Impact of Economic Shocks on Financial Access: Evidence from COVID-19 Pandemic

Anand Goel and Shuang Wu*

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Abstract

We examine the borrowing activity of individuals through small-dollar loans taken from non-depository consumer lenders. We exploit the COVID-19 shock and the subsequent government response to determine the demand for small-dollar loans by analyzing foot traffic to lenders. We find that visits to lenders drop significantly following shelter-in-place orders, new COVID-19 cases, and government relief programs. However, the decline in visits is less pronounced than those of bank consumers suggesting that borrowers from consumer lenders experience more credit constraints than bank borrowers, We control for proxies of online borrowing and credit supply. Our results suggest that government relief programs alleviate consumers' credit constraints.

JEL Classification Codes: G01, G23, G51

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Anand Goel: (201) 216-5421, agoel2@stevens.edu; Shuang Wu: (203) 252-6776, wus2@sacredheart.edu. Anand Goel is the corresponding author.

1 Introduction

The market for credit is segmented. Many households and individuals are unable to tap financial services from traditional financial institutions such as banks or credit unions and resort to non-depository lenders such as payday lenders or installment loan providers (henceforth, consumer lenders). While there is well-developed literature on banking, sparse knowledge about those who borrow from consumer lenders impedes effective regulation of consumer lenders. In this paper, we seek to understand the demand for credit from consumer lenders, particularly how shocks to the cost of accessing credit from consumer lenders and government relief programs impact borrowing from consumer lenders. We also compare these responses to those of bank borrowers. These insights can help us compare the marginal value of loans across bank borrowers and borrowers from consumer lenders.

We consider the COVID-19 pandemic, the associated shelter-in-place restrictions, and the government relief programs during the pandemic as shocks and identify how these shocks impact the demand for loans from consumer lenders. Our measure of demand for consumer lenders is the weekly foot traffic to physical locations of consumer lenders. We analyze variations in foot traffic over time and across different locations, controlling for lender- and time-fixed effects. We relate foot traffic to the severity of the COVID-19 pandemic, shelter-in-place restrictions, the unemployment rate, the insured unemployment rate, and the local adoption of government relief programs on a weekly basis.

We find that the demand for credit from consumer lenders declined in response to COVID-19 shock, shelter-in-place restrictions, and following increasing adoption of government relief programs. A comparison with response of bank customers suggests that borrowers from

consumer lenders assign greater marginal value of loans than bank borrowers. Government welfare programs, like the unemployment insurance and those launched during the pandemic, alleviated consumers' credit constraints and in some cases, these programs complement each other.

Financial services improve social welfare by allowing people to smooth consumption, share risks, and engage more willingly in productive but risky economic activity. Access to financial credit promotes economic growth and stability by making households and businesses resilient to economic shocks. According to Federal Reserve, of the total outstanding consumer credit in the U.S. in September 2020 of 4,16 trillion U.S. dollars, depository institutions held 40%, federal government 33.4%, and credit unions 11.9%. About 13.2% of credit was held by finance companies, which include student loans, personal cash loans, mobile home loans, and loans to purchase other types of consumer goods.

Access to credit varies across households with different incomes, education levels, races, and health conditions. Traditional financial institutions are not accessible to many consumers. According to a 2019 survey (Federal Deposit Insurance Corporation, 2019), 5.4% of U.S. households did not have a checking or savings account at a bank or credit union in 2019. Unbanked rates are higher among low-income, less educated households and households of color. Customers with a sufficient credit history or high credit scores can more easily access bank credit than customers with stale or no credit history. Consumer Financial Protection Bureau (2016) estimates that approximately 45 million Americans are credit invisible and lack access to mainstream banks. Households with limited access to credit are more likely to experience financial hardship when confronting economic shocks (Campbell et al., 2010). Furthermore, a substantial fraction of unbanked or underbanked households can cur-

tail the development of the economy as the widening wealth gap restrains consumption and investment.[1]

Consumer lenders complement mainstream banks by providing alternative loan products to underserved customers or in situations when bank credit is not available.[2] Borrowers seeking credit from consumer lenders are more likely to have lower income and lower wealth. Such consumers are more likely to have been adversely impacted by the COVID-19 pandemic. The COVID-19 pandemic has had a disproportionate impact on low-income, non-white households, and households with children (Monte, 2020; Ganong et al., 2020) from massive layoffs and reduced working hours. The demand for credit from consumer lenders may have increased due to the negative impact of COVID-19. However, there are two countervailing forces. First, social distancing restrictions and health concerns may have prevented people from visiting consumer lenders. Second, the government relief programs during the pandemic may have tempered the demand for credit from consumer lenders.

We examine (i) how the COVID-19 shock and subsequent government relief programs affect demand for credit, (ii) how different relief programs interact in influencing demand for credit, (iii) how the impact of economic shocks on demand for credit varies across banks and consumer lenders, and in financially underserved and metropolitan areas. We use foot traffic to consumer lenders as a measure of the demand for consumer lending and control for macroeconomic and epidemiological variables. Specifically, we use weekly visitor data

[1]Noel et al. (2019) estimates that the dampening effect of widening wealth gap on consumption and investment will cost the U.S. economy between $1 trillion and $1.5 trillion between 2019 and 2028, 4% to 6% of the projected GDP in 2028.

[2]Consumer lenders may offer one or more forms of loans such as payday loans (Advance America), installment loans (World Finance), and auto title loans (Titlemax). Many use alternative data or underwriting models to offer traditional products such as small dollar personal loans (Prosper), auto loans (Lightstream), mortgages (Quicken Loans), and student loans (SoFi).

to brick-and-mortar locations of consumer lenders to estimate the demand for credit from consumer lenders at a granular level. Similar data have been used by other studies to measure business activity.[3]

To show that foot traffic is a reliable measure of demand for credit from consumer lenders, we collect data on both the number and the dollar amount of consumer loans issued in Texas between 2019 and 2020. We find a positive correlation between the annual growth rate of foot traffic to consumer lenders and the annual growth rate of consumer loans in 2020, ranging from 0.11 to 0.44. Further, our analyses suggest that foot traffic changes are driven more by demand-side effects than supply-side effects. Consumer lenders were considered essential businesses, and on average, 98.5% of consumer lenders were open during the pandemic. We conduct additional tests to control for changes in the supply of credit.

We find that consumer lenders saw a sharp decline in foot traffic in early March 2020 across 50 states. Although foot traffic bounced back after April 2020, it did not recover to pre-pandemic levels in most states. Three factors may have contributed to the drop in foot traffic to consumer lenders. First, the statewide shelter-in-place orders restricted mobility and consequently affected most businesses (Cronin and Evans, 2020; Chao and Zimmermann, 2020; Farboodi et al., 2021). Second, surges in new COVID-19 cases and deaths (Maloney and Taskin, 2020) deterred people's willingness to visit consumer lenders in person. Third,

[3]Williams (2020a), Williams (2020b) use foot traffic data to measure economic activity across industries in Wisconsin and find that the decline in storefront visits is positively correlated with reduced sales and business shutdowns. The coincidence of timing between decreased foot traffic and diminished revenues (or economic output) can be detected either at the aggregate level (Bognanni et al., 2020) or at the industry level (SANDAG, 2020). This association is more notable in industries where restrictions had a big impact, such as dine-in bans in restaurants. The effects spill over to complementary industries (Cronin and Evans, 2020). Foot traffic data also shed light on demand for goods and services. Walmsley et al. (2021) estimate the pent-up demand comparing current foot traffic levels to those before the pandemic and validate the measure using consumption data and GPS data from Opportunity Insights and Unacast, respectively. A similar linkage between household consumption decisions and mobility can also be found in Baker et al. (2020).

federally funded relief programs (Karger and Rajan, 2020; Gallagher et al., 2023) supported financially distressed households, reducing their need for credit.

We find that shelter-in-place orders, the number of new COVID-19 cases, the insured unemployment rate, and enrollment in relief programs are all statistically significant in explaining foot traffic to consumer lenders. In particular, the negative impact of shelter-in-place orders on foot traffic to consumer lenders shows that these orders were binding for some consumers and may have made it difficult for consumers to access credit and potentially reduced consumer welfare.

We next examine how government unemployment programs impact demand for credit from consumer lenders. Our results show that the demand for credit from consumer lenders decreases following an increase in the number of consumers registered in regular unemployment insurance (the insured unemployment rate) and in the continued claims for PEUC (Pandemic Emergency Unemployment Compensation). We interpret these results to mean that the relief programs alleviate the financial constraints faced by consumers who rely on consumer lenders for credit. A series of robustness tests demonstrate that our findings are not driven by fluctuations in credit supply, shifts to online loans, changes in willingness to travel, or the use of a specific metric for gauging activity restrictions.

Next, we examine whether the impacts of shelter-in-place orders, new COVID-19 cases, and government relief programs vary across different sources of credit and geographic areas with varying degrees of credit accessibility.

We compare responses of borrowers from consumer lenders and banks to compare their financial constraints. This exercise may seem superfluous as it is commonly believed that consumers seeking loans from consumer lenders are those who cannot borrow from banks.

However, cross-sectional comparisons of financial constraints are ambiguous, both theoretically and empirically. For example, interest rate is not a perfect measure of credit constraints as variation in interest rate may reflect variation in loan risk. Thus, it is plausible that neither bank borrowers nor borrowers from consumer lenders are financially constrained. Farre-Mensa and Ljungqvist (2016) find that firms typically classified as constrained do not actually behave as if they were constrained. We consider the value of a loan to the marginal borrower as a measure of the lack of financial access and develop a simple model of segmented credit markets relating a change in demand for loans following a shock to this measure.

