Extreme Weather and Low-Income Household Finance: Evidence from Payday Loans [*]

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Abstract

This paper explores the impact of extreme weather days on the financial outcomes of low-income households using novel payday loan data covering both application- and loan-level information. We find that both extreme heat and cold days lead to surges in payday loan demand. More extreme heat days result in a reduction of total credit issued and an increase in delinquency and default rates, indicating lenders' concerns about repayment abilities. The effects are especially noticeable for online payday loans. Our study provides new insights into how environmental shocks impact household finance, focusing on alternative credit products used by lower-income households.

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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, such as 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and Burney, 2021), resulting in lost wages, health issues with associated medical costs, inadequate emergency funds, outdated infrastructure and appliances, higher energy bills, and limited knowledge of available insurance options.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, such as the number of inquiries, credit approval, default, and delinquency rates, etc. 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 the 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 dataset is an inquiry-level dataset that provides comprehensive information on the date of application, income, age, and ZIP code of residence, among other things. For the same group of borrowers, we have a second loan level dataset, which contains rich information on the characteristics of the approved loan, including the highest credits, the maturation, the delinquency, and the default dates. To construct daily weather outcomes, we use satellite-based data from ERA5-Land. It contains the daily temperature and precipitation with $0.1° × 0.1°$ horizontal resolution covering the continental United States. 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.

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,

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[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.

[3]For example, Deschênes and Greenstone (2007); Graff Zivin and Neidell (2014); Barreca, Clay, Deschenes, Greenstone and Shapiro (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.

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 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. The total number of payday loans inquiries increases significantly 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 percent increase in total inquiries relative to the baseline. The 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 open. In particular, one extra extreme heat day is associated with a 0.4 percent 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. Taking 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.

We further document asymmetric effects of extreme heat and cold days on labor incomes. We show that extreme heat days negatively affect income, while 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. We first

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[5]According to Woolf, Morina, French, Funk, Sabo, Fong, Hoffman, Chapman and Krist (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.

distinguish between 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 distributional effects across ZCTAs. Our estimates suggest that counties with higher population shares of minorities 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 types of 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, Kim, Taubinsky and Zinman, 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 individual-level, nationally representative panel data allows 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 where interest rates are higher than storefront payday loan markets (Correia et al.,

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[6]Burke, Lanning, Leary and Wang (2014) find that four out of five payday loans are rolled over or renewed within 14 days. The 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.

2022).

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 et al., 2022; Gallagher and Hartley, 2017; Gallagher et al., 2020). We add to this work by focusing on alternative credit products used by lower-income households. Our 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. While existing work finds that spikes in credit card borrowing after natural disasters are modest and short-lived, we show that alternative credit markets may operate differently. With more extreme hot 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; Graff Zivin and Neidell, 2014; Park, Goodman, Hurwitz and Smith, 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.

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

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 $320 per $100 principal balance, equivalent to an interest rate of 400 to 600 annual percentage rate (APR).

There are many reasons why individuals might borrow payday loans despite the outrageous interest rates. About 3% respondents in the Survey of Consumer Finances indicated that they had indeed taken payday loans. The top reasons for choosing payday loans include emergency needs, convenience, and to pay other bills or loans. A significant fraction of respondents take payday loans to pay medical bills or utilities.[9]

The credit data used in this study comes from the Gies Consumer and small business Credit Panel (GCCP), which has been used in studies such as Fonseca (2023). The GCCP is a novel data set that links mainstream credit with alternative credit. We provide a brief overview of the database, with particular emphasis on the details of the alternative credit data. First, a random sample of individuals with mainstream credit reports is obtained from Experian, one of the major credit reporting agencies. This sample provides a snapshot of each individual's credit report as of March every year. Experian provides a borrower key that can be used to link borrowers in mainstream credit data to alternative credit data in the Clarity database, an Experian subsidiary specializing in alternative financial services data. Among the individuals that are present in the 2018 mainstream archive, we obtain their historical Clarity records for alternative credit products.

Two samples of alternative credit data are involved in our analysis. The first is a data set at the inquiry level consisting of consumers from 2012 to 2019. Inquiries are requests made by prospective borrowers to prospective lenders. Each applicant comes with a unique applicant ID. For each inquiry, we observe the date of the application and self-reported information obtained during the application process, including the 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 storefront.[10] 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,

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

[10]Though alternative credit 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 et al., 2022).

and amount past due. The applicant/borrower IDs from two datasets are one-to-one linked. However, we do not have a link between the application and the approval loan at the record level. We do not observe APR in the Clarity data, so we infer them based on observed loan maturity, highest credit amount (loan amount), and repayment amount: APR = 365/LoanMaturity × (Repayment- LoanAmount)/ LoanAmount.

Of the 621K borrowers who submitted an inquiry for any type of subprime credit, 223K borrowers inquired about payday loans and the rest were for other products such as installment loans. We focus on payday lending in this study. We observe 840K payday loan inquiries and 200K payday loans. We follow the approaches in Correia et al. (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.

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 of 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 dollars from storefront lenders and $400 from online lenders respectively. The delinquency rate is on average 8.7 percent and the default rate is 7.3 percent.

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° × 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 nonlinear 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 fourteen bins for every 3°C in between.[11] 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. 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 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.

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[11]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.

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 meet utility bill payments.

To address these challenges, the Low Income Home Energy Assistance Program (LIHEAP)[12] 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.

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 in each year from the Office of Community Services website [13]. Since household size cannot be observed in the payday loan data, we conservatively assume a household size of one, providing a cautious estimate 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 US 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 Sections 3.2 and 3.4 and equilibrium outcomes in Section 3.3. We further investigate the performance of existing accounts in Section 3.5 and examine borrower characteristics in Section 3.6. Finally, we provide several additional robustness checks on our results in Section 3.7.

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[12]See https://www.liheap.org/. See Appendix A.2 for more details of the LIHEAP program.

[13]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 sixteen temperature bins: below -9°C, above 33°C, and fourteen bins for every 3°C in between. We choose -3°C – 27°C as the omitted baseline daytime (between 8am to 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.[14]

Our adoption of the non-linear temperature bin specification follows the recent climate economy literature (Dell et al., 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 in the ergonomics literature documents that task performance losses start to increase in a non-linear manner at high temperature ranges (Hancock, Ross and Szalma, 2007). Other studies also indicate that labor productivity drops significantly as temperature increases.[15]

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 be also associated with regional business cycles, so we include county-year fixed effects. Our identifying variations are

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[14]In Section 3.7, 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.

[15]These include but are not limited to evidence from assembly lines, laboratories, meta-analysis, and self-reported surveys: Adhvaryu, Kala and Nyshadham (2020), Graff Zivin and Neidell (2014), Heal and Park (2020), Niemelä, Hannula, Rautio, Reijula and Railio (2002).

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 provides 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 the number of extreme heat or cold days per month leads to about a 0.4 percent increase in total inquiries relative to the baseline.

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 3.6.

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. 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 33°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 increase in the number of extreme heat days per month leads to about a 0.7 percent increase in account 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 percent 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 due to two reasons. First, payday lenders tend to screen borrowers from very low-income backgrounds. We specifically test this income channel in Section 3.6 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 APR?

We do not directly observe APR from the Clarity data. Instead, it is deduced through the observed loan duration, the maximum credit amount, and the total repayment. Figure 5 reveals that the APR appears unaffected by extreme weather conditions. This finding suggests that the spike in credit demand triggered by severe weather events might predominantly be for emergencies, such as the repair of a malfunctioning air conditioner, implying a relatively inelastic demand.

3.5   Do temperature exposures affect the performance of existing accounts?

We next examine delinquency and default rates associated with extreme weather. Figure 6 reveals that a single extra day with a temperature above 33°C is linked to a 0.09 percentage points increase in delinquency rate and a 0.1 percentage points increase in default rate. In other words, one standard deviation increase in the number of extreme heat days per month leads to about

a 3 percent 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.

3.6 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 7 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 percent 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.[16] For example, Graff Zivin and Neidell (2014) find that time allocated to labor reduces with more extreme heat days but is nonresponsive 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 other channels such as increasing energy or health expenditures also matter.

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

3.7 Placebos and robustness

We perform two *placebo tests* to justify the credibility of our findings. Specifically, we conduct placebo tests by shuffling the temperature vectors. In the first test, we randomly shuffle the temperature vectors throughout the country for a given month. In the second test, we randomly shuffle the temperature vectors for the same month within each region. Across all outcome variables, these manipulations yield consistently insignificant results.

Next, we discuss several additional *robustness checks*. First, we employ alternative approaches to categorize temperature bins. Second, we apply different controls for fixed effects. Third, we incorporate different timings of temperature measurements. Fourth, we include the lags of the dependent variables. Lastly, we use a balanced panel data structure.

Alternative definitions of temperature bins   In our main analysis, we define temperature bins based on daytime (between 8am to 8pm) mean temperature: below -9°C, above 33°C, and fourteen 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 bins in between. We see that an additional day with a daily maximum temperature above 36°C results in increased demand, decreased credits, and increased default and delinquency. Table B.3 presents results where we define the temperature bins using the 24-hour daily mean temperature: below -12°C, above 30°C, and every 3°C bins in between. Again, the main results are similar. Having an additional day in a month with a 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°, the daytime mean temperatures are below the 5th percentile and below -6°, 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".

Alternative fixed effects controls   In our baseline specification, we have included year-month fixed effects to control for seasonality and global warming trends and county-by-year fixed effects for local weather and economic fluctuations. In addition, we incorporate year-month fixed effects, ZCTA fixed effects, as well as region-by-calendar-year and region-by-calendar-month fixed effects. ZCTA fixed effects control for unobserved, area-specific attributes that remain constant over time, ensuring that our analysis captures the effects of temperature independently of these static characteristics. Region-by-calendar-year and region-by-calendar-month fixed

effects account for regional variations and temporal shifts within a year, respectively, providing a finer control for regional dynamics and seasonal patterns. Table B.5 presents the results and shows that our main results are not sensitive to fixed effects.

Timing of the temperature impacts   The baseline estimate is set so that the weather in this month affects the outcomes of the payday loans in the same month. However, this approach may overlook two key issues. First, some weather events may occur after payday loans have been processed. Second, while high temperatures can lead to higher energy bills in the current month, the resultant financial distress may not manifest until a few months later, often when bills become overdue. To address these timing-related concerns associated with extreme weather events, we use the temperature bins from last month as independent variables in Table B.6 and we use the temperature vectors from the next month in Table B.7. Our findings align with the hypothesis on timing: both past and upcoming month's temperatures can impact loan outcomes, underscoring the temporal nuances of weather's effect on financial distress.

Including the lags of the outcome variables   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.8 (using daytime mean temperature), Table B.9 (using daily maximum temperature), and Table B.10 (using 24-hour daily mean temperature). The inclusion of the lagged dependent variable as a regressor significantly reduces our sample size. Estimates on delinquency and default rates are sometimes imprecisely measured, although always positive. Our other main findings are not affected.

Balanced panel   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 perform a robustness check with a fully balanced panel. This involves 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.11, 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 periods 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.11 show that our key results hold up.

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4 Further Discussions

We extend our discussions on 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 8 and Table B.12) and online (Figure 9 and Table B.13) 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 minority population from the 5-year American Community Survey conducted by the Census Bureau. This is particularly relevant given

the predominant employment of these communities in the construction industry and, more broadly, in outdoor occupations that involve high exposure to temperature variations. 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 often lack sufficient protective measures against extreme temperatures.

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

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

where $NonWhite_i$ is a dummy variable that takes the value 1 if the share of minority population share in ZCTA i is above 75% in 2010, 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 ZCTA characteristics.

