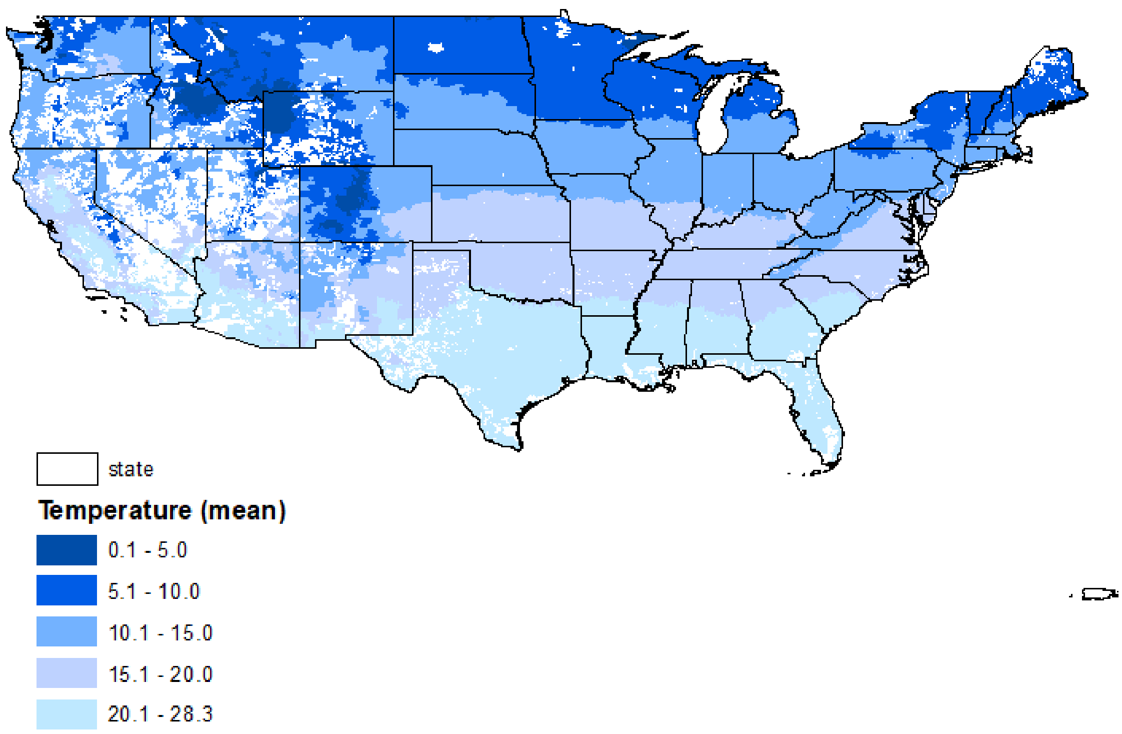


(b) Online



Notes: This figure plots the geographic distribution of loans per capita for storefront (upper) and online (lower) payday loan subsamples, respectively.

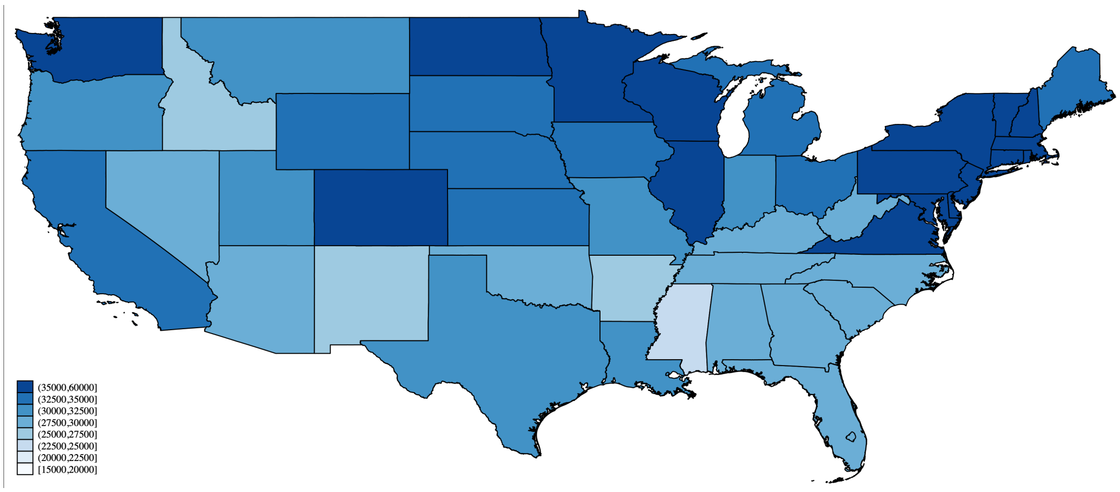
Appendix Figure B.2: Average daytime mean temperature