We then use our data to compare foot traffic to consumer lenders with foot traffic to banks. We find that the demand for credit from consumer lenders is less sensitive to COVID-19 cases than the demand for bank loans. Based on our model's result, this suggests that marginal borrowers from consumer lenders value loans more than marginal borrowers from banks. On the other hand, the demand for credit from consumer lenders is more sensitive to government relief programs than the demand for bank loans. These results are again consistent with higher credit constraints faced by borrowers from consumer lenders.

In terms of geographical variation, we find that higher coverage rates of unemployment insurance and the PEUC program are associated with a greater reduction in credit demand in metropolitan areas than in financially underserved areas. The results suggest that the government relief programs were more effective in alleviating liquidity constraints of residents in metropolitan areas than of residents in financially underserved areas.

We next examine how different government relief programs interact to impact consumers. First, we find that the impact of traditional unemployment insurance in alleviating credit needs became stronger during the pandemic than before the pandemic, suggesting the in-

creased importance of welfare programs during financial stress shocks such as the COVID-19 pandemic. We also find evidence of complementarity rather than substitution between relief programs' impact on consumers. The FPUC program, which provided $600 a week in supplemental compensation for a part of our sample period, and the PEUC program interacted to result in a greater reduction in the demand for credit.

Lastly, we examine whether the distance to a consumer lender impacts a consumer's willingness to visit the consumer lender. We find that visitors who live farther from a consumer lender reduced travel to the lender during shelter-in-place orders more than those who live closer. This effect is weaker in areas with greater poverty and higher car ownership. These results suggest that distance to a lender can be an important determinant of access to credit.

Our empirical analysis controls for the supply of credit, online demand for credit, time variation in the size of our sample, and the unemployment rate. We conduct a series of robustness tests to address the following concerns: the lack of supply-side data about consumer lending activities, borrowers' transition from physical stores to online platforms, and potentially omitted determinants of consumers' willingness to travel.

To address the possibility of changes in supply of credit, we control for "supply rate," defined as the average proportion of consumer lenders with mobile devices staying for more than five minutes to the total number of consumer lenders in a Census Block Group (CBG).[4] We expect this variable to capture closures of consumer lending locations. We further use geographical diversification of lenders as a measure of their ability to change supply of credit.

[4] A Census Block Group is the smallest geographical unit, typically consisting of 600 to 3,000 people, for which the the United States Census Bureau publishes data.

We find that foot traffic does not experience a greater reduction to consumer lenders with greater geographic diversification, suggesting that our results reflect changes in demand rather than changes in supply. As an additional robustness test, we exploit the within-lender variation by focusing on multi-location consumer lenders. By restricting our sample to such lenders and introducing the consumer-lender×week fixed effect, we compare changes in foot traffic to two locations belonging to the same lender. This approach yields results consistent with our main results, reinforcing the conclusion that changes in foot traffic are demand-driven rather than supply-driven.

To address the possibility of a shift to online borrowing, we include the Google Trends Index in each state to control for people's online borrowing behavior. In another robustness test, we scrape websites of consumer lenders to identify consumer lenders that offer online loans. We find that foot traffic reduction is not greater for these lenders, suggesting that the alternative option of online borrowing is unlikely to drive our main results. Furthermore, we create a subsample that exclusively includes consumer lenders located in seven states where online payday lending is prohibited. We find the results from this subsample are qualitatively similar to our main results.

Our inferences do not depend on whether a change in foot traffic to consumer lenders is unique to consumer lenders or reflects a general reduction in foot traffic. We find that visits to consumer lenders are positively correlated with visits to other businesses. However, the demand for consumer credit declines with shelter-in-place orders even after controlling for the general effect of shelter-in-place orders on visits to other businesses. Our results are also robust to an alternate measure of activity restrictions.

Overall, our results suggest that COVID-19 and shelter-in-place restrictions made it

difficult for consumers to access credit, while the government relief programs alleviated consumers' need to do so. A comparison of borrowers from banks and from consumer lenders suggests that marginal borrowers from consumer lenders value their loans more than marginal borrowers from banks. Finally, we show that government relief programs had varying impacts in alleviating credit constraints across different communities.

The remainder of the paper is organized as follows. Section 2 provides a review of the related literature. We present a simple model with a prediction in Section 3. Section 4 describes the data. We present baseline results and interpret the findings in Section 5. Section 6 documents how demand for credit from consumer lenders varies across consumers and across time. Section 7 concludes. A proof is in Appendix A. Appendix B contains all figures and tables with additional empirical results.

2 Literature

In this section, We discuss the related literate on household borrowing decisions and on non-depository consumer lenders.

2.1 Household Borrowing Decisions

The amount of borrowing by a household can change due to shifts in demand or supply. Supply-side changes are often driven by macroeconomic conditions, government policies, changes in technology, and financial innovation. Our focus is on changes in the demand for credit. The canonical model for household borrowing is the life cycle hypothesis or the permanent income model (Modigliani and Brumberg, 1954; Ando and Modigliani, 1963;

Modigliani, 1986). The model proposes that households maximize utility by allocating resources to smooth consumption over their lifetime. Specifically, consumption depends on the sum of liquid assets and borrowings instead of the current income level. Thus, a consumer's expectations about future income impact her saving or borrowing decisions. The main insights of this model have strong empirical support. However, the model has been refined based on some empirical patterns. For example, savings and borrowing can be impacted by a precautionary motive to address future income uncertainty (Carroll, 1994).

Empirical analyses have examined both temporal and cross-sectional variation in savings and borrowing. Morgan and Christen (2005) find a positive impact of income inequality on household debt and argue that the effect is contributed by low-income households attempting to maintain a social position through consumption. However, Coibion et al. (2020) find that this "keeping up" hypothesis does not explain the impact of income inequality on changes in household debt during 2000-2012. They instead find that greater income inequality tilts credit supply away from low-income households and toward high-income households, such that low-income households accumulate more debt in areas with lower inequality than in areas with higher inequality. A similar channel explains the counterintuitive findings of Gropp et al. (1997), who show that following bankruptcy exemptions, credit availability increased for higher-income households and decreased for lower-income households. They suggest that in high-bankruptcy-exemption states, lenders are conservative in making loans to risky borrowers because they suffer greater losses when those borrowers utilize strategic bankruptcy to repay less. We do not direct contribute to this literature as we do not observe the level of household debt.

Our work is more related to the literature on the impact of economic shocks on household

borrowing behavior. Life cycle hypothesis suggests that households should reduce consumption and borrowing when borrowing becomes more expensive. Brissimis et al. (2014) analyze the relationship between the demand and supply of credit during Greece's liberalization period and find that credit supply positively affects households' consumption spending and borrowing, leading to lower savings. Alessie et al. (2005) estimate the demand changes in response to the usury law in Italy which caps interest rates charged on borrowers, and find a negative elasticity of credit demand to interest rates.

If credit demand depends on the consumption level and the sum of liquid assets, low-income households with limited financial access are expected to reduce spending, borrow more, and be less sensitive to loan terms than high-income households. Karlan and Zinman (2005) use data from an experiment implemented by a consumer microfinance lender in South Africa to show that higher-income individuals are more sensitive to price changes but less sensitive to maturity changes than lower-income individuals. They conclude that their findings are consistent with liquidity constraints that decrease with income. Similarly, Alan and Loranth (2013) use a lender's randomized price experiment to approximate the credit demand elasticity to an interest rate increase. They find that the majority of subprime borrowers are insensitive to the shock.

Changes in household debt holding following economic shocks also exhibit heterogeneity. Most households reduce their consumption spending during uncertain times (Brissimis et al., 2014), consistent with the permanent income theory. Households adjust consumption only when they expect the shocks to have a long-term impact on income (Hall and Mishkin, 1982). However, the reduction is greater among less risky borrowers (Horvath et al., 2021) and lower-income borrowers (Carroll et al., 2003). Similar patterns are also found in the

mortgage market as the weighted mean loan-to-value ratio decreases in counties with lower credit scores (Maggio et al., 2017). Evidence from credit card borrowing is also consistent with this pattern. The decrease in credit card balance due to greater unpredictability in future mortgage payments is less for riskier borrowers. These results can be interpreted as a lower default cost for riskier borrowers (Maggio et al., 2017) and more selective credit access for riskier consumers (Gropp et al., 2014).

We add to this literature by examining the impact of COVID-19 shock, shelter-in-place orders, and government relief programs on the demand for credit from consumer lenders, and thereby inferring the level of credit constraints. We hypothesize that visits to consumer lenders will decrease when health concerns and shelter-in-place orders increase the cost of visiting consumer lenders. However, the extent of this change may depend on how credit constrained borrowers are. We then compare the cross-sectional variation in this response to draw inferences about the variation in credit constraints.

COVID-19 was a complex shock with many effects that may impact our findings. We consider three such effects. First, the COVID-19 shock may have impacted expectations of future income. Second, the supply of consumer credit may have changed. Third, consumers may have shifted from physical visits to consumer lenders to online borrowing. We attempt to control for these confounding factors in robustness analyses.

One objective of regulating consumer lending can be to alleviate frictions that prevent consumers from smoothing consumption as recommended by the permanent income model. These frictions are typically considered to result in financially constrained or credit-rationed consumers. However, there is lack of consensus on the measurement of financial constraints or credit rationing.