Table B.14 reports the estimates of γ's for eight dependent variables. The results indicate that ZCTAs with a larger share of the minority 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, 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.15 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, for the increases in extreme heat days are not associated with greater delinquency. Figure 10 illustrates these results. This evidence suggests that lenders are more willing to extend credit like installment loans when demands increase 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 previously discussed, one potential factor contributing to the rising demand for payday loans during extreme temperatures is the increase in heating or cooling energy 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.[17] 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 which equals to one if the payday loan applicant/borrower i is *eligible* for the LIHEAP program in month t and equals to zero otherwise. In addition to 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, since household size information is not available for payday loan borrowers, we conservatively assume a household size of one to define Treat_{it}. Consequently, our estimates for β may exhibit a bias towards zero, as we take a cautious approach in assessing the impact of LIHEAP.

In our main analysis, we adopt a bandwidth of $1,000 around the eligibility income threshold in each state. As reported in Table 4, we found no significant evidence that the eligibility for

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

LIHEAP changes most payday loan market outcomes, such as inquiries, default, or delinquency rates. As a robustness check, we adopt an alternative bandwidth of $2,000 around the eligibility income thresholds, as shown in Table B.16. The estimates on highest credit are negative in both cases and we also observe an increase in delinquency rate, which could potentially be driven by the small but meaningful differences in income between the treatment and control groups.

There are many reasons why we may not see a significant impact of LIHEAP on payday loan market outcomes, related to the program's design and accessibility across different states. For instance, in states like California, LIHEAP is available once a year but accessible throughout the year. 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 towards zero. So 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 credits market measures. Our findings indicate the 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 due to the increased risk of delinquency and default.

Our study sheds light on the relationship between environmental shocks and household finance, particularly regarding the utilization of alternative 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
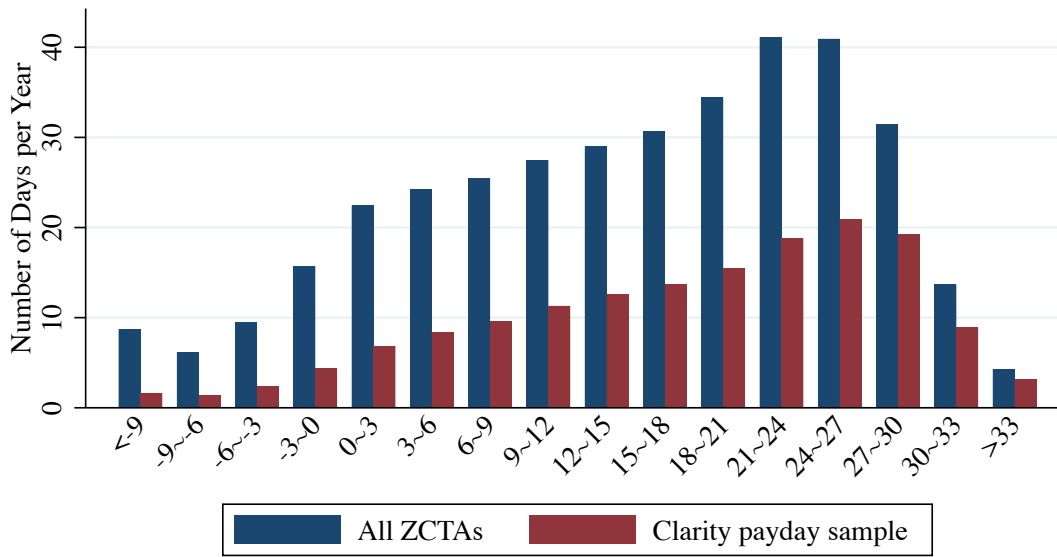
Notes: The figure shows the historical average distribution of daytime mean temperatures across 16 temperature-day bins. Each bar represents the average number of days per year in each temperature bin from 2012-2019. The "All ZCTAs" dataset represents ZCTAs of the continental U.S., summing to 365 days 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
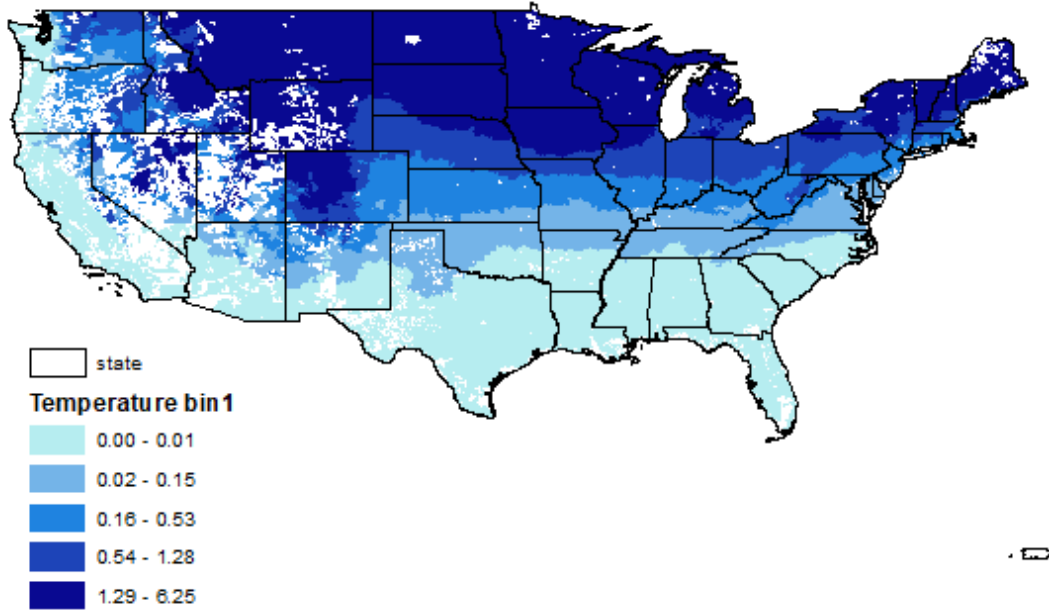
(b) AVERAGE MONTHLY NUMBER OF DAYS WITH DAYTIME MEAN TEMPERATURE ABOVE 33°C
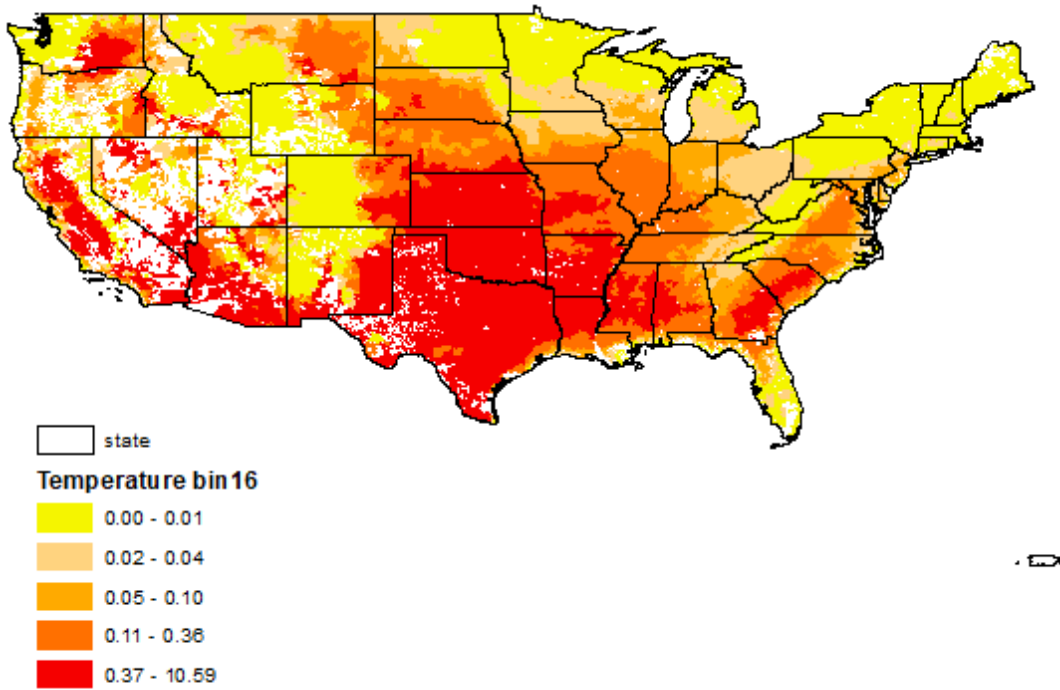
Notes: The figure shows the spatial distribution across ZCTAs of the monthly number of days that had daytime (between 8am to 8pm) mean temperatures below -9°C in panel (a) and above 33°C in panel (b), respectively.

Figure 3: IMPACT ON TOTAL INQUIRIES AND UNIQUE INQUIRIES
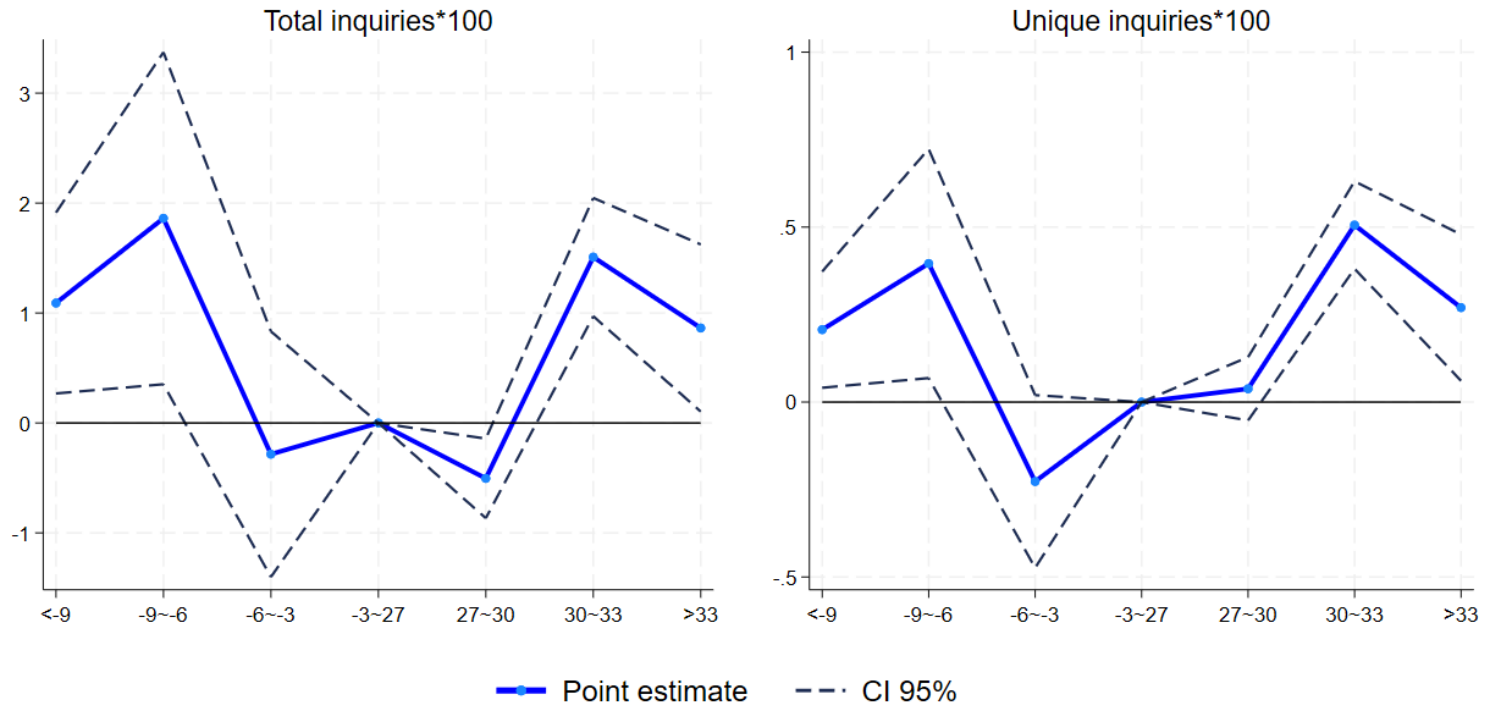
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins on number of total inquiries (left) and unique inquiries (right), relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95 percent confidence intervals are based on standard errors clustered at the ZCTA level.