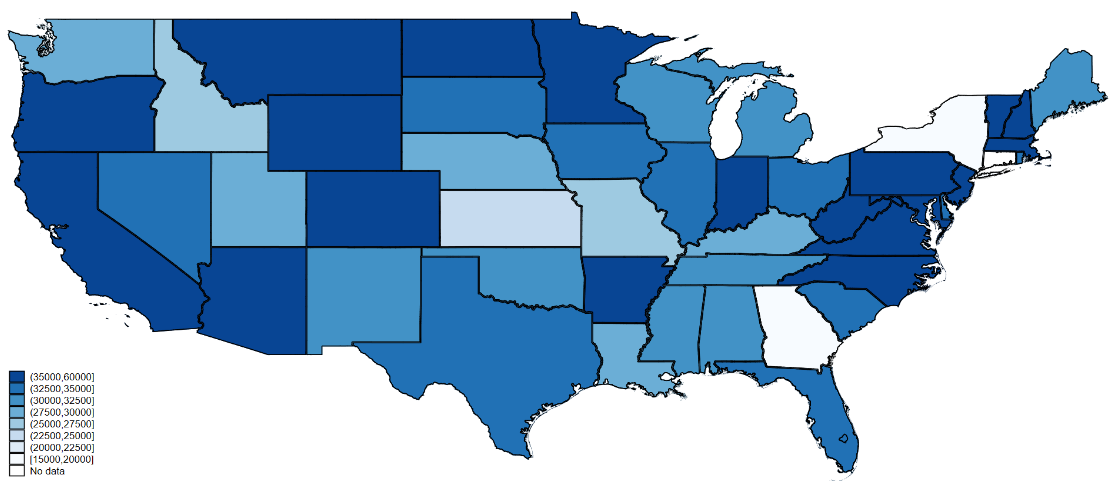
Notes: The figure shows the spatial distribution of the daytime (between 8am and 8pm) mean temperatures across ZCTAs, averaged from 2012–2019. Around 5% ZCTA-day level observations have a daytime mean temperature above the 30°C threshold, and around 5% ZCTA-day level observations have a daytime mean temperature below the -5°C threshold.

Appendix Figure B.3: Geographic distribution of income and LIHEAP eligibility

(a) LIHEAP Eligibility



(b) Income of Payday Loan Borrowers



Notes: This figure plots the geographic distribution of LIHEAP eligibility cutoff (upper) and income of payday loan borrowers (lower), respectively.

Appendix Table B.1: Robustness check: controlling for average income

	(1) total inquires *100	(2) unique inquires*100	(3) account open *100	(4) log(credits)*100	(5) delinquency rate	(6) default rate
Days below -9C	1.256**	0.260**	0.557	-0.336	-0.024	-0.098
	(0.519)	(0.105)	(0.411)	(0.249)	(0.097)	(0.083)
Days between -9C and -6C	2.061**	0.399*	1.073	0.702	-0.033	0.180
	(0.961)	(0.207)	(0.802)	(0.471)	(0.190)	(0.168)
Days between -6C and -3C	-0.431	-0.249	0.887	0.278	0.108	-0.032
	(0.718)	(0.157)	(0.567)	(0.317)	(0.137)	(0.120)
Days between 27C and 30C	-0.632***	0.029	-0.296**	-0.115	-0.028	0.003
	(0.227)	(0.056)	(0.133)	(0.074)	(0.029)	(0.027)
Days between 30C and 33C	1.377***	0.510***	-0.210	0.011	0.022	0.016
	(0.335)	(0.077)	(0.154)	(0.084)	(0.035)	(0.033)
Days above 33C	0.610	0.220*	-0.664***	-0.501***	0.102**	0.127***
	(0.471)	(0.129)	(0.216)	(0.121)	(0.050)	(0.048)
Precipitation	1,109.098**	197.105*	50.061	-92.023	200.117***	152.962***
	(466.878)	(107.568)	(232.759)	(140.525)	(57.151)	(53.556)
log(avg income)	-0.493***	0.059***	0.001	0.125***	-0.025***	-0.021***
	(0.021)	(0.006)	(0.014)	(0.008)	(0.002)	(0.002)
Observations	439,568	439,568	82,114	81,521	82,114	82,114
R-squared	0.200	0.254	0.268	0.271	0.186	0.166
Year-month FE	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for six different outcome variables. Average income is included as a control variable. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.2: Robustness check: daily max temperature