Leon (2015) reports survey findings that bank competition improves credit availability to firms but acknowledges that Whether bank competition helps or hinders small firms' access to finance is a much debated question in the economic literature. On the consumer side, Grant (2007) reports that around 31% of households are constrained, with young college educated households being the most constrained. The paper notes that there is considerable debate about the incidence of constraints because supply and demand are difficult to disentangle from the observed borrowing. If investment or consumption is observable, sensitivity of investment or consumption to cash flow can be used to indirectly measure credit constraints (Fazzari et al., 1987; Chen and Chen, 2012; Garicano and Steinwender, 2016). However, detailed consumption data is typically not available for consumers that lack access to bank credit. We contribute to this literature by using foot traffic to lenders as a novel measure of consumer demand. We also develop a model that interprets credit constraint as the marginal value of a loan to the borrower and relates it to the change in credit demand following a shock to the cost of accessing credit. Our results also show heterogeneity in credit constraints based on geographical location and access to transport.

2.2 Consumer Lending

Borrowers who access credit from consumer lenders typically cannot get loans from banks because of perceived high risks of default and consequently pay a high price for loans from consumer lenders (Bhutta et al., 2015). Unbanked households tend to have a thin margin between income and expenses, face fluctuating income, lack financial literacy, and often make unsound financial decisions (Campbell et al., 2012).

Recent literature has examined credit provided by alternative lenders. These typically include non-depository financial institutions whose loans differ from bank loans in having shorter duration, being faster to obtain, and not requiring collateral. Bhutta et al. (2016) document that about 12% of consumers have used an alternative financial service at one time or another. The use of alternative financial products is more prevalent among females, unmarried individuals, non-whites, young people, lower-income individuals, the unemployed, and those with only a high-school education. The most commonly stated uses of alternative credit are basic living expenses, making up for lost income, or purchasing or repairing of a house, car, or appliance. Common reasons for using a lender other than a traditional bank include ease or speed, the unavailability of small-dollar loans from banks, and the inability to get a loan from a bank. Variation in lending laws across time and states has been used to examine the impact of the supply of credit by consumer lenders.

Empirical research on the welfare effects of access to consumer credit is mixed. Consumer lenders provide financially constrained households with cheaper credit than banks (Morgan et al., 2012), help them smooth consumption, and allow them to make better economic decisions (Barr, 2004; Zinman, 2010). Unsecured credit from consumer lenders helps consumers maintain liquidity to weather unpredictable shocks (Morse, 2011), smooth consumption around extreme weather events (Dobridge, 2020), and build long-term assets (Elliehausen and Lawrence, 2001). Restricting access to consumer lending deteriorates consumers' financial condition as limited alternatives make consumers turn to suboptimal credit choices (Zinman, 2010).

The literature has also documented adverse consequences of consumer credit, such as the possibility of a "debt trap." Skiba and Tobacman (2008) investigate financial hardship after

accessing consumer credit and find that consumers' financial conditions, measured by the number of bankruptcy filings, worsen. Melzer (2011) uses the proximity to the nearest state that allows payday loans as a measure of access to consumer credit and shows that access to payday loans results in delays in making important payments such as medical and utility bills. Bhutta et al. (2015) do not find a positive or negative effect of access to consumer credit on financial well-being. Using the gap in payday loan approval rates to investigate the effect of payday loans on creditworthiness, they detect no differential effects on consumers whose credit records are close to the approval threshold. It is possible that the limited average effects are attributed to the already constrained financial condition, leaving little room for the further shortfall.

We contribute to this literature by examining the impact of economic-related factors on the demand for consumer credit and using these results to draw inference about the welfare effect of consumer credit. Much of the literature uses geographical variation in access to credit to draw conclusions about the consequences of access to credit. Access to consumer lenders in an area can impact economic development and the availability of other financial services, effects which are hard to control for. While we do not directly measure the welfare consequences of access to credit, foot traffic data enables us to explicitly measure the demand for credit from consumer lenders and examine if demand patterns are consistent with credit constraints. Our findings reveal that foot traffic to consumer lenders decreases in areas with shelter-in-place orders, a surge in new COVID-19 cases, and a broader coverage of unemployment insurance and federal relief programs. Our findings suggest that the borrower of a marginal loan from a consumer lender values the loan more than the borrower of a marginal loan from a bank.

3 Predictions

In this section, we show how a decline in demand for loans following a shock to the cost of accessing loans can be used to draw inferences about the value of loans to borrowers. We do this by modeling a segmented credit market.

Consider a single-period model with two dates, Date 1 followed by Date 2. There is universal risk neutrality and the risk-free rate is zero. There is a continuum of consumers with utility quasilinear in Date 1 money consumption and Date 2 money consumption. Each consumer realizes an opportunity at Date 1 that they may accept or reject. The opportunity of consumer i, if taken, changes her utility by V_i. The opportunity requires an investment of L at Date 1. However, consumers start with no money and each chooses whether to take her opportunity by taking a loan for amount L at Date 1 to be repaid at Date 2.

A loan's risk to the lender depends on the borrower's ability to pay and the borrower's willingness to pay. All consumers have sufficient resources at Date 2 to repay loans. However, some consumers repay their loan in full while others default without repaying anything. Consumers differ in their willingness to pay (WTP), defined as the probability with which they repay their loans.

Credit market is segmented. Consumers can be divided into two groups. It is common knowledge that the WTP is w_b ($0 < w_b \leq 1$) for consumers in the first group. These consumers potentially seek loans from one set of financial intermediaries. We call these intermediaries banks and these consumers bank consumers. We call the second set of consumers "credit-weak." The WTP w_i for credit-weak consumer i is her private information. However, it is common knowledge that w_i is drawn from probability distribution g. These consumers

may seek loans from financial intermediaries that we call consumer lenders. Banks and consumers lenders may be distinct or may overlap. However, both sets of lenders are perfectly competitive.

A consumer's decision to take a loan depends both on the value of the opportunity available to the consumer and on the NPV of the loan to the consumer. The value V_i of the opportunity to consumer i is her private information. It is common knowledge that V_i is independently and identically distributed across bank consumers with cumulative distribution function F_b and the corresponding probability density function f_b. It is also common knowledge that V_i is independently and identically distributed across credit-weak consumers with cumulative distribution function F_c and the corresponding probability density function f_c.

Assumption 1. *The probability density function f_c is log-concave: $f(\lambda x_1 + (1-\lambda)x_2) \geq f(x_1)^{\lambda} f(x_2)^{1-\lambda}$ for $\lambda \in [0.1]$.*

Log-concavity implies the increasing hazard rate property: conditional on V_i exceeding ℓ, the probability that V_i exceeds $\ell + \lambda$ ($\lambda > 0$) is decreasing in ℓ. Log-concavity is satisfied by many common distributions, including uniform, normal, and logistic (An, 1995; Bagnoli and Bergstrom, 2005).

The NPV of a loan for a consumer depends on the loan interest rate, the deadweight costs of borrowing, the probability with which the consumer will repay the loan, and any consequences of default. Let R_b and R_c be the endogenous interest rates on loans offered by banks and consumer lenders, respectively, to bank consumers and credit-weak consumers, respectively. Let d_b and d_c be the deadweight costs of borrowing for bank consumers and

credit-weak consumers, respectively. Finally, let y_b and y_c be the expected utility loss conditional on default by a bank consumer and by a credit-weak consumer, respectively.

We consider a Nash equilibrium in which each consumer chooses whether to borrow or not and each lender determines the interest rate at which it is willing to lend. We characterize equilibria independently for bank consumers and for credit-weak consumers as they operate in a segmented market. If consumer i is a bank consumer, she takes a loan if her net benefit b_i from the loan is non-negative:

$$b_i \equiv V_i + L - d_b - w_b R_b L - (1 - w_b) y_b \geq 0. \tag{1}$$

Banks competitively set interest rate so that they earn zero expected profit on the marginal loan:

$$w_b R_b L - L = 0. \tag{2}$$

Thus,

$$R_b = \frac{1}{w_b} \tag{3}$$

Substituting in (1), consumer i takes a loan if

$$V_i \geq d_b + (1 - w_b) y_b. \tag{4}$$

The proportion of bank consumers who take a loan is

$$\alpha_b = 1 - F_b\left(d_b + (1 - w_b)y_b\right). \tag{5}$$

If consumer i is a weak-credit consumer, she takes a loan if her net benefit from the loan is non-negative:

$$b_i \equiv V_i + L - d_c - w_i R_c L - (1 - w_i)y_c \geq 0. \tag{6}$$

The proportion of weak-credit consumers who take a loan is

$$\alpha_c = \int_0^1 \left\{1 - F_c\left(d_c + wR_cL + (1 - w)y_c - L\right)\right\} g(w)\mathrm{d}w. \tag{7}$$

The average WTP of weak-credit consumers who take a loan is

$$\bar{w} = \frac{\int_0^1 w\left\{1 - F_c\left(d_c + wR_cL + (1 - w)y_c - L\right)\right\} g(w)\mathrm{d}w}{\int_0^1 \left\{1 - F_c\left(d_c + wR_cL + (1 - w)y_c - L\right)\right\} g(w)\mathrm{d}w}. \tag{8}$$

Consumer lenders compete and set interest rate so that they earn zero expected profit on the marginal loan:

$$\bar{w}R_cL - L = 0. \tag{9}$$

Substituting $\bar{w}$ from (8), the equilibrium condition for R_c is

$$R_c = \frac{1}{\bar{w}} = \frac{\int_0^1 \{1 - F_c(d_c + wR_cL + (1-w)y_c - L)\} g(w)\mathrm{d}w}{\int_0^1 w\{1 - F_c(d_c + wR_cL + (1-w)y_c - L)\} g(w)\mathrm{d}w}. \tag{10}$$

The competitive equilibrium interest rate is the minimum value of R_c that satisfies the above equation.