Figure 4: IMPACT ON ACCOUNT OPEN AND TOTAL CREDITS
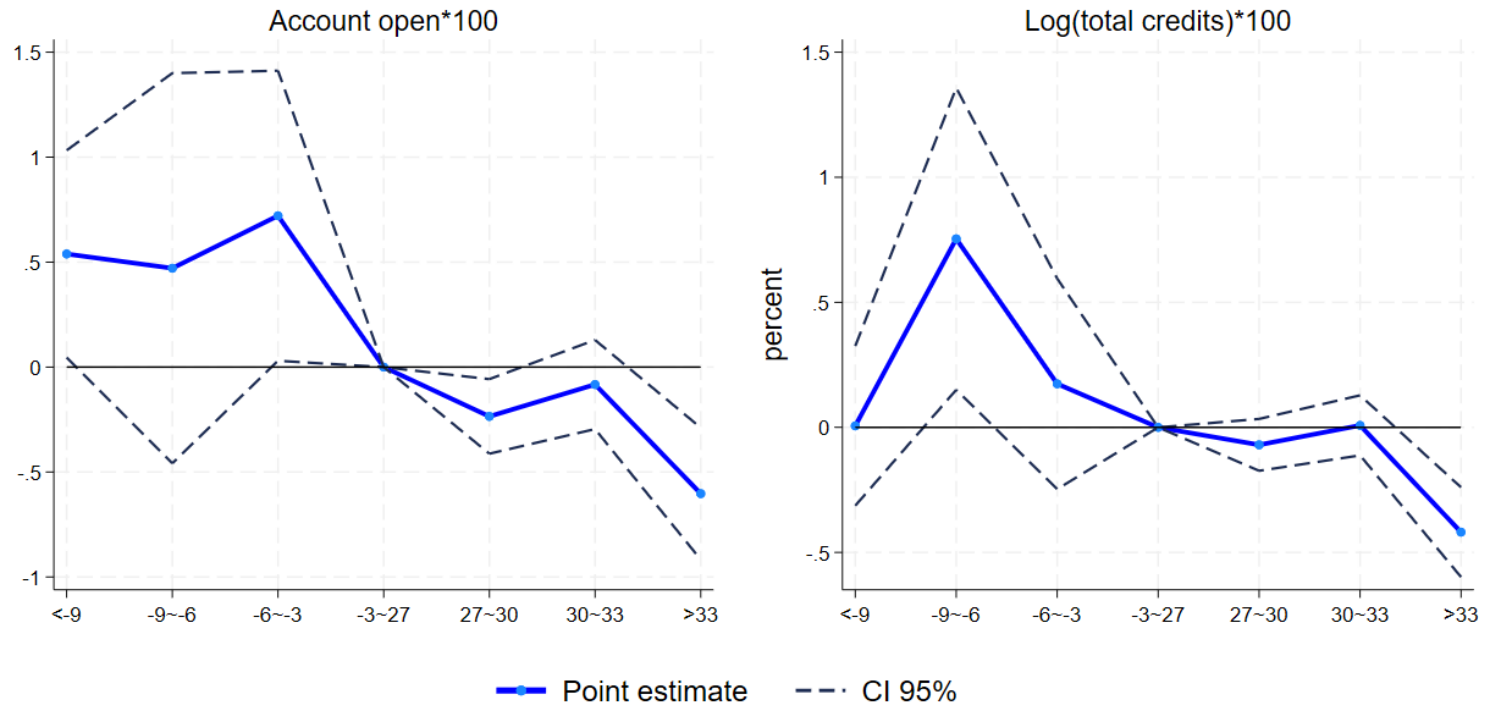
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins on number of account open (left) and log of total credits (right), relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95 percent confidence intervals are based on standard errors clustered at the ZCTA level.

Figure 5: IMPACT ON APR
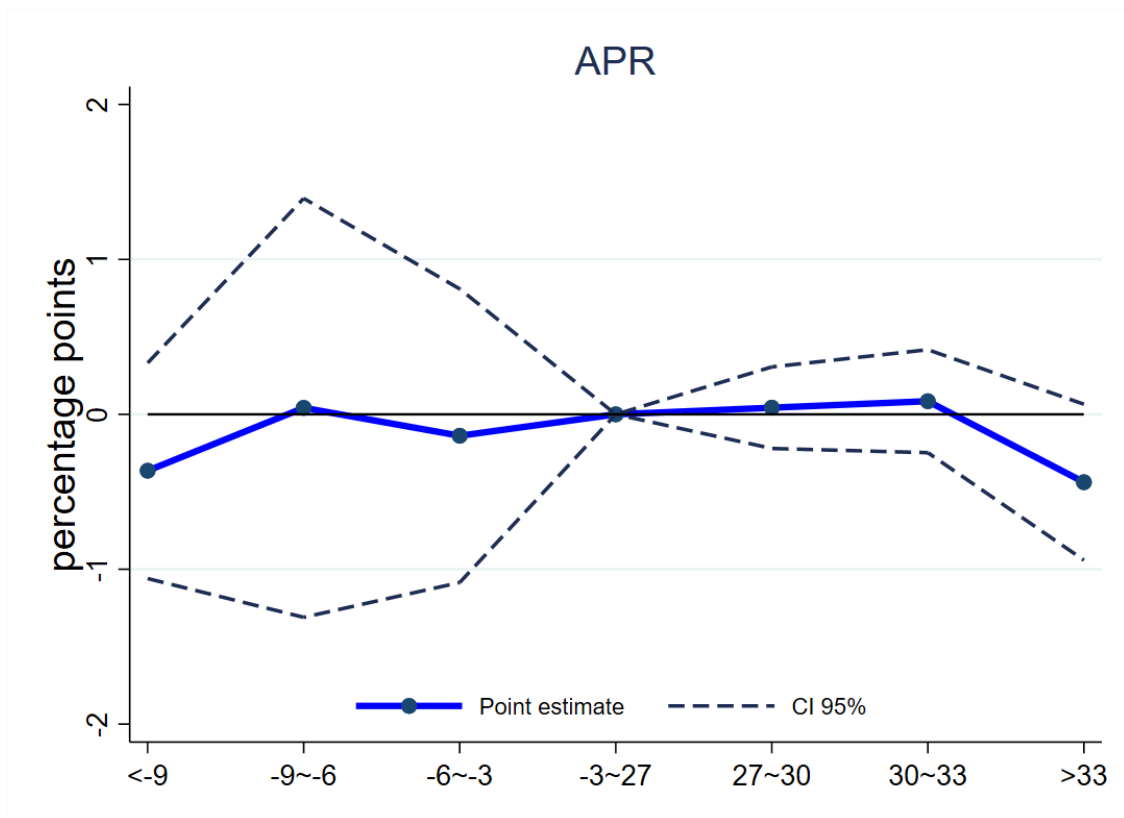
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins on APR, relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95 percent confidence interval is based on standard errors clustered at the ZCTA level.

Figure 6: IMPACT ON DELINQUENCY RATE AND DEFAULT RATE
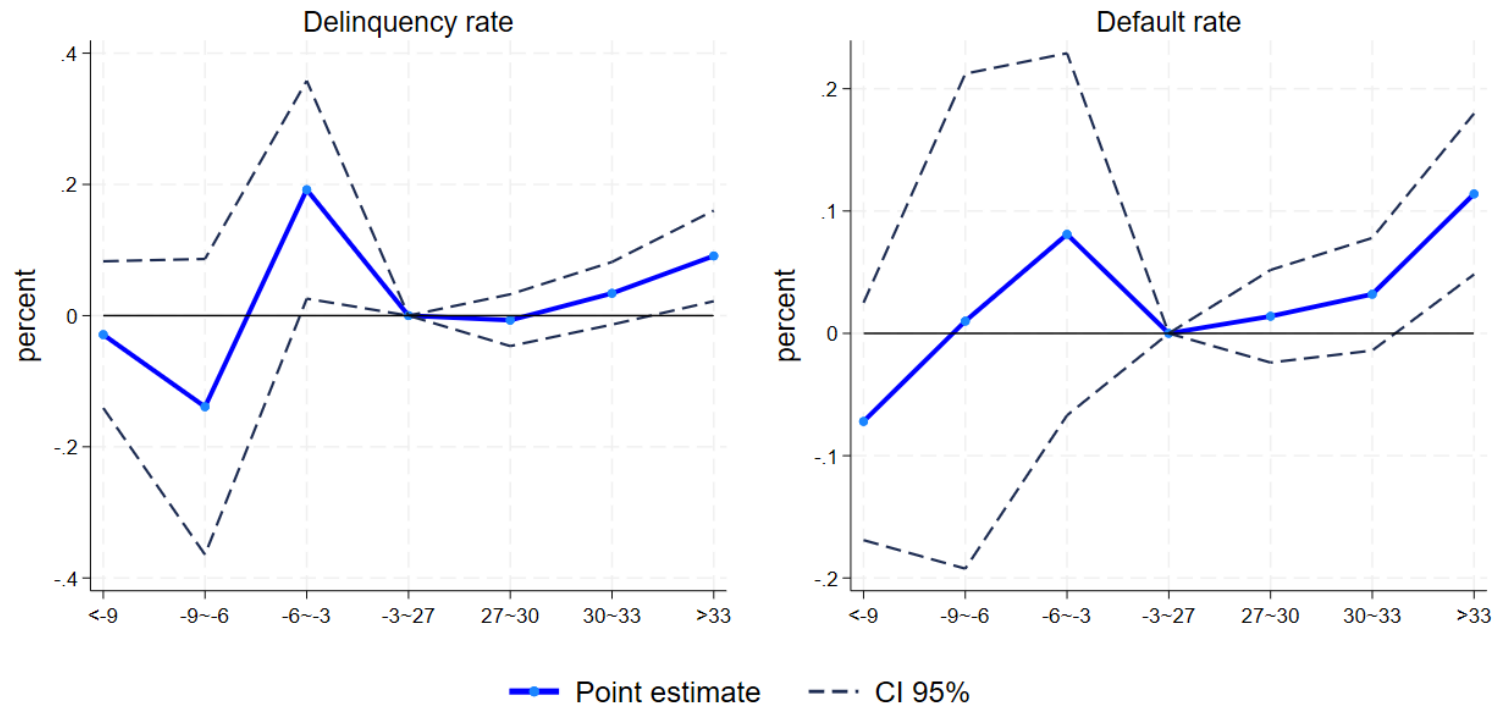
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins on delinquency rate (left) and default rate (right), relative to a day in the -3°C to 27°C bins. Responses are estimated using specification (1). The 95 percent confidence intervals are based on standard errors clustered at the ZCTA level.