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -6C	0.055	1.450**	0.292**	0.887**	0.185	-0.094	-0.117
	(0.076)	(0.583)	(0.117)	(0.355)	(0.225)	(0.090)	(0.077)
Days between -6C and -3C	-0.129	-1.360	-0.577***	-0.865*	-0.011	0.080	0.115
	(0.118)	(0.940)	(0.196)	(0.492)	(0.331)	(0.130)	(0.112)
Days between -3C and 0C	0.049	0.701	0.260*	1.115***	0.392*	0.079	0.021
	(0.077)	(0.643)	(0.146)	(0.344)	(0.224)	(0.084)	(0.075)
Days between 30C and 33C	-0.092***	-0.064	0.082	-0.245*	-0.068	-0.009	0.013
	(0.024)	(0.252)	(0.069)	(0.125)	(0.069)	(0.025)	(0.024)
Days between 33C and 36C	-0.070***	1.366***	0.477***	-0.023	0.017	0.028	0.021
	(0.027)	(0.338)	(0.083)	(0.139)	(0.076)	(0.030)	(0.028)
Days above 36C	-0.118***	1.099***	0.350***	-0.483***	-0.325***	0.082**	0.099***
	(0.032)	(0.405)	(0.113)	(0.173)	(0.094)	(0.034)	(0.033)
Precipitation	-62.570	1,099.071***	199.937**	-114.348	-92.196	153.490***	119.788***
	(46.157)	(420.493)	(100.351)	(172.860)	(113.071)	(43.948)	(41.439)
Observations	441,842	464,452	464,452	111,124	110,302	111,124	111,124
R-squared	0.156	0.195	0.241	0.226	0.283	0.179	0.160
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The independent variables are the number of days in a month with daily maximum temperature within a specific range. We use 16 temperature bins: below -6°C, above 36°C, and 14 3°C bins in between. The "Days between 0°C and 30°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between 0°C and 30°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.3: Robustness check: 24-hour mean temperature

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -12C	0.007	0.878	0.230*	0.475	0.165	-0.111	-0.141*
	(0.087)	(0.621)	(0.129)	(0.385)	(0.253)	(0.090)	(0.078)
Days between -12C and -9C	-0.039	2.029*	0.174	1.196*	0.350	0.211	0.184
	(0.147)	(1.160)	(0.250)	(0.698)	(0.429)	(0.152)	(0.127)
Days between -9C and -6C	0.061	0.692	-0.015	0.445	0.289	0.008	0.016
	(0.102)	(0.815)	(0.173)	(0.478)	(0.299)	(0.120)	(0.108)
Days between 24C and 27C	-0.052**	-0.529***	0.007	-0.214**	-0.049	-0.037	-0.017
	(0.020)	(0.198)	(0.048)	(0.102)	(0.057)	(0.023)	(0.022)
Days between 27C and 30C	-0.118***	0.918***	0.405***	-0.089	0.028	0.041*	0.039*
	(0.021)	(0.237)	(0.055)	(0.103)	(0.061)	(0.023)	(0.021)
Days above 30C	-0.115***	1.183***	0.333***	-0.582***	-0.377***	0.068*	0.090**
	(0.030)	(0.391)	(0.103)	(0.158)	(0.096)	(0.038)	(0.036)
Precipitation	-27.028	775.340*	27.222	-73.425	-88.748	137.286***	106.046**
	(45.881)	(417.775)	(100.134)	(176.575)	(113.472)	(43.957)	(41.441)
Observations	441,842	464,452	464,452	111,124	110,302	111,124	111,124
R-squared	0.156	0.195	0.241	0.226	0.283	0.179	0.160
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The independent variables are the number of days in a month with 24-hour daily mean temperature within a specific range. We use 16 temperature bins: below -12°C, above 30°C, and 14 2°C bins in between. The "Days between -6°C and 24°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -6°C and 24°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.4: Robustness check: local extreme temperature