Proposition 1. *Following a shock that increases deadweight cost of loans by δ, the decline in the demand for bank loans equals the measure of bank borrowers with the net benefit of loan less than δ while the decline in the demand for consumer lender loans exceeds the measure of credit-weak borrowers with the net benefit of loan less than δ.*

The intuition behind this result is as follows. As the systematic shock increases the cost of taking a loan, some consumers who would otherwise have taken a loan but have low benefit from borrowing decide not to borrow. This results in a decline in the number of borrowers. For banks, the reduction in demand is a measure of the fraction of consumers whose net benefit from loan is less than the increase in the cost of taking the loan. This reduction in demand for loans is also observed in credit-weak consumers. However, there is a second-order effect due to the heterogeneity in WTP of credit-weak consumers. Marginal borrowers with a larger WTP have a larger need for loan than marginal borrowers with a lower WTP. Marginal borrowers with a smaller WTP and a smaller need for loan are less sensitive to the cost shock than marginal borrowers with a higher WTP and a higher need for loan. Therefore, the shock results in greater reduction in demand by those with larger WTP, and reduces the average WTP of borrower pool, increasing loan risk for lenders, who respond by increasing interest rate. This increase in interest rate causes a further decline in

the number of credit-weak borrowers.

Our empirical analysis measures the decline in demand for loans following several shocks. This result allows to use these findings to draw inferences about the value of loans to bank borrowers and credit-weak consumers.

4 Data

4.1 Foot Traffic

We use foot traffic data at consumer lenders as a measure of demand for credit from nonbank financial intermediaries. This measure offers several advantages. The high frequency of this data allows for more precise detection of changes in credit demand in response to evolving COVID-19 conditions or government relief programs. Compared to loan transaction data, foot traffic is more likely to represent demand rather than supply. However, there are some disadvantages: we do not observe all visits to consumer lenders, nor do we know the purpose of each visit. Despite these limitations, we believe they do not significantly impact our conclusions, as our analysis focuses on changes in the number of visits rather than the absolute number.

We obtain the foot traffic data from SafeGraph, a firm that provides aggregated, anonymized, privacy-safe data on the spatial behaviors of more than 45 million mobile devices in the United States.[5] We use two datasets from their free "COVID-19 Dataset." One is the "Core Places" dataset, which contains location information and categories for about 3.5 million

[5]SafeGraph is a data company that aggregates anonymized location data from numerous applications to provide insights about physical places, via the Placekey Community. To enhance privacy, SafeGraph excludes CBG information if fewer than five devices visited an establishment in a month from a given CBG.

Points of Interest (POIs) in the U.S. The other one is the "Weekly Patterns" dataset, which includes aggregated GPS-identified visits to POIs with exact known locations at a weekly frequency. We use the "Core Places" data to identify consumer lenders as points of interest categorized as nondepository credit intermediaries and obtain data on visits to these consumer lenders from the "Weekly Pattern" data. While our main analysis focuses on consumer lenders, we also use foot traffic data to banks and some other businesses in additional analyses. We extract information about a consumer lender's location, the number of visitors and visits, other brands visited by those visitors within the same week, visitors' home CBG, median travel distance, and dwell time.

We foresee two concerns about employing foot traffic as a proxy for credit demand. The first is that variation in foot traffic may not represent variations in credit demand. To address this concern, we gather data on consumer loans issued in Texas between 2019 and 2020 from the Texas Office of Consumer Credit Commissioner.[6] In contrast to other states that either do not mandate consumer lenders to report details on consumer lending or only disclose the overall lending amount at the state level, Texas discloses aggregate dollar amount and the number of loans by Metropolitan Statistical Areas (MSAs). We utilize FIPS Code to match our foot traffic data with this data and compare percentage changes in consumer loans and foot traffic between 2019 and 2020. In Panel A of A.2 in Appendix, we consider all consumer lender locations with foot traffic reported in January 2019. The correlation between the changes in the number of visitors and the changes in the aggregate dollar volume of loans from 2019 to 2020 across MSAs is 0.37. It is 0.11 between changes in the number of visitors and the number of loans. In Panel B, we calculate the change in the average number of

[6]The consumer loans here include payday loans and title loans.

visitors to each consumer lender location within a MSA, assuming that the foot traffic is zero for weeks with missing observations between weeks with positive foot traffic. The correlation between the changes in the average number of visitors and the changes in the dollar volume of loans from 2019 to 2020 is 0.26. The correlation between the changes in the average number of visitors and changes in the number of loans is 0.44. Thus, foot traffic data appears to capture variation in demand for credit, even though it is a noisy measure.

The second concern pertains to the reliance on cell phone GPS data for measuring foot traffic, which may result in an underrepresentation of individuals less likely to own phones. However, the SafeGraph data are representative at the county level across many demographic dimensions (Squire, 2019).

Our data covers 13,165 locations across 50 states with 520,143 observations between January 2019 and December 2020. Figure F.2 depicts foot traffic to consumer lenders for 49 states during this period. Less than half of the states saw a decline in foot traffic to consumer lenders upon the first documentation of COVID-19 cases. However, 28 out of 43 states witnessed a drop in the number of visitors to consumer lenders when the shelter-in-place order was first issued. Although foot traffic in many states slightly bounced up in the following weeks, it did not fully recover to the pre-pandemic level even after the shelter-in-place order was rescinded.

4.2 Unemployment Assistance Programs

To study the impact of government aid on the demand for consumer credit, we focus on the traditional state-funded unemployment insurance program and three federally funded

supplemental COVID-19 relief programs: the Pandemic Unemployment Assistance (PUA) program, the Pandemic Emergency Unemployment Compensation (PEUC) program, and the Federal Pandemic Unemployment Compensation (FPUC) program.

Unemployment insurance in the U.S. is a joint state-federal program designed to provide temporary financial assistance to individuals facing unemployment. Each state sets specific eligibility requirements, benefit amounts, and the duration for which benefits can be received. While benefits are typically provided for up to 26 weeks, extensions may be available during periods of elevated unemployment, such as the COVID-19 pandemic. We extract the state-level count of continued claims in total insured employment from the U.S. Bureau of Labor Statistics and scale it by the total labor force in that state for the corresponding week. To address multicollinearity with the unemployment rate, that we use as a control for economic conditions, we obtain *insured.rate* by subtracting the unemployment rate from the insured unemployment rate, the percentage of the labor force currently unemployed and covered by state unemployment insurance.

The CARES Act, passed in April 2020, supplemented the state unemployment insurance programs with several measures to provide relief to individuals adversely affected by the pandemic and facing unemployment. We focus on three initiatives. The Pandemic Unemployment Assistance (PUA) program aimed to provide payments through September 4, 2021, to individuals not traditionally eligible for unemployment benefits, such as the self-employed, who are unable to work directly due to the pandemic. The Pandemic Emergency Unemployment Compensation (PEUC) provided an additional 13 weeks of unemployment benefits through September 4, 2021, assisting those who remain unemployed after exhausting state unemployment benefits. The Federal Pandemic Unemployment Compensation (FPUC)

program was designed to pay an additional $600 per week until July 31, 2020, to individuals eligible for state unemployment insurance or relief programs (PUA and PEUC).[7] Figure F.3 summarizes the target population, timeline, and benefits associated with these programs.

We normalize the weekly number of continued claims for the PUA and PEUC programs obtained from the Department of Labor by the total labor force to derive two ratios: $PUA.CC.rate$ and $PEUC.CC.rate$, representing the share of the labor force that is unemployed and receiving financial assistance through the PUA and PEUC programs, respectively. Figure F.4 shows that initially, the aggregate number of continued claims for the PUA program surpassed that of the PEUC program. However, over time, the two numbers converged.

4.3 Socioeconomic and Epidemiological Variables

To identify financially underserved areas, we adopt the classification criteria from Kashian et al. (2015), where an area is classified as a bank desert if it has fewer than 0.02 branches per 1,000 residents or less than one-tenth of the mean. We utilize the list of metropolitan/micropolitan areas released by the Census Bureau to identify metropolitan areas. Our sample contains 4,685 and 5,543 Zip Codes in 2019 and 2020. Among these, 11.21% and 10.92% are identified as bank deserts, while 81.88% and 81.45% are identified as metropolitan areas.

We collect demographic data from the Census Bureau to compute several county-level indicators, including car ownership, poverty level, the percentage of renters in the population,

[7]The FPUC program was reauthorized, providing an extra $300 per week for the unemployed from December 26, 2020, to September 4, 2021. Additionally, the PUA and PEUC programs were extended to September 4, 2021. However, our data do not cover this period.

internet access rate, and health insurance coverage.[8]

The epidemiological data comprises the daily count of new COVID-19 cases at a county level sourced from the New York Times. We compile the schedules for state-level shelter-in-place (SIP) orders using timelines sourced from Keystone Strategy, ABC News, CNN, NPR, Littler, and the New York Times. Figure F.1 shows the timing of these orders. California was the first state to issue a statewide mandatory shelter-in-place order, followed by another 34 states in March 2020. In April 2020, an additional nine states either required or recommended the residents to stay at home, while the remaining six states (Wyoming, South Dakota, Nebraska, North Dakota, Iowa, and Arkansas) did not issue a mandatory shelter-in-place order. The shelter-in-place dummy is one if the state had a mandatory shelter-in-place order in the given week, otherwise it is zero.