Figure 7: IMPACT ON AVERAGE INCOME
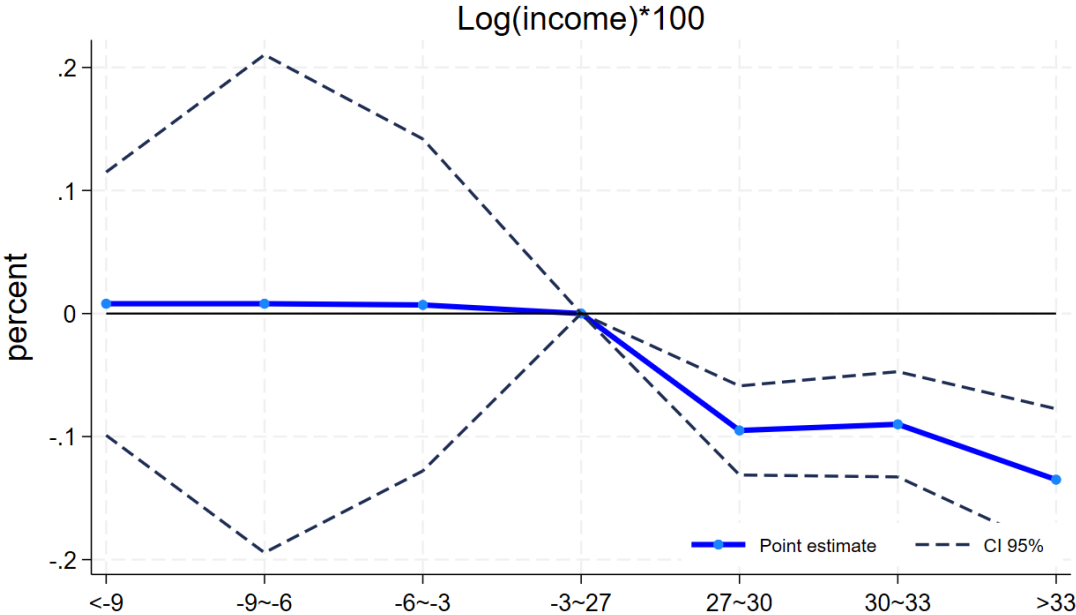
Log(income)*100

Notes: The figure provides the estimated impact of a day in 6 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 percent confidence interval is based on standard errors clustered at the ZCTA level.

Figure 8: STOREFRONT PAYDAY LOANS
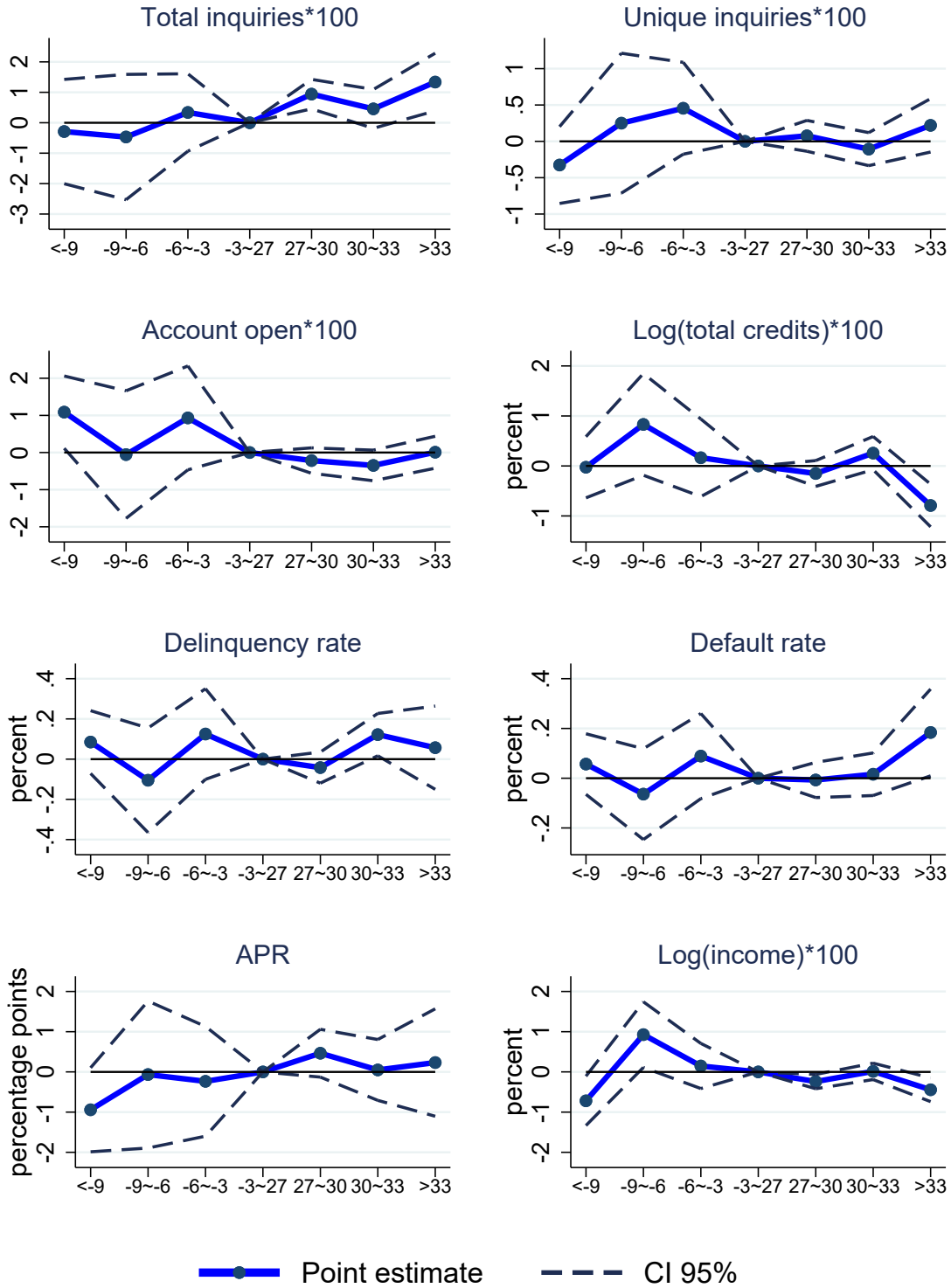
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins relative to a day in the -3°C to 27°C bins on the storefront payday loan market. Dependent variables considered are number of total inquiries (top left), unique inquiries (top right), number of accounts open (2nd row left), log of total credits (2nd row right), delinquency rate (3rd row left), default rate (3rd row right), APR (bottom left) and log of income (bottom right). Responses are estimated using specification (1). The 95 percent confidence interval is based on standard errors clustered at the ZCTA level.

Figure 9: ONLINE PAYDAY LOANS
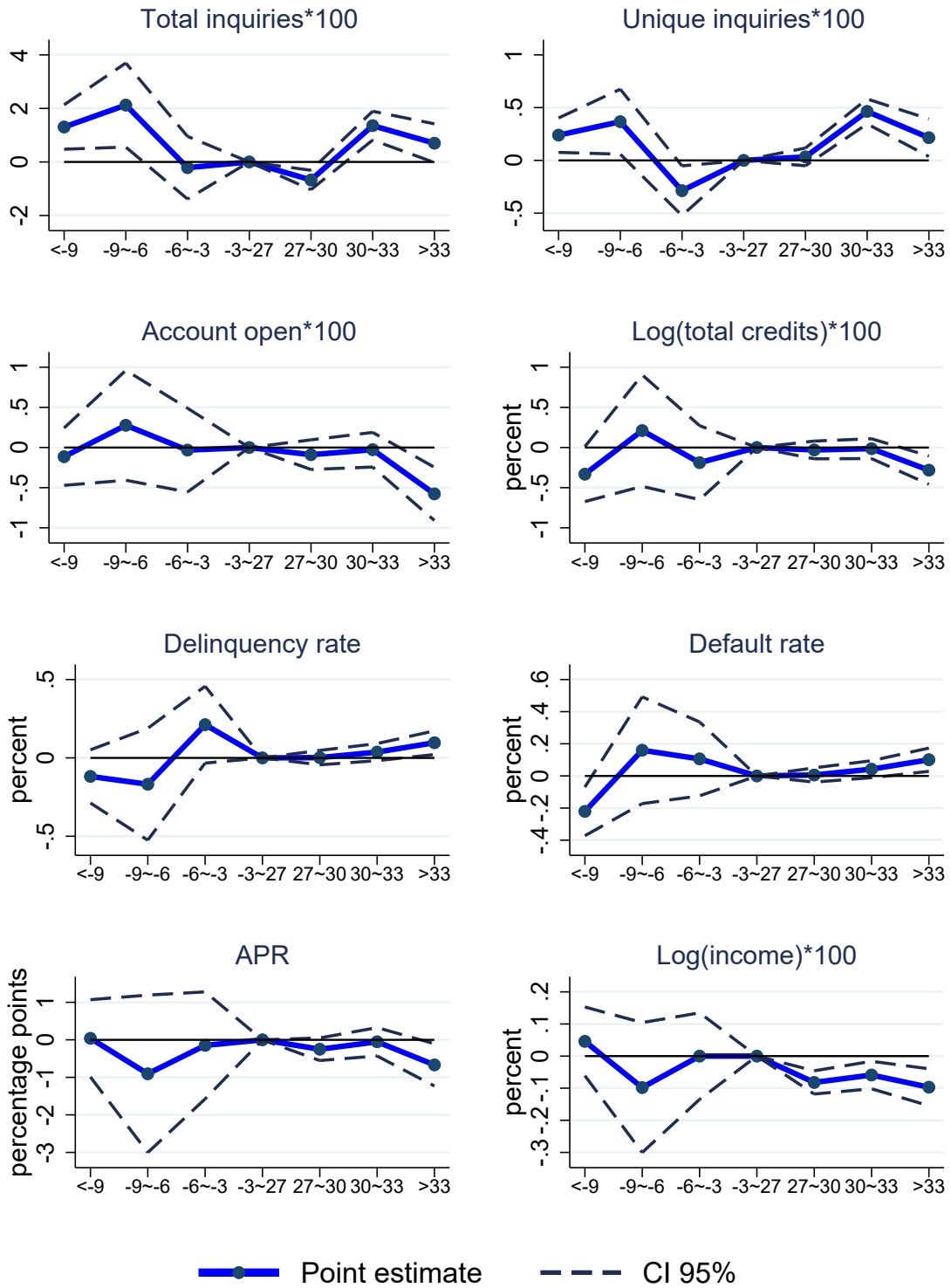
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins relative to a day in the -3°C to 27°C bins on the online payday loan market. Dependent variables considered are number of total inquiries (top left), unique inquiries (top right), number of accounts open (2nd row left), log of total credits (2nd row right), delinquency rate (3rd row left), default rate (3rd row right), APR (bottom left) and log of income (bottom right). Responses are estimated using specification (1). The 95 percent confidence interval is based on standard errors clustered at the ZCTA level.