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below min(-6C, 5th percentile)	-0.037	1.799***	0.348***	1.154***	0.449***	-0.084*	-0.087**
	(0.054)	(0.463)	(0.101)	(0.247)	(0.143)	(0.045)	(0.040)
Days above max(33C, 95th percentile)	-0.112***	1.411***	0.664***	-0.105	-0.014	0.104**	0.093**
	(0.035)	(0.368)	(0.084)	(0.189)	(0.105)	(0.041)	(0.039)
Precipitation	-10.407	1,119.272***	37.628	-139.382	-107.111	122.955***	93.978**
	(45.950)	(423.157)	(101.039)	(178.874)	(118.450)	(44.795)	(42.199)
Observations	441,393	463,795	463,795	111,701	110,822	111,701	111,701
R-squared	0.107	0.150	0.201	0.169	0.216	0.112	0.097
Year-month FE	X	X	X	X	X	X	X
County FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The independent variables are the number of days in a month with daytime mean temperature within a specific range. We use three temperature bins: below the minimum of -6°C and below the 5th percentile temperature in the ZCTA's history, above the maximum of 33°C and above 95th percentile temperature in the ZCTA's history, and temperature in between. The last bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between the two extreme values. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.5: Robustness check: controlling for lags of dependent variable

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -9C	0.163*	1.174	0.332*	-0.540	-0.221	-0.018	-0.048
	(0.084)	(0.764)	(0.171)	(0.399)	(0.232)	(0.061)	(0.049)
Days between -9C and -6C	-0.133	3.813***	1.051***	-0.060	0.364	-0.104	0.056
	(0.162)	(1.414)	(0.322)	(0.778)	(0.439)	(0.122)	(0.102)
Days between -6C and -3C	-0.022	-1.516	-0.579**	1.640***	0.768***	0.203**	0.114
	(0.105)	(1.002)	(0.237)	(0.532)	(0.294)	(0.092)	(0.073)
Days between 27C and 30C	-0.076***	-0.573**	-0.040	-0.236*	-0.077	0.013	0.031
	(0.026)	(0.278)	(0.065)	(0.130)	(0.066)	(0.022)	(0.021)
Days between 30C and 33C	-0.070**	1.204***	0.378***	-0.081	0.068	0.050*	0.030
	(0.029)	(0.382)	(0.081)	(0.151)	(0.077)	(0.029)	(0.027)
Days above 33C	-0.100***	1.112**	0.241**	-0.522***	-0.308***	0.015	0.051
	(0.038)	(0.502)	(0.111)	(0.190)	(0.108)	(0.041)	(0.039)
Precipitation	0.204***	1,424.161**	296.600**	-318.021	-136.330	66.932	47.426
	(0.004)	(591.465)	(138.467)	(238.527)	(133.597)	(42.647)	(38.280)
lag of dep. var	-47.568	0.364***	0.514***	0.518***	0.506***	0.108***	0.082***
	(53.872)	(0.008)	(0.008)	(0.017)	(0.008)	(0.009)	(0.010)
Observations	261,224	281,151	281,151	70,013	69,711	70,013	70,013
R-squared	0.211	0.309	0.437	0.450	0.504	0.157	0.126
Year-month FE	X	X	X	X	X	X	
County*Year FE	X	X	X	X	X	X	

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The lag of dependent variable is included as a control variable. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature in between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.6: Robustness check: daily max temperature and controlling lag of dependent variable

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -6C	0.197*	1.351	0.484**	0.189	-0.028	-0.044	-0.068
	(0.101)	(0.908)	(0.199)	(0.502)	(0.270)	(0.088)	(0.070)
Days between -6C and -3C	-0.061	-0.512	-0.400	-2.511***	-0.423	-0.058	0.056
	(0.159)	(1.456)	(0.323)	(0.776)	(0.418)	(0.119)	(0.092)
Days between -3C and 0C	-0.110	0.349	0.242	2.026***	0.867***	0.186**	0.126**
	(0.097)	(0.926)	(0.219)	(0.465)	(0.260)	(0.076)	(0.063)
Days between 30C and 33C	-0.059**	-0.053	0.013	-0.187	-0.076	0.016	0.036*
	(0.028)	(0.315)	(0.075)	(0.148)	(0.070)	(0.023)	(0.022)
Days between 33C and 36C	-0.045	1.001**	0.319***	-0.039	0.071	0.037	0.013
	(0.029)	(0.396)	(0.087)	(0.162)	(0.079)	(0.029)	(0.027)
Days above 36C	-0.082**	1.270***	0.284***	-0.404**	-0.232***	0.036	0.063**
	(0.035)	(0.440)	(0.098)	(0.168)	(0.089)	(0.033)	(0.031)
Precipitation	-54.240	1,240.376**	295.072**	-328.192	-148.389	64.127	46.888
	(52.179)	(565.080)	(133.128)	(228.140)	(126.673)	(41.593)	(37.555)
lag of dep. var	0.204***	0.364***	0.514***	0.518***	0.505***	0.109***	0.083***
	(0.004)	(0.008)	(0.008)	(0.017)	(0.008)	(0.009)	(0.010)
Observations	262,442	282,533	282,533	70,489	70,187	70,489	70,489
R-squared	0.212	0.309	0.436	0.450	0.503	0.157	0.126
Year-month FE	X	X	X	X	X	X	
County*Year FE	X	X	X	X	X	X	