Since statewide mandated shelter-in-place orders ended in all states by June 2020, the shelter-in-place dummy may not fully capture local activity restrictions imposed after the resurgence of COVID-19 infections in fall 2020. To account for the impact of local policies and individuals' voluntary choices to stay at home, we construct a social distancing index using SafeGraph's "Social Distancing Metrics" dataset. The social distancing index is computed as the weekly average proportion of tracking devices residing at home.[9] This variable ranges from zero to one, where one representing the strictest adherence to social distancing policies and zero being the least.

[8]Car ownership is calculated as the fraction of people whose main transportation method is a car, truck, or van (drive alone). The poverty level represents the fraction of households with incomes no more than half of the federal poverty line in 2018. The renters-population percentage indicates the share of people who share housing/rooms with non-relatives. The internet access rate reflects the percentage of households with internet access. The health insurance coverage rate denotes the percentage of the population covered by at least one insurance plan. All calculations are based on the American Community Survey data from 2018.

[9]SafeGraph defines a device as completely at home if it does not leave home during the nighttime (6 pm-7 am) for over six weeks.

4.4 Control Variables

Since the number of cellphones tracked by SafeGraph has changed over our sample period, we normalize visits to a location in a week by the natural logarithm of the number of devices residing in the CBG of the location during that week. To control for online access to financial services, we include a control variable proxying for online traffic to consumer lenders: the state-level Google Trends Index for the keyword "Cash Loan."

To control for the shock to the supply of credit, we construct the variable "supply_rate" by considering a store as closed if there are no devices staying there for more than five minutes. The "supply_rate" is calculated as the share of open stores in the CBG of the location during a given week. Additionally, we incorporate economic conditions using the state-level unemployment rate as a control variable. The summary statistics for these variables are presented in Table 1.

5 Results

We start our analysis by studying how an economic shock affects credit demand, followed by a comprehensive set of robustness tests aimed at substantiating our findings and mitigating concerns about omitted variables, particularly changes in credit supply.

5.1 Impact of Pandemic and Relief Programs on the Demand for Credit from Consumer Lenders

Our initial OLS regression estimates the following equation:

$$Y_{i,t} = \alpha + \beta_1 SIP_{s,t} + \beta_2 ln(\#case + 1)_{c,t} + \gamma \boldsymbol{X_{s,t}} + \kappa \boldsymbol{Controls}_{b/s,t} + \eta_i + \delta_t + \epsilon_{i,t} \quad (11)$$

where $Y_{i,t}$ denotes the natural logarithm of the number of visitors to consumer lenders in location i during week t. Since there can be multiple consumer lender locations within a county, we choose our unit of observation as a lender location in a given week. $SIP_{s,t}$ is a dummy variable indicating whether state i implemented shelter-in-place orders during week t. $ln(\#case + 1)_{c,t}$ denotes the natural logarithm of one plus the number of new COVID-19 cases in county c during week t. X is a set of state-level variables representing the enrollment rate in government relief programs, including the difference between the state-level insured unemployment rate and the unemployment rate (*insured.rate*), PUA continued claims rate (*PUA.CC.rate*), and PEUC continued claims rate (*PEUC.CC.rate*). The control variables include the unemployment rate, the natural logarithm of the number of devices residing in CBG b, the supply rate of credit in CBG b, and the Google Trends Index for state s. All control variables are measured on a weekly basis.

We include location-specific fixed effects that allow us to capture differences across locations within the same county. Given that locations vary dramatically in both credit supply and demand, analyzing within-location variations in foot traffic is crucial for assessing the impact of economic shocks. By including week fixed effects, we compare foot traffic across

locations within the same week.

The regression results are reported in Table 2. Column 1 presents results of a regression without any fixed-effect. The results show that shelter-in-place orders significantly decrease foot traffic to consumer lenders. This effect is additional to the impact of the COVID-19 pandemic, suggesting that shelter-in-place orders may have restricted access to credit. This highlights a cost imposed by shelter-in-place orders primarily on individuals who rely on credit from consumer lenders.

The coefficient on new COVID-19 cases is negative and statistically significant at the 1% level, suggesting that visits to consumer lenders decrease as public health conditions worsen. Thus, any increase in demand for credit from the weaker economic outlook accompanying COVID-19 was more than offset by their concern about traveling to consumer lenders during COVID-19. The negative and statistically significant coefficient on the insured unemployment rate suggests that financial aid provided through the unemployment insurance program reduces the need for unemployed individuals to seek credit.[10] Regarding federal programs, increased enrollment in PUA and PEUC programs is associated with fewer visits to consumer lenders. This implies that the financial support provided or promised by these programs reduced the need for borrowing from consumer lenders.

In Column 2 of Table 2, we introduce week and location fixed-effects to account for location-specific heterogeneity and omitted temporal factors. The results from Column 1

[10]The result reflects the liquidity-enhancing effect of insured unemployment. It is not driven by an alternative mechanism where the unemployed feel discouraged about borrowing in anticipation of a denial of credit. It is important to note the distinction between the unemployment rate and the insured unemployment rate. While both are correlated, they offer different insights into labor market conditions. The unemployment rate reflects cumulative economic effects over time across the labor force, whereas the insured unemployment rate provides a more immediate snapshot based on insured workers, reported weekly. This distinction is crucial as highlighted by Burtless (1983), emphasizing the different definitions and measurements of these rates. Our results remain robust to excluding the unemployment rate variable.

continue to hold: shelter-in-place orders and increases in COVID-19 cases are associated with reduced foot traffic to consumer lenders, while higher rates of continued claims under state unemployment insurance and COVID-19 related relief programs contribute to decreased lender visits.

In Column 3 of Table 2, we augment the model with additional controls including the unemployment rate, the natural logarithm of devices residing in the lender's CBG, the normalized Google search volume for "cash loans," and the proportion of consumer lenders open. These controls address changes in economic conditions, variations in SafeGraph coverage, shifts toward online credit, and shocks to credit supply.

The findings in Column 3 are qualitatively similar to those in Column 2, except for the PUA continued claims rate. While the coefficient of PEUC continues to be negative and statistically significant, the coefficient of PUA continued claims rate is no longer statistically significant, suggesting that PUA program was less effective in meeting liquidity needs of those covered. The two programs target different sets of consumers. The PEUC program was designed for employed individuals eligible for state unemployment insurance, who may have received regular paychecks before unemployment. PUA recipients, however, may have more volatile incomes, and possibly a greater need for credit.

Prior evidence is mixed on whether traditional credit, such as that from banks, and alternative credit from consumer lenders are substitutes. Fonseca (2023), using a shock to debt collection regulations, finds evidence indicating that mainstream credit and alternative credit are substitutes. However, Miller and Shoo (2020) use removal of Chapter 7 bankruptcy as a shock to conclude that expanded traditional credit access does not reduce alternative credit use. Our results suggest that government relief programs act as substitutes for alternative

credit.

The effects we document was economically significant. The coefficients of shelter-in-place orders show that these orders resulted in at least a 2.7% reduction in visitors to consumer lenders. A one percent increase in number of COVID-19 cases resulted in about a 2.3% decrease in visitors to consumer lenders. Using the coefficients in Column 3 and the summary statistics reported in 1, we find that increases in insured unemployment rate and PEUC continued claims rate of one standard deviation reduced the number of visitors to consumer lenders by about 1% and 2%, respectively.

Overall, our results indicate that (1) COVID-19 reduced visits to consumer lenders, possibly due to health concerns and consumers' perceptions of the future, (2) shelter-in-place orders restricted access to credit, and (3) government relief programs likely reduced credit demand for consumer lenders.

5.2 Robustness Checks

We conduct additional tests to address three main concerns. First, to mitigate the potential influence of supply-side shocks, we employ the lender-level location-based Herfindahl-Hirschman Index to exploit the variation in lenders' capacity to allocate credit across counties. In a supplemental test, we focus on multi-location consumer lenders and leverage within-lender variation by adding lender×week fixed effects.

Next, to provide evidence against shifts in customers' behavior towards online borrowing, we classify lenders offering online loans by scraping their website for relevant keywords. We then compare changes in foot traffic between lenders that exclusively offer in-person loans

and those providing both in-person and online loans. Additionally, we utilize differences in state payday lending policies to strengthen our analysis.

Lastly, considering the possibility that changes in foot traffic may reflect a broader shift in people's willingness to travel, we introduce foot traffic to the three most popular brands as additional controls. Furthermore, we construct an alternative measure of activity restriction. We find that our main results in Table 2 continue to hold in these additional tests.

5.2.1 The Shock to Credit Supply

Although we control for credit supply, our measure of credit supply is imperfect. It is possible that changes in foot traffic to consumer lender reflect unobserved changes in credit supply that we do not control for. In this section, we provide an additional test based on the geographic diversification of lenders to control for variation in credit supply.

Changes in the supply of credit can be involuntary, such as those stemming from lock-downs or restrictions on operating hours, or voluntary in response to economic shocks. We rule out the first possibility because financial intermediation is considered essential in most states, and consumer lenders were allowed to remain open. Our data shows that, on average, more than 98% of consumer lender locations were open during the pandemic.