Figure 10: ALTERNATIVE SUBPRIME CREDIT: INSTALLMENT LOANS
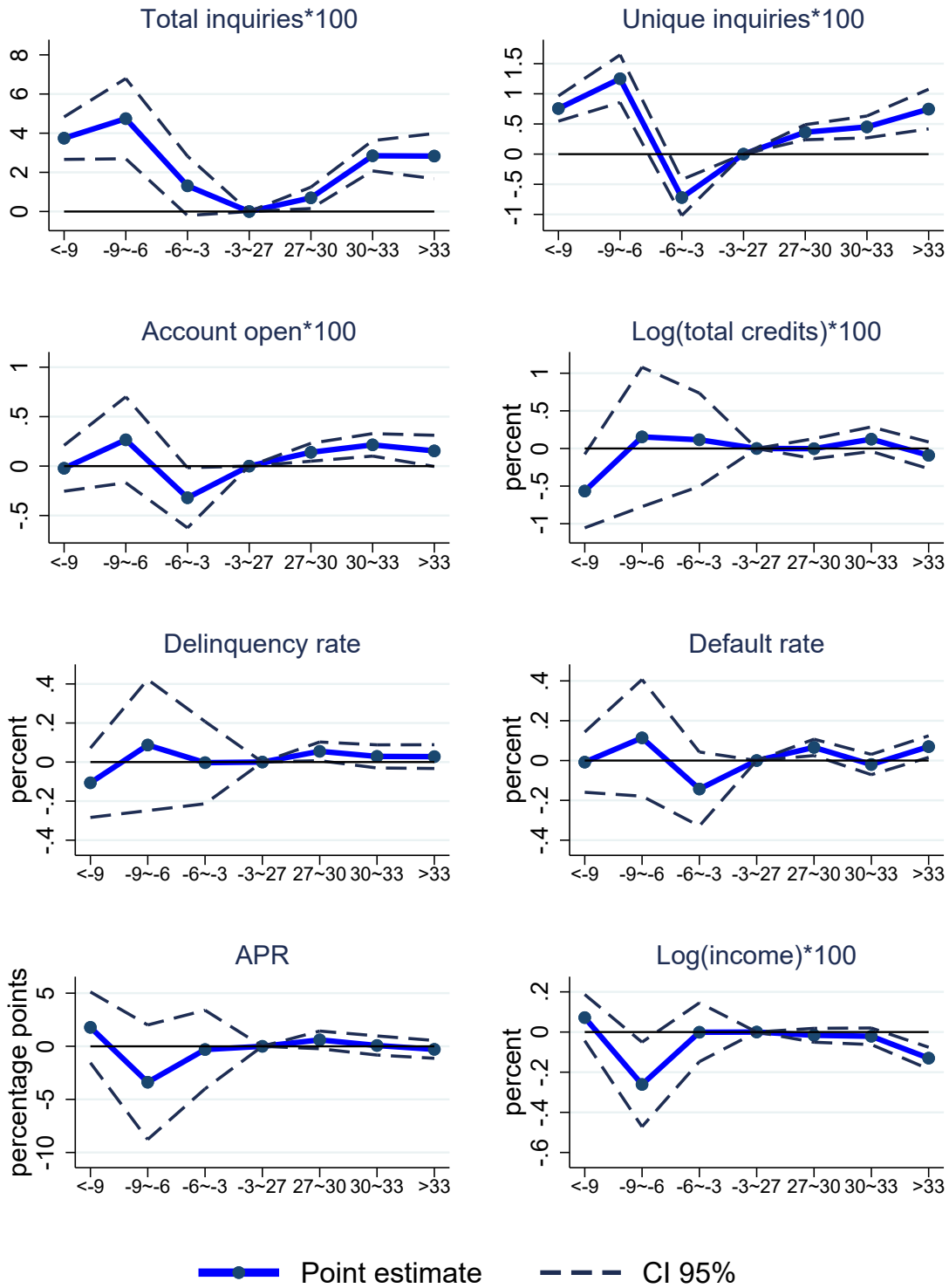
Notes: The figure provides the estimated impact of a day in 6 different daytime mean temperature bins relative to a day in the -3°C to 27°C bins on installment loans. Dependent variables considered are number of total inquiries (top left), unique inquiries (top right), number of accounts open (2nd row left), log of total credits (2nd row right), delinquency rate (3rd row left), default rate (3rd row right), APR (bottom left) and log of income (bottom right). Responses are estimated using specification (1). The 95 percent 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					
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					
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

	mean	sd	p99	p95	p90	p50	p10	p5	p1
	All ZCTAs								
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 to 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) APR	(7) delinquency rate	(8) default rate
T <-9C	0.008	1.091**	0.207**	0.539*	0.006	-0.364	-0.029	-0.072
	(0.065)	(0.500)	(0.101)	(0.300)	(0.194)	(0.423)	(0.068)	(0.059)
-9C <T<-6C	0.008	1.862**	0.396**	0.471	0.754**	0.042	-0.139	0.010
	(0.123)	(0.918)	(0.199)	(0.565)	(0.367)	(0.822)	(0.137)	(0.123)
-6C <T<-3C	0.007	-0.284	-0.227	0.721*	0.174	-0.138	0.192*	0.081
	(0.082)	(0.679)	(0.150)	(0.420)	(0.256)	(0.576)	(0.101)	(0.090)
27C <T<30C	-0.095***	-0.504**	0.038	-0.235**	-0.070	0.043	-0.007	0.014
	(0.022)	(0.220)	(0.055)	(0.108)	(0.063)	(0.160)	(0.024)	(0.023)
30C <T<33C	-0.090***	1.509***	0.506***	-0.083	0.008	0.085	0.034	0.032
	(0.026)	(0.327)	(0.076)	(0.129)	(0.073)	(0.202)	(0.029)	(0.028)
T >33C	-0.135***	0.864*	0.270**	-0.603***	-0.419***	-0.438	0.091**	0.114***
	(0.035)	(0.462)	(0.127)	(0.191)	(0.109)	(0.306)	(0.042)	(0.040)
Precipitation	777.694***	1,294.401***	195.912*	-97.662	-84.979	352.677	163.910***	126.838***
	(0.222)	(439.052)	(103.660)	(182.022)	(119.894)	(306.551)	(46.061)	(43.275)
Observations	439,568	461,993	461,993	110,246	109,424	90, 766	110,246	110,246
R-squared	0.156	0.195	0.241	0.225	0.283	0.298	0.179	0.159
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 eight 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 -3C and 27C" 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 -3C and 27C. 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 one an individual's income is above $1000 of the cut-off for LIHEAP eligibility. We also include the temperature bins and the precipitation. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix For Online Publication

Appendix A   Background information

Appendix A.1   Reasons for taking payday loans

In 2013, 2016, and 2019 waves of the Survey of Consumer Finances[18], respondents were asked two specific questions related to their utilization 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. It is about three percent 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 percent 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
8. "Christmas"
9. Help family
10. "Emergency"/"needed quick money"
11. "Convenient"
12. "Only option"

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

Appendix Figure A.1: REASONS FOR TAKING PAYDAY LOANS
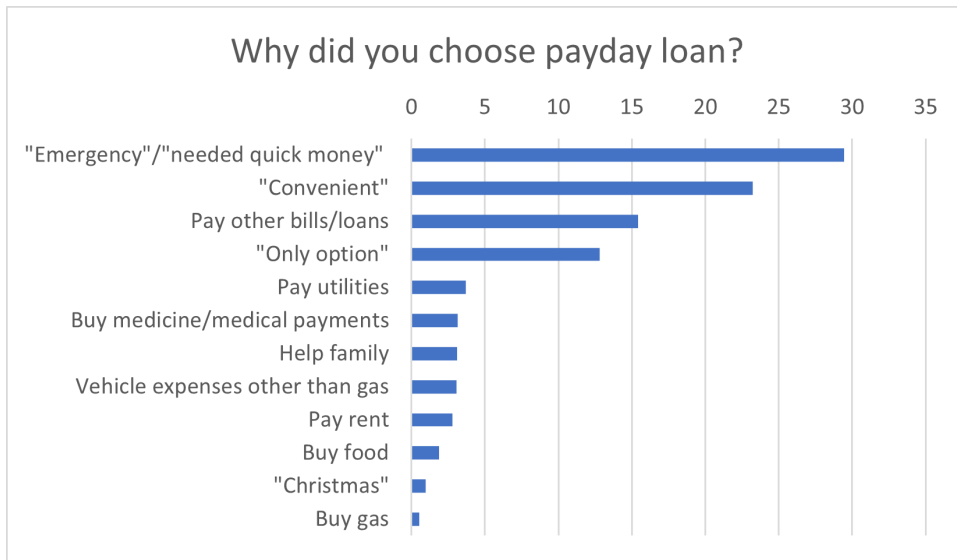
Notes: The figure presents the percentages representing individual reasons, calculated based on responses from the Survey of Consumer Finances for the years 2013, 2016, and 2019. The reasons are ordered and plotted in descending order from top to bottom. The percentage indicates how many respondents, out of the total responses, selected each specific reason. The percentages add up to 100.

Appendix A.2   LIHEAP program

Since its inception in 1981, LIHEAP 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 (https://www.liheap.org/). 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. Additionally, LIHEAP extends support to eligible households by allocating funds for weatherization measures and energy-related home repairs. In particular, the heating and cooling payment assistance program stands as the largest component of LIHEAP. Each year, nearly two-thirds of the 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 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 assistance with home heating or cooling bills and/or energy assistance twice a year, operating on a first-come, first-served basis until funds are depleted. According to the latest White paper, cold weather states traditionally spend more than 70 percent 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
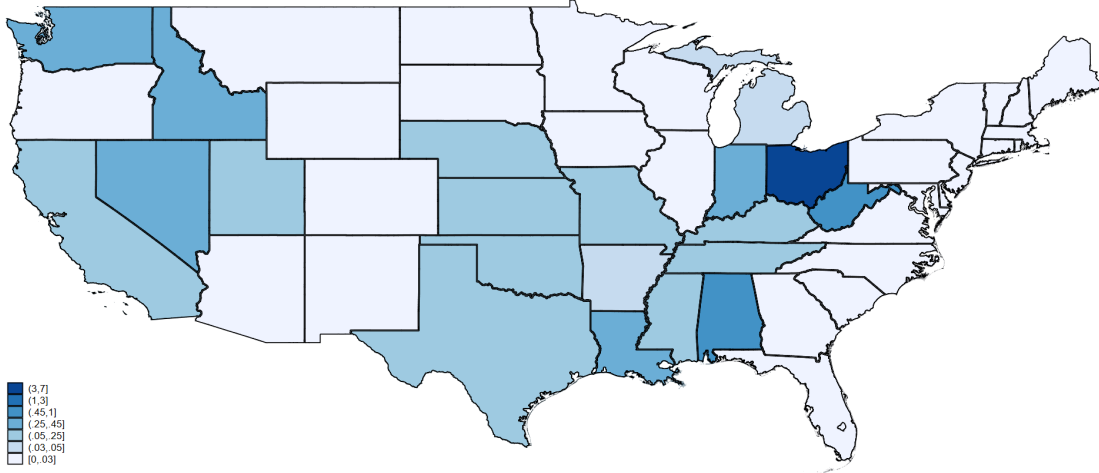
(b) ONLINE
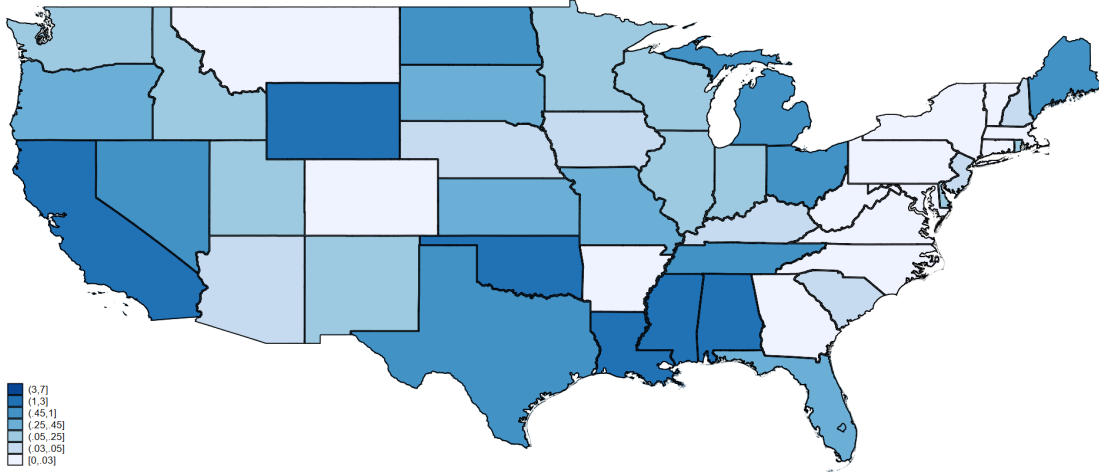
Notes: This figure plots the geographic distribution of loans per capita for storefront (upper) and online (lower) payday loan subsamples, respectively.