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The lag of dependent variable is included as a control variable. The independent variables are the number of days in a month with daily maximum temperature within a specific range. We use 16 temperature bins: below -6°C, above 36°C, and 14 3°C bins in between. The "Days between 0°C and 30°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between 0°C and 30°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.7: Robustness check: 24-hour mean temperature and controlling lag of dependent variable

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -12C	0.231**	0.890	0.391*	-0.099	0.193	-0.070	-0.067
	(0.114)	(0.968)	(0.215)	(0.538)	(0.307)	(0.086)	(0.069)
Days between -12C and -9C	-0.120	3.013*	0.500	0.424	0.083	0.016	0.067
	(0.197)	(1.744)	(0.418)	(0.922)	(0.514)	(0.130)	(0.098)
Days between -9C and -6C	-0.069	0.766	-0.010	-0.016	0.148	0.132	0.099
	(0.132)	(1.216)	(0.283)	(0.698)	(0.359)	(0.111)	(0.092)
Days between 24C and 27C	-0.033	-0.398	0.030	-0.095	-0.044	-0.013	0.004
	(0.024)	(0.258)	(0.060)	(0.122)	(0.062)	(0.020)	(0.019)
Days between 27C and 30C	-0.098***	0.574**	0.252***	-0.117	0.059	0.052**	0.042**
	(0.023)	(0.280)	(0.061)	(0.115)	(0.061)	(0.022)	(0.020)
Days above 30C	-0.081**	1.506***	0.328***	-0.466***	-0.272***	0.016	0.041
	(0.032)	(0.429)	(0.095)	(0.167)	(0.100)	(0.038)	(0.035)
Precipitation	-25.211	1,032.087*	166.360	-346.897	-198.784	36.904	24.970
	(51.984)	(560.747)	(132.086)	(225.638)	(126.011)	(41.485)	(37.539)
lag of dep. var	0.204***	0.364***	0.514***	0.518***	0.505***	0.109***	0.083***
	(0.004)	(0.008)	(0.008)	(0.017)	(0.008)	(0.009)	(0.010)
Observations	262,442	282,533	282,533	70,489	70,187	70,489	70,489
R-squared	0.212	0.309	0.436	0.449	0.503	0.157	0.126
Year-month FE	X	X	X	X	X	X	
County*Year FE	X	X	X	X	X	X	

Notes: The estimation results for Equation (1) are presented for seven different outcome variables. The lag of dependent variable is included as a control variable. The independent variables are the number of days in a month with 24-hour daily mean temperature within a specific range. We use 16 temperature bins: below -12°C, above 30°C, and 14 3°C bins in between. The "Days between -6°C and 24°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -6°C and 24°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.8: Robustness check: balanced and partially balanced panels