We argue that voluntary changes in credit supply in response to economic shocks (e.g., shelter-in-place restrictions) are likely to be more pronounced for geographically diversified lenders. These lenders can reallocate credit supply across locations if some locations are more exposed to these shocks than others. In contrast, geographically concentrated lenders have less flexibility to reallocate credit supply, making their credit supply less variable. Consequently, credit-supply related changes in foot traffic are likely to be stronger for more

geographically diversified consumer lenders than for less geographically diversified ones.

We calculate a consumer lender's county-level Herfindahl-Hirschman Index (HHI) as a proxy for the geographic concentration of consumer lenders. Specifically, the HHI for consumer lender I in week t is calculated as follows:

$$geo_HHI_{I,t} = \sum_{c=1}^{J} (\frac{n_{I,c,t}}{N_{I,t}})^2 \tag{12}$$

where $n_{I,c,t}$ and $N_{I,t}$ denote the number of locations of consumer lender I in county c at time t and its total number of locations across all counties at time t, respectively. We construct a dummy, *geo_div*, to represent geographically diversified consumer lenders. The dummy takes the value one when a consumer lender's HHI is smaller than the average, otherwise it is zero. We interact this dummy with variables representing local health and economic conditions, specifically the number of new COVID-19 cases, the shelter-in-place orders, and the unemployment rate. The results of the regression are shown in Table 3.

If our results are exclusively driven by changes in credit supply, the coefficients on the uninteracted economic shocks should not be significant, while the coefficients on the interaction terms should have the same signs as the corresponding uninteracted variables in Table 2. The results in Table 3 show that the coefficient for the shelter-in-place dummy remains negative and statistically significant, while the coefficient for the interaction between the shelter-in-place dummy and *geo_div* is positive and statistically significant. This suggests that the reduction in foot traffic to consumer lenders is unlikely to be driven by changes in credit supply. In fact, it appears that the reduction in demand for credit is partially offset by an increase in credit supply by geographically diversified lenders. The positive coefficient on

the interaction between the number of cases and *geo_div* indicates that our results in Table 2 reflect changes in demand rather than supply.

The coefficient on the interaction term between high diversification and the unemployment rate is statistically negative, with the same sign but smaller in magnitude than the coefficient for the unemployment rate. This suggests that unemployment impacts foot traffic to consumer lenders through both demand and supply effects, but the effects identified in Table 2 cannot be attributed solely to changes in credit supply.

As a supplemental test, we follow Amiti and Weinstein (2018) and Khwaja (2008)'s method to separate demand-side shocks from supply-side shocks by exploiting within-lender variation in foot traffic across locations. Specifically, we narrow the sample to only include multi-location consumer lenders. By introducing consumer-lender×week fixed effect, we compare changes in foot traffic to different locations of the same consumer lender, each experiencing different levels of impact from the economic shock. The detailed results are presented in Appendix A.3. In Column 1, we include location and consumer-lender×week fixed effects. In Column 2, we include both fixed effects along with a set of control variables. The findings are consistent with the results in Table 2, showing that the implementation of shelter-in-place orders, a surge in COVID-19 cases, and the state unemployment program all contribute to a decrease in foot traffic to consumer lenders.

In summary, both the geographic diversification design and the within-lender variation test indicate that the decline in visits to consumer lenders is not attributable to supply-side changes.

5.2.2 Switch to Online Lending

Some consumers may have shifted to borrowing online from consumer lenders during the pandemic, potentially explaining the reduction in foot traffic. To address this concern, we compare the responses to shelter-in-place orders from borrowers across consumer lenders equipped to offer online loans and those that are not. If the decrease in foot traffic is due to the transition toward online loans, we should observe a more pronounced decline in foot traffic among consumer lenders providing online application avenues, in contrast to consumer lenders lacking such provisions.

We identify consumer lenders offering online loan options by searching for keywords such as "online loan," "online application," and "apply online" on each lender's website in Feruary 2022.[11] We create a dummy variable for each keyword, which equals one if the keyword appears on consumer lenders' websites and zero otherwise. We interact each dummy with the shelter-in-place dummy in three different analyses and report the results in Table 4. A negative sign detected in the interaction term would indicate a correlation between a decrease in foot traffic and the availability of online loan services among consumer lenders.

In Columns 1-3 of Table 4, we find consistent positive and statistically significant coefficients across all interaction terms. It means that amidst shelter-in-place orders, consumer lenders offering online loans experience higher foot traffic compared to those exclusively providing in-person loan services. The result implies that switching to online services is unlikely to be the driving force behind our main results presented in Table 2.

To further rule out the influence of online lending, we narrow down the sample to encom-

[11]The rationale behind selecting these specific keywords stems from their prevalence as the most commonly used terms indicating online lending options on consumer lenders' official websites.

pass solely seven states where online payday lending is prohibited. These states comprise Georgia, Iowa, Kentucky, Nebraska, New York, North Carolina, Ohio, Pennsylvania, Vermont, and West Virginia. We replicate the main regression analysis using the subsample and detail the outcomes in Table A.4 in the Appendix. The results are qualitatively similar to the main results in Table 2. In summary, both analyses show that the transition towards online lending cannot account for the decline in foot traffic, and our main results are robust.

5.2.3 Willingness to Travel

Visits to consumer lenders may be impacted by omitted variables that affect people's willingness to travel. If these omitted factors are uncorrelated with our independent variables of interest, their omission should not impact our results. Nonetheless, we attempt to control for changes in willingness to travel that impacts travel to all businesses, not just consumer lenders, by including visits to other brands as control variables. For each state, we identify the three brands most frequently visited by visitors to consumer lenders in the same week during 2019. There is significant overlap in these brands across states. For example, Walmart is one of the top three brands in 28 states. Among the 51 brands identified across all states, 21 are retail, grocery, and convenience stores, 8 are oil, fuel, and energy companies, and the remaining are fast food chains and drug stores. We include the foot traffic of the three most visited brands for each state as control variables and report the results in Table 5.[12] Due to space consideration, we report coefficients for the three brands with the highest number of visits from visitors to consumer lenders in 2019: Walmart, Dollar General, and McDonald's.

[12]If a top-three brand for state A is not a top-three brand for state B, its foot traffic is equated to zero in observations for state B.

We find that controlling for willingness to travel does not qualitatively change our results. In Table 5, we show that shelter-in-place orders and government relief programs reduce foot traffic to consumer lenders. The results also show that the number of visits to Walmart, Dollar General, and McDonald's is positively associated with number of visits to consumer lenders within the same week. Unreported results show that visits to all brands are positively related to the foot traffic to consumer lenders. Thus, the foot traffic pattern we document cannot be attributed entirely to general willingness to travel and is partially driven by changes in consumer's financial conditions and perceptions.

5.2.4 Alternative Measure of Activity Restrictions

The shelter-in-place orders and the number of new COVID-19 cases, which reflect travel restrictions and health concerns, together serve as a measure of activity constraints. However, these may be imperfect measures of the degree to which people restricted activities outside their homes. We construct a social distancing index, defined as the average proportion of devices residing at home in each CBG, as an alternative measure of activity restrictions. We substitute the social distancing index for the shelter-in-place dummy and the number of new COVID-19 cases in our main model in Table 2. The results, shown in Table 6, are qualitatively similar to those in the main model. In another analysis, we include the number of new COVID-19 deaths as an alternative measure of health concerns. We find that the statistical significance and the magnitude of the coefficient barely change.

6 Heterogeneity in Demand for Credit

We now examine how the impacts of shelter-in-place orders, COVID cases, and unemployment on foot traffic to consumer lenders vary across sources of credit and geographic areas with varying degrees of credit accessibility. Next, we examine how the impact of government welfare programs on foot traffic to consumer lenders varies over time. Finally, we explore consumers' behavioral changes in terms of choosing between nearby and distant consumer lenders during the pandemic.

6.1 Visits to Consumer Lenders versus Visits to Banks

We now compare the effect of economic shocks and relief programs on consumers' demand for bank products versus consumer lenders' products. Consumer lenders typically lend to borrowers with a higher risk of non-payment, often through uncollateralized loans. Banks offer convenience and flexibility through their branch banking systems and provide lower-cost financing to their targeted borrowers. However, some consumer lenders utilize alternative data and alternative screening mechanisms to assess consumers' creditworthiness (de Roure et al., 2016) and offer cheaper credit for some borrowers than banks do (Jagtiani and Lemieux, 2017).

Whether consumer lenders are good or bad for a consumer depends on the reason that banks do not extend credit to certain consumers. If banks are unwilling to lend to some consumers because lending to these consumers is not economically feasible, then not lending to these consumers is a Pareto-superior outcome. In this case, if a consumer lender profitably lends to an underserved consumer, the consumer must necessarily be worse off. However,

if banks find it unviable to lend to some consumers due to costly frictions in the lending process, consumer lenders with different business models may mitigate these frictions and offer credit to underserved consumers and improve their welfare. While our data do not permit us to explain the market segementation between banks and consumer lenders, we attempt to seek our data to compare credit constraints faced by borrowers from banks and consumer lenders.

We identify foot traffic to banks as the number of visitors to locations classified as depository credit intermediaries and merge this data with foot traffic to consumer lenders to get a consolidated dataset with 7,814,077 observations for consumer lenders and banks. We create a dummy variable, *bank*, which takes the value of one in observations for banks. We add interactions of this dummy with other variables of interest to the regression in Column 3 of Table 2 and report the results in Table 7.