Appendix Figure B.2: AVERAGE DAYTIME MEAN TEMPERATURE
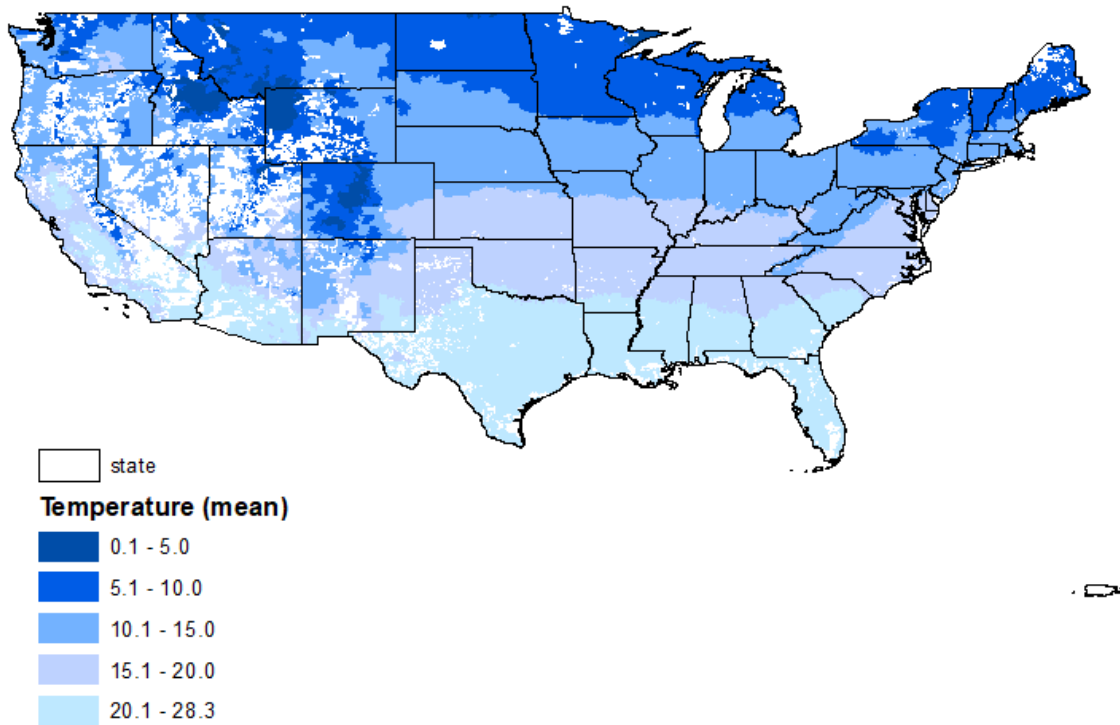
Notes: The figure shows the spatial distribution of the daytime (between 8am to 8pm) mean temperatures across ZCTAs, averaged from 2012-2019. Around 5% ZCTA-day level observations have a daytime mean temperature above the 30°C threshold, and around 5% ZCTA-day level observations have a daytime mean temperature below the -5°C threshold.

Appendix Figure B.3: GEOGRAPHIC DISTRIBUTION OF INCOME AND LIHEAP ELIGIBILITY

(a) LIHEAP ELIGIBILITY
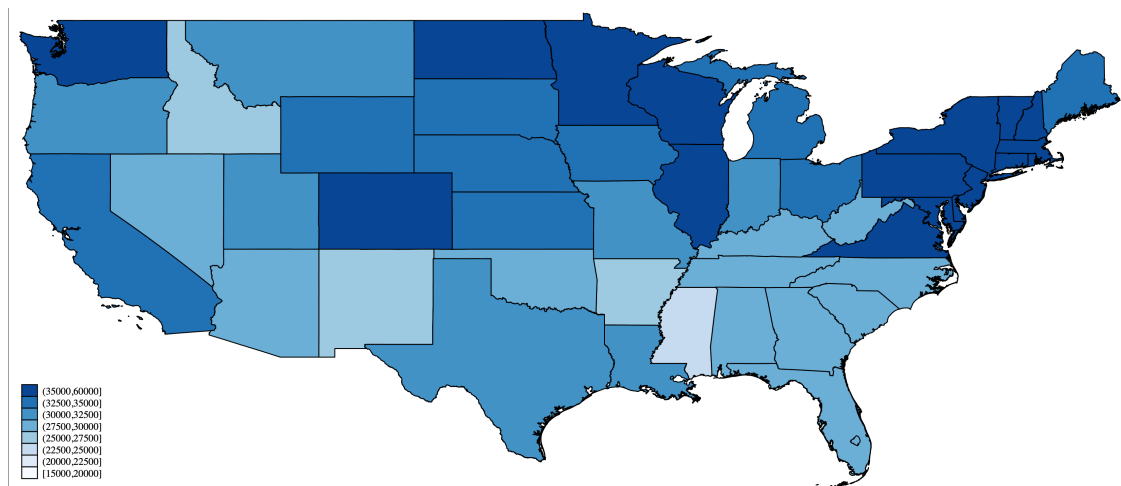
(b) INCOME OF PAYDAY LOAN BORROWERS
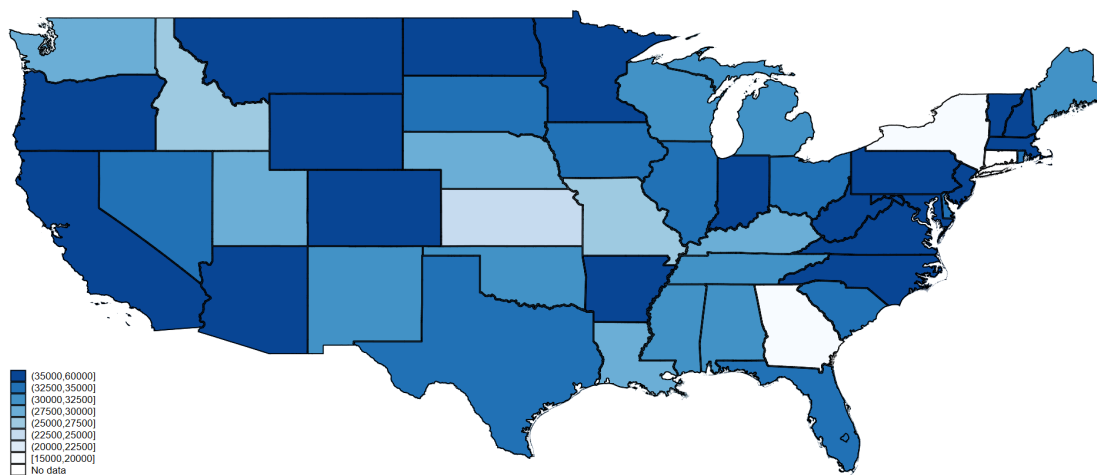
Notes: This figure plots the geographic distribution of LIHEAP eligibility cutoff (upper) and income of payday loan borrowers (lower), respectively.

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) APR	(6) delinquency rate	(7) default rate
T<-9C	1.256**	0.260**	0.557	-0.336	-0.389	-0.024	-0.098
	(0.519)	(0.105)	(0.411)	(0.249)	(0.589)	(0.097)	(0.083)
-9C <T<-6C	2.061**	0.399*	1.073	0.702	0.556	-0.033	0.180
	(0.961)	(0.207)	(0.802)	(0.471)	(1.101)	(0.190)	(0.168)
-6C <T<-3C	-0.431	-0.249	0.887	0.278	-0.164	0.108	-0.032
	(0.718)	(0.157)	(0.567)	(0.317)	(0.758)	(0.137)	(0.120)
27C <T<30C	-0.632***	0.029	-0.296**	-0.115	-0.027	-0.028	0.003
	(0.227)	(0.056)	(0.133)	(0.074)	(0.183)	(0.029)	(0.027)
30C <T<33C	1.377***	0.510***	-0.210	0.011	0.189	0.022	0.016
	(0.335)	(0.077)	(0.154)	(0.084)	(0.238)	(0.035)	(0.033)
T>33C	0.610	0.220*	-0.664***	-0.501***	-0.503	0.102**	0.127***
	(0.471)	(0.129)	(0.216)	(0.121)	(0.327)	(0.050)	(0.048)
Precipitation	1,109.098**	197.105*	50.061	-92.023	646.628*	200.117***	152.962***
	(466.878)	(107.568)	(232.759)	(140.525)	(382.076)	(57.151)	(53.556)
log(avg income)	-0.493***	0.059***	0.001	0.125***	0.064***	-0.025***	-0.021***
	(0.021)	(0.006)	(0.014)	(0.008)	(0.017)	(0.002)	(0.002)
Observations	439,568	439,568	82,114	81,521	66,121	82,114	82,114
R-squared	0.200	0.254	0.268	0.271	0.272	0.186	0.166
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. 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 -3C and 27C" 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 -3C and 27C. 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) APR	(7) delinquency rate	(8) default rate
T<-6C	0.055	1.450**	0.292**	0.887**	0.185	-0.217	-0.094	-0.117
	(0.076)	(0.583)	(0.117)	(0.355)	(0.225)	(0.522)	(0.090)	(0.077)
-6C <T<-3C	-0.129	-1.360	-0.577***	-0.865*	-0.011	-0.417	0.080	0.115
	(0.118)	(0.940)	(0.196)	(0.492)	(0.331)	(0.775)	(0.130)	(0.112)
-3C <T<0C	0.049	0.701	0.260*	1.115***	0.392*	-0.110	0.079	0.021
	(0.077)	(0.643)	(0.146)	(0.344)	(0.224)	(0.524)	(0.084)	(0.075)
30C <T<33C	-0.092***	-0.064	0.082	-0.245*	-0.068	0.076	-0.009	0.013
	(0.024)	(0.252)	(0.069)	(0.125)	(0.069)	(0.173)	(0.025)	(0.024)
33C <T<36C	-0.070***	1.366***	0.477***	-0.023	0.017	0.016	0.028	0.021
	(0.027)	(0.338)	(0.083)	(0.139)	(0.076)	(0.205)	(0.030)	(0.028)
T>36C	-0.118***	1.099***	0.350***	-0.483***	-0.325***	-0.250	0.082**	0.099***
	(0.032)	(0.405)	(0.113)	(0.173)	(0.094)	(0.249)	(0.034)	(0.033)
Precipitation	-62.570	1,099.071***	199.937**	-114.348	-92.196	313.342	153.490***	119.788***
	(46.157)	(420.493)	(100.351)	(172.860)	(113.071)	(288.605)	(43.948)	(41.439)
Observations	441,842	464,452	464,452	111,124	110,302	91,505	111,124	111,124
R-squared	0.156	0.195	0.241	0.226	0.283	0.298	0.179	0.160
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 eight different outcome variables. The independent variables are the number of days in a month with daily maximum temperature within a specific range. We use sixteen temperature bins: below -6°C, above 36°C, and fourteen 3°C bins in between. The "Days between 0C and 30C" 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 0C and 30C. 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) APR	(7) delinquency rate	(8) default rate
T<-12C	0.007	0.878	0.230*	0.475	0.165	-0.744	-0.111	-0.141*
	(0.087)	(0.621)	(0.129)	(0.385)	(0.253)	(0.577)	(0.090)	(0.078)
-12C <T<-9C	-0.039	2.029*	0.174	1.196*	0.350	1.119	0.211	0.184
	(0.147)	(1.160)	(0.250)	(0.698)	(0.429)	(0.893)	(0.152)	(0.127)
-9C <T<-6C	0.061	0.692	-0.015	0.445	0.289	-0.514	0.008	0.016
	(0.102)	(0.815)	(0.173)	(0.478)	(0.299)	(0.731)	(0.120)	(0.108)
24C <T<27C	-0.052**	-0.529***	0.007	-0.214**	-0.049	-0.013	-0.037	-0.017
	(0.020)	(0.198)	(0.048)	(0.102)	(0.057)	(0.144)	(0.023)	(0.022)
27C <T<30C	-0.118***	0.918***	0.405***	-0.089	0.028	0.107	0.041*	0.039*
	(0.021)	(0.237)	(0.055)	(0.103)	(0.061)	(0.155)	(0.023)	(0.021)
T>30C	-0.115***	1.183***	0.333***	-0.582***	-0.377***	-0.395	0.068*	0.090**
	(0.030)	(0.391)	(0.103)	(0.158)	(0.096)	(0.276)	(0.038)	(0.036)
Precipitation	-27.028	775.340*	27.222	-73.425	-88.748	332.453	137.286***	106.046**
	(45.881)	(417.775)	(100.134)	(176.575)	(113.472)	(286.501)	(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	X
County*Year FE	X	X	X	X	X	X	X	X