	balanced				partially balanced			
	(1) total inquiry*100	(2) unique inquiry*100	(3) account open*100	(4) log(credits)*100	(5) total inquiry*100	(6) unique inquiry*100	(7) account open*100	(8) log(credits)*100
Days below -6C	0.484***	0.109***	0.123***	0.006	0.586***	0.109***	0.470***	0.006
	(0.078)	(0.021)	(0.036)	(0.194)	(0.141)	(0.038)	(0.115)	(0.194)
Days between -6C and -3C	0.624***	0.150***	0.076	0.754**	0.950***	0.227***	0.127	0.754**
	(0.164)	(0.046)	(0.075)	(0.367)	(0.294)	(0.081)	(0.231)	(0.367)
Days between -3C and 0C	-0.149	-0.121***	0.104*	0.174	-0.340	-0.196***	0.070	0.174
	(0.143)	(0.042)	(0.062)	(0.256)	(0.242)	(0.068)	(0.172)	(0.256)
Days between 30C and 33C	0.229***	0.183***	-0.088***	-0.070	0.092	0.177***	-0.174***	-0.070
	(0.082)	(0.026)	(0.027)	(0.063)	(0.110)	(0.033)	(0.053)	(0.063)
Days between 33C and 36C	1.029***	0.319***	0.045	0.008	1.238***	0.398***	0.017	0.008
	(0.130)	(0.037)	(0.033)	(0.073)	(0.172)	(0.047)	(0.061)	(0.073)
Days above 36C	0.936***	0.321***	-0.175**	-0.419***	0.908***	0.307***	-0.313***	-0.419***
	(0.244)	(0.083)	(0.071)	(0.109)	(0.294)	(0.095)	(0.113)	(0.109)
Precipitation	253.279*	37.464	-8.949	-84.979	461.867**	96.214*	-82.862	-84.979
	(134.968)	(39.466)	(40.596)	(119.894)	(196.540)	(55.090)	(80.458)	(119.894)
Observations	1,983,936	1,983,936	771,960	109,424	1,249,745	1,249,745	321,532	109,424
R-squared	0.203	0.265	0.189	0.283	0.206	0.267	0.214	0.283
Year-month FE	X	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for four different outcome variables using balanced or partially balanced panels. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature in between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.9: Storefront payday loan market

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -9C	-0.720*	-0.289	-0.326	1.088*	-0.026	0.085	0.057
	(0.373)	(1.042)	(0.321)	(0.592)	(0.372)	(0.095)	(0.074)
Days between -9C and -6C	0.927*	-0.469	0.250	-0.055	0.831	-0.105	-0.064
	(0.496)	(1.252)	(0.585)	(1.044)	(0.618)	(0.158)	(0.111)
Days between -6C and -3C	0.147	0.338	0.455	0.933	0.164	0.125	0.089
	(0.341)	(0.773)	(0.384)	(0.850)	(0.471)	(0.137)	(0.104)
Days between 27C and 30C	-0.240**	0.941***	0.076	-0.216	-0.151	-0.042	-0.007
	(0.108)	(0.295)	(0.129)	(0.208)	(0.157)	(0.047)	(0.043)
Days between 30C and 33C	0.014	0.456	-0.107	-0.347	0.257	0.122*	0.016
	(0.124)	(0.388)	(0.138)	(0.250)	(0.202)	(0.064)	(0.052)
Days above 33C	-0.444**	1.338**	0.220	0.008	-0.791***	0.057	0.184*
	(0.179)	(0.576)	(0.223)	(0.261)	(0.259)	(0.126)	(0.106)
Precipitation	238.505	-1,040.247**	-330.609	-161.737	-17.555	166.106	24.858
	(239.716)	(443.716)	(246.392)	(380.107)	(326.824)	(114.989)	(98.605)
Observations	31,070	52,589	52,589	30,081	30,081	30,081	30,081
R-squared	0.307	0.334	0.242	0.311	0.445	0.244	0.172
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables based on the storefront payday loan market. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.10: Online payday loan market

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -9C	0.046	1.306***	0.239**	-0.114	-0.331	-0.118	-0.221**
	(0.065)	(0.505)	(0.099)	(0.217)	(0.208)	(0.103)	(0.092)
Days between -9C and -6C	-0.098	2.125**	0.367*	0.277	0.211	-0.168	0.160
	(0.123)	(0.954)	(0.187)	(0.416)	(0.422)	(0.217)	(0.202)
Days between -6C and -3C	0.000	-0.214	-0.287**	-0.032	-0.188	0.212	0.106
	(0.082)	(0.711)	(0.143)	(0.317)	(0.280)	(0.149)	(0.140)
Days between 27C and 30C	-0.082***	-0.672***	0.033	-0.089	-0.030	0.002	0.006
	(0.022)	(0.220)	(0.051)	(0.112)	(0.067)	(0.028)	(0.027)
Days between 30C and 33C	-0.059**	1.356***	0.464***	-0.027	-0.014	0.037	0.042
	(0.026)	(0.327)	(0.072)	(0.131)	(0.075)	(0.033)	(0.032)
Days above 33C	-0.097***	0.702	0.215**	-0.577***	-0.282***	0.097**	0.101**
	(0.035)	(0.439)	(0.108)	(0.201)	(0.107)	(0.046)	(0.044)
Precipitation	-92.237*	1,340.747***	170.709*	-190.852	-114.387	199.849***	171.400***
	(47.162)	(456.438)	(101.488)	(186.691)	(123.221)	(52.285)	(50.379)
Observations	427,243	440,260	440,260	84,580	83,689	84,580	84,580
R-squared	0.147	0.190	0.227	0.168	0.190	0.189	0.170
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables based on the online payday loan market. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.11: Heterogenous effects