The coefficient associated with the interaction term of *bank* and *SIP* is positive but not statistically significant. This is presumably because shelter-in-place orders are equally likely to be binding on all borrowers. In unreported results, we replace the shelter-in-place dummy with the social distancing index as a robustness check and find qualitatively similar results.

The coefficient on the term representing the interaction between bank and COVID cases is negative and statistically significant. Proposition 1 shows that in our model the reduction in foot traffic to banks due to COVID cases is a measure of the consumers for whom the net benefit of a loan is less than the deadweight cost imposed by COVID cases. Further, the reduction in foot traffic to consumer lenders is an upper bound on the measure of the consumers for whom the net benefit of a loan is less than the deadweight cost imposed by COVID cases. The negative coefficient on the interaction between bank and COVID cases

shows that the foot traffic to consumer lenders declines less than the foot traffic to banks. Based on Proposition 1 then, the proportion of borrowers for whom the net benefit of a loan exceeds the cost imposed by COVID cases is greater for consumer lenders than for banks.

This evidence indicates that borrowers from consumer lenders are more credit-constrained than borrowers from banks. Since this evidence doesn't rely on a comparison of interest rates, it is robust to risk differences. However, our data doesn't allow us to determine how much of this apparent higher net benefit of loans to borrowers represents net present value of borrowers' needs and how much arises from borrowers' intention to default.

Our analysis is robust to a possible shift in bank customers towards digital banking, as we include both location fixed effects and week fixed effects. We cannot isolate visitors to banks seeking loans from other visitors to banks, such as those seeking mortgages. However, Newton and Vickery (2022) report that banks saw a boom in mortgage originations and refinancings in 2020, which cannot by itself explain our finding that visits to banks declined more than visits to consumer lenders.

, this is not a concern as long as the mix of consumers visiting banks is stable. Our comparison Demand for mortgages also had many distinct and sudden changes during this period that would drive foot traffic differentially to or away from traditional banks in a way that seems to lead to estimates that are invalid externally to this particular situation.

The positive and statistically significant coefficient on the interaction term of *bank* and *insured.rate* means that a higher insured unemployment rate is associated with an increase in foot traffic to banks relative to foot traffic to consumer lenders. In other words, a higher coverage of the unemployed through unemployment insurance results in a more pronounced reduction in visitors to consumer lenders than to banks. These results align with the find-

ings of Cox et al. (2020) and Karger and Rajan (2020) that stimulus payments played an important role in supporting low-income households during the pandemic.

6.2 Bank Deserts and Metropolitan Areas

The economic shocks such as the COVID pandemic and the relief programs may have heterogenous effects on borrowers from consumer lenders across financially underserved areas[13] and metropolitan areas. To identify these differences, we create one dummy variable for bank deserts and another for metropolitan areas. We interact main independent variables of interest in Table 2 with these two dummies and report regression results in Table 8.

In Column 1, we examine whether the impacts of economic shocks in bank deserts differ from those in other areas. A statistically insignificant coefficient on the interaction term between the insured unemployment rate and the bank desert dummy indicates that the impact of traditional unemployment insurance in reducing the demand for credit from consumer lenders is similar across bank deserts and other areas. However, a positive and statistically significant coefficient on the interaction term between the PEUC continued claims rate and the bank desert dummy suggests that the PEUC program did not achieve the same reduction in credit demand in bank deserts as it did in the other areas.

In Column 2, we repeat the regression in Column 1, replacing the bank desert dummy with the metropolitan dummy. The results show that the negative impacts of both the insured unemployment rate and the PEUC continued claims rate are more pronounced in metropolitan areas. Comparing the two regressions indicates that reductions in visits to consumer lenders due to shelter-in-place orders or government relief programs were more

[13]We use the terms bank deserts and financially underserved areas interchangeably.

significant in metropolitan areas than in bank deserts.[14] These results are unlikely to arise from geographical variation in enforcement of policies unless the enforcement of these policies is correlated with measures of government relief programs. One possible interpretation is that people in bank deserts were less affected by shelter-in-place orders and experienced smaller liquidity benefits from government relief programs. Another possible interpretation is that the excess demand for credit from consumer lenders is so high that much larger shocks are required to reduce this demand.

6.3 Time Variation in Impact of Welfare Programs

To examine the time variation in the impact of insured unemployment on visits to consumer lenders, we split the data into "pre-pandemic" and "during pandemic" periods. Column 1 in Table 9 shows the results of a regression based on pre-pandemic observations (before January 21, 2020, the date of the first documented COVID-19 cases). A statistically significant negative coefficient of the insured unemployment rate shows that unemployment insurance benefits serve as a substitute for credit from consumer lenders.

We next create the *pandemic* dummy that equals one for weeks after January 21, 2020 and zero before that date. Column 2 has results of a regression using observations spanning the entire time period and with pandemic dummy and its interaction with the insured unemployment rate as additional variables. The statistically significant and negative coefficient of the interaction of the pandemic dummy and the insured unemployment rate demonstrates that the insured unemployment lead to a greater reduction in visits to consumer lenders

[14] These results cannot be attributed to different sizes of lender locations in bank deserts and metropolitan areas, because our dependent variable is in log and the coefficients measure percentage rather than absolute changes in the number of visitors.

during the pandemic, suggesting that routine government welfare programs play a more pronounced role in meeting consumers' financial needs during an economic shock like the COVID-19 pandemic.

The three government relief programs introduced during the pandemic coexisted in time, sometimes sharing beneficiaries, and could act as substitutes or complements. To investigate whether the presence of one relief program decreases or increases the effectiveness of another program, we create an FPUC dummy which is one for the period from March 29, 2020, to July 31, 2020, and zero otherwise. We include interactions of the FPUC dummy with other relief programs in a regression and report the results in the Column 3. The coefficients of two interactions are negative and statistically significant at the 1% level, while the coefficient of the third interaction is positive and statistically significant at the 5% level. Recall that the FPUC program was designed for beneficiaries of the traditional unemployment insurance program. The negative coefficient on the interaction of FPUC and the unemployment insurance program suggests that these programs complement each other. That is, multiple simultaneous government relief programs have a greater combined impact on potential borrowers from consumer lenders than the sum of the impacts of individual programs. However, this is not true for the FPUC and PUA programs, likely because they had different intended beneficiaries. The results suggest that focused relief programs providing greater relief to a specific group may lead to a more significant reduction in the need for borrowing than programs that provide fewer dollars to a broader base.

6.4 Distance to Consumer Lenders

A shelter-in-place order is more likely to discourage visits from borrowers who must travel longer distances to get to a consumer lender, potentially influencing the composition of borrowers during such restrictions. However, this effect may vary across regions due to differing ease of travel and the levels of credit constraints. In areas with high car ownership, foot traffic is expected to be less sensitive to distance from consumer lenders. Conversely, in areas with high poverty rates, customers may travel farther to seek better interest rates due to greater credit constraints.

We define a visitor to a consumer lender as local if they originate from the same CBG as the consumer lender. We perform a regression where the dependent variable is the natural logarithm of the ratio of local visitors to distant visitors. We include variables such as car ownership rates, internet access rates, health insurance coverage, percentage of renters, and poverty levels, as these factors may impact consumers' sensitivity to the distance from a consumer lender. Additionally, we control for differences in geographical distribution of lenders by controlling for median distance of the consumer lender location to home and the proportion of local visitors to banks in the Zip Code.

The results, reported in Column 1 of Table 10, indicate that the proportion of local visitors to consumer lenders increases during shelter-in-place orders. This finding suggests that the decline in visits to consumer lenders is not solely driven by supply effects or changes in perceptions of future income and expenses, as such factors would not explain a shift in the composition of visitors.

We find that a greater median distance from visitors' homes to consumer lenders is

associated with a smaller proportion of local visitors. This relationship may be partly due to the endogeneity of median distance from visitors' homes. Alternatively, in locations where consumers travel longer distance, such as suburban areas, visitors are more likely to come from other CBGs compared to areas with close proximity to consumer lenders. The positive and statistically significant coefficient on the interaction between distance to home and shelter-in-place orders in Column 2 of Table 10 suggests that even in suburban areas, there is an increase in the share of local visitors to consumer lenders during shelter-in-place orders.

The statistically insignificant coefficient on the fraction of local visitors to banks indicates that the shift towards local borrowers during shelter-in-place orders is independent to any corresponding shift in banks. This again points to a segmentation in the market where factors influencing demand for credit differ between those seeking credit from banks and those seeking credit from consumer lenders.

Lastly, demographic characteristics play a role in credit demand. The results in Column 2 show that a higher car ownership rate and poverty rate are associated with a decrease in the share of local visitors. The former association implies that individuals who own cars may not be as affected by the distance to a consumer lender when deciding to visit. The latter association suggests that the shift to local visitors during shelter-in-place orders is not present or weaker in areas with greater poverty. This might be due to limited alternatives to consumer lenders in these economically disadvantaged areas, thereby making borrowers less able to access other local sources of credit.

Overall, the results in this section confirm that shelter-in-place orders made travel difficult and made it costly for consumers to seek credit from consumer lenders. This effect is stronger

for borrowers from consumer lenders than for bank consumers. Incorporating this asymmetry in our comparison of the borrowers from consumer lenders and banks in Section 6.1 will further strengthen our finding that the marginal value of a loan to a borrower is likely to be higher for loans from consumer lenders than for bank loans.