Notes: The estimation results for equation (1) are presented for eight 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 sixteen temperature bins: below -12°C, above 30°C, and fourteen 2°C bins in between. The "Days between -6C and 24C" 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 -6C and 24C. 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
T <min(-6C, 5th pctl)	-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)
T >max(33C, 95th pctl)	-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 in betwen 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: IMPACTS OF EXTREME TEMPERATURES ON PAYDAY LOAN MARKETS, ALTERNATIVE FIXED EFFECTS

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) APR	(7) delinquency rate	(8) default rate
T<-9C	-0.023	1.996***	0.376***	0.513	0.399**	-0.009*	-0.061	-0.092
	(0.068)	(0.546)	(0.104)	(0.315)	(0.203)	(0.005)	(0.070)	(0.063)
-9C <T<-6C	0.058	0.913	-0.108	-0.181	0.582	0.012	-0.128	-0.058
	(0.119)	(0.921)	(0.195)	(0.609)	(0.376)	(0.008)	(0.138)	(0.123)
-6C <T<-3C	-0.064	0.569	0.149	1.765***	0.762***	-0.011*	0.124	-0.016
	(0.083)	(0.671)	(0.146)	(0.461)	(0.277)	(0.006)	(0.105)	(0.093)
27C <T<30C	-0.069***	-1.672***	-0.118**	-0.239**	-0.026	-0.001	-0.021	0.009
	(0.024)	(0.245)	(0.054)	(0.109)	(0.066)	(0.002)	(0.027)	(0.026)
30C <T<33C	-0.088***	1.153***	0.335***	0.050	0.033	0.001	0.039	0.035
	(0.028)	(0.322)	(0.069)	(0.137)	(0.080)	(0.002)	(0.033)	(0.031)
T>33C	-0.070**	0.257	0.181**	-0.339**	-0.218**	-0.004	0.134***	0.150***
	(0.034)	(0.375)	(0.083)	(0.164)	(0.104)	(0.003)	(0.041)	(0.039)
Precipitation	-3.988	1,994.771***	448.437***	102.018	-215.335*	4.764	88.102*	71.858
	(46.890)	(446.134)	(98.179)	(188.753)	(124.923)	(3.175)	(49.402)	(46.509)
Observations	438,645	461,066	461,066	109,804	108,934	90,684	109,804	109,804
R-squared	0.217	0.307	0.462	0.395	0.414	0.376	0.215	0.197
Year-month FE	X	X	X	X	X	X	X	X
ZCTA FE	X	X	X	X	X	X	X	X
Region*Year FE	X	X	X	X	X	X	X	X
Region*Month FE	X	X	X	X	X	X	X	X

Notes: The estimation results for equation (1) are presented for eight 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 -3C and 27C" 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 -3C and 27C. 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: TEMPERATURE BINS FROM PAST MONTH

	(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
T<-9C	-0.024	3.100***	0.851***	-0.609**	-0.181	-0.031	-0.019
	(0.071)	(0.564)	(0.115)	(0.290)	(0.198)	(0.067)	(0.063)
-9C <T<-6C	-0.124	1.466	0.531***	0.555	0.393	-0.030	-0.036
	(0.128)	(0.985)	(0.199)	(0.569)	(0.355)	(0.125)	(0.112)
-6C <T<-3C	0.228***	2.504***	0.669***	1.502***	0.191	0.097	0.083
	(0.088)	(0.752)	(0.163)	(0.413)	(0.259)	(0.094)	(0.084)
27C <T<30C	-0.092***	-0.046	0.115**	-0.255**	-0.081	-0.005	0.011
	(0.022)	(0.223)	(0.058)	(0.114)	(0.063)	(0.023)	(0.021)
30C <T<33C	-0.092***	1.338***	0.416***	-0.082	0.046	0.038	0.024
	(0.026)	(0.307)	(0.075)	(0.127)	(0.072)	(0.029)	(0.027)
T>33C	-0.151***	-0.244	0.268**	-0.548***	-0.332***	0.062	0.077**
	(0.035)	(0.420)	(0.128)	(0.199)	(0.114)	(0.039)	(0.038)
Precipitation	-11.995	696.142	50.779	-130.857	-96.655	136.159***	108.555**
	(46.877)	(432.166)	(103.746)	(183.104)	(117.910)	(45.205)	(42.340)
Observations	436,022	458,298	458,298	110,246	109,424	110,246	110,246
R-squared	0.156	0.196	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 past month with daytime mean temperature within a specific range. The "Days between -3C and 27C" 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 -3C and 27C. 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: TEMPERATURE BINS FROM THE NEXT MONTH

	(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
T<-9C	-0.014	-0.926*	-0.368***	0.245	0.308*	-0.017	-0.027
	(0.060)	(0.481)	(0.097)	(0.300)	(0.183)	(0.076)	(0.068)
-9C <T<-6C	0.083	-3.037***	-0.696***	0.891	0.184	-0.052	-0.027
	(0.111)	(0.915)	(0.197)	(0.549)	(0.344)	(0.140)	(0.126)
-6C <T<-3C	0.077	0.497	-0.245	-0.202	-0.126	0.178*	0.101
	(0.079)	(0.678)	(0.156)	(0.420)	(0.254)	(0.094)	(0.085)
27C <T<30C	-0.086***	0.152	0.114**	-0.242**	-0.068	0.053**	0.052**
	(0.023)	(0.227)	(0.056)	(0.123)	(0.066)	(0.025)	(0.023)
30C <T<33C	-0.039	1.088***	0.233***	0.045	0.035	0.005	0.008
	(0.026)	(0.336)	(0.076)	(0.126)	(0.076)	(0.031)	(0.029)
T>33C	-0.101***	0.686	0.169	-0.639***	-0.433***	0.089**	0.105**
	(0.036)	(0.468)	(0.126)	(0.196)	(0.110)	(0.041)	(0.042)
Precipitation	-8.979	810.453*	69.975	-203.607	-137.847	136.419***	113.780***
	(48.623)	(440.560)	(105.796)	(188.484)	(122.335)	(46.254)	(43.342)
Observations	433,811	455,768	455,768	108,705	107,886	108,705	108,705
R-squared	0.157	0.194	0.240	0.226	0.285	0.180	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 the next month with daytime mean temperature within a specific range. The "Days between -3C and 27C" 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 -3C and 27C. 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: 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) APR	(7) delinquency rate	(8) default rate
T<-9C	0.163*	1.174	0.332*	-0.540	-0.221	-0.152	-0.018	-0.048
	(0.084)	(0.764)	(0.171)	(0.399)	(0.232)	(0.474)	(0.061)	(0.049)
-9C <T<-6C	-0.133	3.813***	1.051***	-0.060	0.364	-1.237	-0.104	0.056
	(0.162)	(1.414)	(0.322)	(0.778)	(0.439)	(0.796)	(0.122)	(0.102)
-6C <T<-3C	-0.022	-1.516	-0.579**	1.640***	0.768***	0.324	0.203**	0.114
	(0.105)	(1.002)	(0.237)	(0.532)	(0.294)	(0.624)	(0.092)	(0.073)
27C <T<30C	-0.076***	-0.573**	-0.040	-0.236*	-0.077	0.169	0.013	0.031
	(0.026)	(0.278)	(0.065)	(0.130)	(0.066)	(0.156)	(0.022)	(0.021)
30C <T<33C	-0.070**	1.204***	0.378***	-0.081	0.068	-0.112	0.050*	0.030
	(0.029)	(0.382)	(0.081)	(0.151)	(0.077)	(0.209)	(0.029)	(0.027)
T>33C	-0.100***	1.112**	0.241**	-0.522***	-0.308***	-0.582*	0.015	0.051
	(0.038)	(0.502)	(0.111)	(0.190)	(0.108)	(0.323)	(0.041)	(0.039)
Precipitation	0.204***	1,424.161**	296.600**	-318.021	-136.330	430.824	66.932	47.426
	(0.004)	(591.465)	(138.467)	(238.527)	(133.597)	(327.917)	(42.647)	(38.280)
lag of dep. var	-47.568	0.364***	0.514***	0.518***	0.506***	0.361***	0.108***	0.082***
	(53.872)	(0.008)	(0.008)	(0.017)	(0.008)	(0.008)	(0.009)	(0.010)
Observations	261,224	281,151	281,151	70,013	69,711	59,560	70,013	70,013
R-squared	0.211	0.309	0.437	0.450	0.504	0.445	0.157	0.126
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 eight 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 -3C and 27C" 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 -3C and 27C. 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: 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) APR	(7) delinquency rate	(8) default rate
T<-6C	0.197*	1.351	0.484**	0.189	-0.028	0.235	-0.044	-0.068
	(0.101)	(0.908)	(0.199)	(0.502)	(0.270)	(0.617)	(0.088)	(0.070)
-6C <T<-3C	-0.061	-0.512	-0.400	-2.511***	-0.423	-1.540*	-0.058	0.056
	(0.159)	(1.456)	(0.323)	(0.776)	(0.418)	(0.800)	(0.119)	(0.092)
-3C <T<0C	-0.110	0.349	0.242	2.026***	0.867***	0.025	0.186**	0.126**
	(0.097)	(0.926)	(0.219)	(0.465)	(0.260)	(0.549)	(0.076)	(0.063)
30C <T<33C	-0.059**	-0.053	0.013	-0.187	-0.076	-0.023	0.016	0.036*
	(0.028)	(0.315)	(0.075)	(0.148)	(0.070)	(0.166)	(0.023)	(0.022)
33C <T<36C	-0.045	1.001**	0.319***	-0.039	0.071	-0.011	0.037	0.013
	(0.029)	(0.396)	(0.087)	(0.162)	(0.079)	(0.210)	(0.029)	(0.027)
T>36C	-0.082**	1.270***	0.284***	-0.404**	-0.232***	-0.542**	0.036	0.063**
	(0.035)	(0.440)	(0.098)	(0.168)	(0.089)	(0.251)	(0.033)	(0.031)
Precipitation	-54.240	1,240.376**	295.072**	-328.192	-148.389	364.572	64.127	46.888
	(52.179)	(565.080)	(133.128)	(228.140)	(126.673)	(315.626)	(41.593)	(37.555)
lag of dep. var	0.204***	0.364***	0.514***	0.518***	0.505***	0.360***	0.109***	0.083***
	(0.004)	(0.008)	(0.008)	(0.017)	(0.008)	(0.008)	(0.009)	(0.010)
Observations	262,442	282,533	282,533	70,489	70,187	59,972	70,489	70,489
R-squared	0.212	0.309	0.436	0.450	0.503	0.445	0.157	0.126
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 eight 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 sixteen temperature bins: below -6°C, above 36°C, and fourteen 3°C bins in between. The "Days between 0C and 30C" 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 0C and 30C. 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: 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) APR	(7) delinquency rate	(8) default rate
T<-12C	0.231**	0.890	0.391*	-0.099	0.193	0.235	-0.070	-0.067
	(0.114)	(0.968)	(0.215)	(0.538)	(0.307)	(0.617)	(0.086)	(0.069)
-12C <T<-9C	-0.120	3.013*	0.500	0.424	0.083	-1.540*	0.016	0.067
	(0.197)	(1.744)	(0.418)	(0.922)	(0.514)	(0.800)	(0.130)	(0.098)
-9C <T<-6C	-0.069	0.766	-0.010	-0.016	0.148	0.025	0.132	0.099
	(0.132)	(1.216)	(0.283)	(0.698)	(0.359)	(0.549)	(0.111)	(0.092)
24C <T<27C	-0.033	-0.398	0.030	-0.095	-0.044	-0.023	-0.013	0.004
	(0.024)	(0.258)	(0.060)	(0.122)	(0.062)	(0.166)	(0.020)	(0.019)
27C <T<30C	-0.098***	0.574**	0.252***	-0.117	0.059	-0.011	0.052**	0.042**
	(0.023)	(0.280)	(0.061)	(0.115)	(0.061)	(0.210)	(0.022)	(0.020)
T>30C	-0.081**	1.506***	0.328***	-0.466***	-0.272***	-0.542**	0.016	0.041
	(0.032)	(0.429)	(0.095)	(0.167)	(0.100)	(0.251)	(0.038)	(0.035)
Precipitation	-25.211	1,032.087*	166.360	-346.897	-198.784	364.572	36.904	24.970
	(51.984)	(560.747)	(132.086)	(225.638)	(126.011)	(315.626)	(41.485)	(37.539)
lag of dep. var	0.204***	0.364***	0.514***	0.518***	0.505***	0.360***	0.109***	0.083***
	(0.004)	(0.008)	(0.008)	(0.017)	(0.008)	(0.008)	(0.009)	(0.010)
Observations	262,442	282,533	282,533	70,489	70,187	59,972	70,489	70,489
R-squared	0.212	0.309	0.436	0.449	0.503	0.445	0.157	0.126
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 eight 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 sixteen temperature bins: below -12°C, above 30°C, and fourteen 3°C bins in between. The "Days between -6C and 24C" 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 -6C and 24C. 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: 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
T<-9C	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)
-9C <T<-6C	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)
-6C <T<-3C	-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)
27C <T<30C	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)
30C <T<33C	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)
T>33C	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 -3C and 27C" 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 -3C and 27C. 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: STOREFRONT PAYDAY LOAN