Hispanic ×	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -6C	0.191	-5.211	-1.962	0.525	-5.295	1.581	1.473
	(0.876)	(4.390)	(1.681)	(2.383)	(3.229)	(1.555)	(1.526)
Days between -6C and -3C	-0.796	12.923	3.392*	-1.271	-0.839	-1.166	-0.597
	(0.899)	(8.082)	(2.044)	(3.305)	(3.453)	(1.239)	(1.221)
Days between -3C and 0C	-0.317	-1.251	-0.883	0.636	2.180	-1.057	-1.288**
	(0.513)	(4.631)	(1.141)	(2.199)	(2.149)	(0.710)	(0.647)
Days between 30C and 33C	0.030	-0.654	-0.117	0.027	-0.012	-0.039	-0.056
	(0.039)	(0.483)	(0.108)	(0.190)	(0.104)	(0.042)	(0.040)
Days between 33C and 36C	0.078	1.668**	0.485***	-0.023	-0.271*	0.067	0.058
	(0.049)	(0.760)	(0.167)	(0.243)	(0.140)	(0.059)	(0.056)
Days above 36C	-0.099	0.031	-0.206	-0.369	0.143	-0.124	-0.177**
	(0.071)	(1.064)	(0.284)	(0.325)	(0.199)	(0.079)	(0.075)
Observations	439,462	461,881	461,881	110,246	109,424	110,246	110,246
R-squared	0.156	0.195	0.241	0.225	0.283	0.179	0.159
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (2) are presented for several specifications. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix Table B.12: Alternative subprime credit

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) delinquency rate	(7) default rate
Days below -9C	0.072	3.746***	0.756***	-0.022	-0.566*	-0.106	-0.008
	(0.070)	(0.659)	(0.127)	(0.141)	(0.297)	(0.108)	(0.092)
Days between -9C and -6C	-0.261**	4.743***	1.251***	0.266	0.154	0.087	0.114
	(0.128)	(1.245)	(0.240)	(0.264)	(0.563)	(0.204)	(0.178)
Days between -6C and -3C	-0.001	1.313	-0.720***	-0.320*	0.116	-0.003	-0.143
	(0.089)	(0.922)	(0.181)	(0.185)	(0.377)	(0.128)	(0.113)
Days between 27C and 30C	-0.016	0.697**	0.364***	0.140**	-0.002	0.055*	0.066***
	(0.021)	(0.332)	(0.076)	(0.055)	(0.081)	(0.029)	(0.025)
Days between 30C and 33C	-0.021	2.847***	0.451***	0.215***	0.124	0.029	-0.020
	(0.025)	(0.470)	(0.110)	(0.069)	(0.099)	(0.036)	(0.031)
Days above 33C	-0.130***	2.832***	0.747***	0.154	-0.091	0.028	0.070**
	(0.033)	(0.702)	(0.200)	(0.096)	(0.108)	(0.037)	(0.033)
Precipitation	-33.585	637.916	95.391	-104.090	-24.907	74.216	19.083
	(44.244)	(665.711)	(141.651)	(114.752)	(178.037)	(63.625)	(55.048)
Observations	498,199	654,366	654,366	161,322	161,194	161,322	161,322
R-squared	0.119	0.313	0.330	0.158	0.190	0.115	0.101
Year-month FE	X	X	X	X	X	X	X
County*Year FE	X	X	X	X	X	X	X

Notes: The estimation results for Equation (1) are presented for seven different outcome variables based on alternative subprime credit. The independent variables are the number of days in a month with daytime mean temperature within a specific range. The "Days between -3°C and 27°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daytime mean temperature within each respective temperature bin, relative to the impact of a day with daytime mean temperature between -3°C and 27°C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.