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) APR	(7) delinquency rate	(8) default rate
T<-9C	-0.720*	-0.289	-0.326	1.088*	-0.026	-0.942	0.085	0.057
	(0.373)	(1.042)	(0.321)	(0.592)	(0.372)	(0.635)	(0.095)	(0.074)
-9C <T<-6C	0.927*	-0.469	0.250	-0.055	0.831	-0.066	-0.105	-0.064
	(0.496)	(1.252)	(0.585)	(1.044)	(0.618)	(1.111)	(0.158)	(0.111)
-6C <T<-3C	0.147	0.338	0.455	0.933	0.164	-0.234	0.125	0.089
	(0.341)	(0.773)	(0.384)	(0.850)	(0.471)	(0.830)	(0.137)	(0.104)
27C <T<30C	-0.240**	0.941***	0.076	-0.216	-0.151	0.465	-0.042	-0.007
	(0.108)	(0.295)	(0.129)	(0.208)	(0.157)	(0.361)	(0.047)	(0.043)
30C <T<33C	0.014	0.456	-0.107	-0.347	0.257	0.049	0.122*	0.016
	(0.124)	(0.388)	(0.138)	(0.250)	(0.202)	(0.460)	(0.064)	(0.052)
T>33C	-0.444**	1.338**	0.220	0.008	-0.791***	0.233	0.057	0.184*
	(0.179)	(0.576)	(0.223)	(0.261)	(0.259)	(0.812)	(0.126)	(0.106)
Precipitation	238.505	-1,040.247**	-330.609	-161.737	-17.555	0.839	166.106	24.858
	(239.716)	(443.716)	(246.392)	(380.107)	(326.824)	(680.870)	(114.989)	(98.605)
Observations	31,070	52,589	52,589	30,081	30,081	26,895	30,081	30,081
R-squared	0.307	0.334	0.242	0.311	0.445	0.485	0.244	0.172
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 eight 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 -3C and 27C" 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 -3C and 27C. 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.13: ONLINE PAYDAY LOAN

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) APR	(7) delinquency rate	(8) default rate
T<-9C	0.046	1.306***	0.239**	-0.114	-0.331	0.040	-0.118	-0.221**
	(0.065)	(0.505)	(0.099)	(0.217)	(0.208)	(0.626)	(0.103)	(0.092)
-9C <T<-6C	-0.098	2.125**	0.367*	0.277	0.211	-0.905	-0.168	0.160
	(0.123)	(0.954)	(0.187)	(0.416)	(0.422)	(1.275)	(0.217)	(0.202)
-6C <T<-3C	0.000	-0.214	-0.287**	-0.032	-0.188	-0.149	0.212	0.106
	(0.082)	(0.711)	(0.143)	(0.317)	(0.280)	(0.867)	(0.149)	(0.140)
27C <T<30C	-0.082***	-0.672***	0.033	-0.089	-0.030	-0.251	0.002	0.006
	(0.022)	(0.220)	(0.051)	(0.112)	(0.067)	(0.183)	(0.028)	(0.027)
30C <T<33C	-0.059**	1.356***	0.464***	-0.027	-0.014	-0.052	0.037	0.042
	(0.026)	(0.327)	(0.072)	(0.131)	(0.075)	(0.230)	(0.033)	(0.032)
T>33C	-0.097***	0.702	0.215**	-0.577***	-0.282***	-0.668*	0.097**	0.101**
	(0.035)	(0.439)	(0.108)	(0.201)	(0.107)	(0.342)	(0.046)	(0.044)
Precipitation	-92.237*	1,340.747***	170.709*	-190.852	-114.387	880.725**	199.849***	171.400***
	(47.162)	(456.438)	(101.488)	(186.691)	(123.221)	(350.417)	(52.285)	(50.379)
Observations	427,243	440,260	440,260	84,580	83,689	66,889	84,580	84,580
R-squared	0.147	0.190	0.227	0.168	0.190	0.233	0.189	0.170
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 eight 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 -3C and 27C" 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 -3C and 27C. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

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Appendix Table B.14: HETEROGENOUS EFFECTS

NonWhite ×	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) APR	(7) delinquency rate	(8) default rate
T<-9C	-0.022	-0.003	0.204	-2.060**	-1.477**	-0.000	-0.270	-0.373
	(0.217)	(2.398)	(0.566)	(0.882)	(0.694)	(0.015)	(0.306)	(0.289)
-9C <T<-6C	-0.118	1.771	0.722	0.581	-0.218	-0.035	0.428	1.099*
	(0.366)	(4.304)	(1.018)	(1.847)	(1.274)	(0.033)	(0.617)	(0.596)
-6C <T<-3C	-1.320***	20.184***	7.819***	4.725***	1.525	-0.017	0.138	-0.260
	(0.242)	(3.464)	(1.030)	(1.777)	(1.029)	(0.018)	(0.391)	(0.350)
27C <T<30C	-0.347***	7.095***	2.876***	0.798***	0.125	0.000	0.096**	0.072*
	(0.042)	(0.872)	(0.301)	(0.294)	(0.147)	(0.003)	(0.045)	(0.043)
30C <T<33C	-0.342***	5.128***	1.006**	0.131	-0.297*	0.007	0.013	0.017
	(0.057)	(1.501)	(0.408)	(0.294)	(0.177)	(0.005)	(0.066)	(0.063)
T>33C	-0.199***	0.850	0.403	0.212	-0.001	-0.000	0.042	0.036
	(0.074)	(1.696)	(0.515)	(0.358)	(0.261)	(0.007)	(0.089)	(0.087)
Observations	439,568	461,993	461,993	110,246	109,424	90,766	110,246	110,246
R-squared	0.157	0.196	0.245	0.226	0.283	0.298	0.179	0.159
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 (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.15: ALTERNATIVE SUBPRIME CREDIT

	(1) log(income)*100	(2) total inquires *100	(3) unique inquires*100	(4) account open *100	(5) log(credits)*100	(6) APR	(7) delinquency rate	(8) default rate
T<-9C	0.072	3.746***	0.756***	-0.022	-0.566*	1.786	-0.106	-0.008
	(0.070)	(0.659)	(0.127)	(0.141)	(0.297)	(2.028)	(0.108)	(0.092)
-9C <T<-6C	-0.261**	4.743***	1.251***	0.266	0.154	-3.381	0.087	0.114
	(0.128)	(1.245)	(0.240)	(0.264)	(0.563)	(3.277)	(0.204)	(0.178)
-6C <T<-3C	-0.001	1.313	-0.720***	-0.320*	0.116	-0.305	-0.003	-0.143
	(0.089)	(0.922)	(0.181)	(0.185)	(0.377)	(2.249)	(0.128)	(0.113)
27C <T<30C	-0.016	0.697**	0.364***	0.140**	-0.002	0.603	0.055*	0.066***
	(0.021)	(0.332)	(0.076)	(0.055)	(0.081)	(0.505)	(0.029)	(0.025)
30C <T<33C	-0.021	2.847***	0.451***	0.215***	0.124	0.076	0.029	-0.020
	(0.025)	(0.470)	(0.110)	(0.069)	(0.099)	(0.548)	(0.036)	(0.031)
T>33C	-0.130***	2.832***	0.747***	0.154	-0.091	-0.291	0.028	0.070**
	(0.033)	(0.702)	(0.200)	(0.096)	(0.108)	(0.510)	(0.037)	(0.033)
Precipitation	-33.585	637.916	95.391	-104.090	-24.907	-1,261.186	74.216	19.083
	(44.244)	(665.711)	(141.651)	(114.752)	(178.037)	(1,120.238)	(63.625)	(55.048)
Observations	498,199	654,366	654,366	161,322	161,194	17,540	161,322	161,322
R-squared	0.119	0.313	0.330	0.158	0.190	0.293	0.115	0.101
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 eight 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 -3C and 27C" 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 -3C and 27C. 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.16: ROBUSTNESS CHECK: THE EFFECTS OF LIHEAP ON PAYDAY LOAN MARKETS

	(1) inquiries*100	(2) log(credits)*100	(3) delinquency rate	(4) default rate
Treat	0.076	-2.967***	1.445**	1.175*
	(1.24)	(0.688)	(0.494)	(0.532)
Observations	80,985	11,436	11,482	11,482
R-squared	0.157	0.453	0.289	0.262
Year-month FE	X	X	X	X
County*Year FE	X	X	X	X
Renter FE	X	X	X	X
Age group FE	X	X	X	X

Notes: The estimation results for equation (3) are presented for five different outcome variables. The independent variables are the Treat dummy variable, precipitation, the number of days in a month with daytime mean temperature within a specific range. The "Days between -3C and 27C" bin is the omitted category. Treat is equal to one an individual's income is within $2000 of the cut-off for LIHEAP eligibility. Standard errors clustered at the ZCTA level are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.