7 Conclusion

We use foot traffic data that provides granular information about the demand for credit from consumer lenders to examine how COVID-19 and the following government response impacted the demand for credit among borrowers who rely on nonbank lenders. After controlling for proxies such as credit supply, alternative online borrowing, and changes in sample size (the natural logarithm of the number of devices) over time, we find that statewide shelter-in-place orders, new COVID-19 cases, and the adoption of the COVID-19 related unemployment relief program (PEUC) are all associated with a significant drop in foot traffic to consumer lenders. Our robustness tests confirm that these results are not driven by changes in credit supply or a shift to online financial services.

A drop in foot traffic alone cannot determine the impact of these shocks on consumer welfare. Therefore, we employ additional cross-sectional tests to identify the population segments most affected by shelter-in-place orders or relief programs. Our findings and implications are threefold.

First, our results provide welfare implications for government relief programs. While traditional unemployment insurance generally helps alleviate financial distress, it is particularly effective in reducing foot traffic during the pandemic. Furthermore, we demonstrate

the complementary effect of multiple relief programs: additional $600 per week paychecks significantly reduce visits to consumer lenders in areas with high PEUC enrollment rates. PEUC plays a more important role in reducing demand for credit from consumer lenders in metropolitan areas compared to bank deserts, highlighting the barriers consumers in financially underserved areas face in accessing these relief programs.

Second, we show that shelter-in-place orders impose a cost on credit-constrained consumers. The decline in visits to consumer lenders due to shelter-in-place orders is not moderated by supply changes, a shift to online lenders, or a voluntary reduction in demand due to changes in perceptions of future income and expenses. This means that the reduction in foot traffic reflects an involuntary decline in borrowing due to the increased risk associated with accessing credit.

In addition, shelter-in-place orders impact consumers' sensitivity to travel distance. While shelter-in-place orders are in effect, consumers are more likely to visit local consumer lenders rather than nearby consumer lenders. Moreover, in areas with high car ownership and poverty rates, consumers are more likely to choose nearby consumer lenders over local ones. This indicates that consumers with cars are less concerned about distance during shelter-in-place orders, while poorer consumers are less influenced by distance in their decisions, indicating they are less selective.

Third, we demonstrate that bank customers and customers of consumer lenders react differently to economic shocks. In the face of health concerns, bank customers reduce their visits more than customers of consumer lenders, suggesting that visits to lenders are more discretionary for bank customers. Combining our theoretical and empirical results implies that borrowers loans from consumer lenders are more valuable to borrowers than marginal

bank loans. Additionally, government relief programs are more effective in reducing foot traffic to consumer lenders, consistent with prior literature that highlights the importance of these government benefits for low-income families during the pandemic.

Table 1: **Summary Statistics**

This table provides the summary statistics for the variables used in the paper. Panel A presents statistics on the main dependent variable. Panel B focuses on Non-Pharmaceutical Interventions (NPIs) and the public health condition. Panel C reports statistics related to the unemployment condition and unemployment benefits from both state unemployment insurance and COVID-19-related federal programs. Panel D exhibits county-level demographics. Panel E sheds light on foot traffic to the 3 most popular brands visited by consumers within the same week as their interaction with consumer lenders. Panel F consists of control variables and those employed in additional analyses. To maintain the complete data sample, we populate the COVID-19 related variables, including new weekly COVID-19 cases, PUA CC rate, and PEUC CC rate, with 0 for weeks before their first documentation in 2020. Further details regarding the data sources are elaborated in Section 4. The frequency and unit of variables are specified within parentheses. All observations are confined to the period between January 2019 and December 2020.

	N	Mean	Std. Dev	Min	Median	Max
Panel A: Visitor pattern (weekly/location)						
#Visitors to consumer lenders	520,143	6.94	31.42	1.00	3.00	11195.00
Unique location	13,165					
Unique city	3,200					
Unique FIPS code	1,694					
Unique state	50					
Panel B: Epidemiological variables (weekly/county)						
#New weekly cases	186,987	165,488.10	427,469.40	1.00	18,511.00	5,423,697.00
Social distancing index (CBG)	401,556	0.31	0.08	0.01	0.30	0.82
Panel C: Unemployment condition (monthly/state) & relief programs (weekly/state)						
Unemployment rate	520,143	0.06	0.03	0.02	0.04	0.30
Insured rate (weekly)	513,162	-0.02	0.02	-0.13	-0.02	0.17
PUA CC rate	178,943	0.05	0.06	0.00	0.03	0.66
PEUC CC rate	178,943	0.01	0.02	0.00	0.00	0.09
Panel D: Demographic characteristics (county/2018 Census Bureau)						
Car-ownership rate	370,994	0.78	0.08	0.06	0.80	0.90
Poverty level	428,425	0.14	0.05	0.02	0.14	0.38
Internet access rate	428,425	0.88	0.05	0.36	0.89	0.98
Health insurance coverage rate	428,425	0.89	0.05	0.69	0.91	0,98
Renters/population	428,402	0.02	0.01	0.00	0.02	0.15
Metropolitan areas dummy	520,143	0.83	0.37	0.00	1.00	1.00
Bank desert dummy	493,121	0.105	0.31	0.00	0.00	1.00
Panel E: Visits to other brands (weekly/location)						
Walmart	520,119	7.08	15.02	0.00	0.00	91.00
Dollar General	520,119	1.27	6.41	0.00	0.00	98.00
McDonald's	520,119	2.96	8.94	0.00	0.00	92.00
Panel F: Other variables (weekly)						
#Local visitors to consumer lenders (location)	520,143	0.36	1.43	0.00	0.00	54.00
Local visitors to banks (location)	501,086	76.09	213.64	0.00	4.00	6285.00
Google Trends (state)	520,143	36.07	23.30	0.00	34.00	100.00
#Device residing (CBG)	404,405	116.29	126.64	1.00	86.00	5770.00
Supply_rate(CBG)	520,143	0.99	0.11	0.00	1.00	1.00
Median distance (meter/CBG)	195,635	13,978.17	58,878.54	11.00	8,164.00	9,278,297.00

Table 2: **Impacts of Pandemic and Relief Programs on Demand for Consumer Credit**

This table shows the results of the location-week-level regression by estimating the following model:

$$Y_{i,t} = \alpha + \beta_1 SIP_{s,t} + \beta_2 ln(\#case + 1)_{c,t} + \gamma \boldsymbol{X_{s,t}} + \kappa \boldsymbol{Controls}_{b/s,t} + \eta_i + \delta_t + \epsilon_{i,t}$$

where $Y_{i,t}$ denotes the natural logarithm of the number of visitors to consumer lenders in location i during week t. It is noteworthy that consumer lenders may operate multiple locations within a county, making our unit of observation the foot traffic per location in a given week. $SIP_{s,t}$ is a dummy variable that indicates whether state i implemented shelter-in-place orders during week t. $ln(\#case + 1)_{c,t}$ denotes the natural logarithm of the number of new COVID-19 cases in county c during week t plus one. X is a set of state-level variables designed to represent the enrollment rate in government relief programs, including the difference between the state-level insured unemployment rate and the unemployment rate (*insured.rate*), PUA continued claims rate (*PUA.CC.rate*), and PEUC continued claims rate (*PEUC.CC.rate*). The control variables include the unemployment rate, the natural logarithm of the number of devices residing in census block group (CBG) b, the supply rate of credit in CBG b, and the Google Trends Index for state s. All control variables are measured on a weekly basis. In Column 1, we do not include any controls or fixed effects. In Column 2, we introduce week and location fixed effects. In Column 3, we incorporate controls along with fixed effects into the analysis. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	ln(#visitors to consumer lenders)		
	(1)	(2)	(3)
SIP	−0.124***	−0.030***	−0.027***
	(0.005)	(0.005)	(0.006)
ln(#case + 1)	−0.008***	−0.030***	−0.023***
	(0.0003)	(0.001)	(0.001)
insured.rate	−0.118*	−0.320***	−0.484***
	(0.062)	(0.040)	(0.049)
PUA.CC.rate	−0.322***	−0.118***	0.041*
	(0.036)	(0.020)	(0.024)
PEUC.CC.rate	−2.060***	−0.692***	−0.993***
	(0.152)	(0.105)	(0.271)
Controls	No	No	Yes
Week Fixed Effect	No	Yes	Yes
Location Fixed Effect	No	Yes	Yes
Observations	513,162	513,162	351,322
Adjusted R^2	0.007	0.768	0.791

Table 3: **Robustness Check: Credit Supply Changes**

This table presents the results of examining the role of credit supply in the impact of an economic shock on credit demand. The dependent variable is the natural logarithm of foot traffic to consumer lenders in location i and week t. We calculate a consumer lender's geographic location-based Herfindahl-Hirschman Index by aggregating the squared ratios of the lender's locations in each county relative to its total number of locations in a given year. We construct a new dummy variable "geo_div" that takes the value one if consumer lenders' county-level HHI is below the average, otherwise it is zero. Other independent variables are the same as the variables in Table 2. The control variables are the natural logarithm of the number of devices residing in CBG c and the Google Trends Index for state s. We interact the "geo_div" with variables representing shelter-in-place orders and local health and economic conditions. We control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	ln(#visitors to consumer lenders)
	(1)
SIP	-0.051^{***}
	(0.006)
$ln(\#case+1)$	-0.029^{***}
	(0.001)
$insured.rate$	-0.487^{***}
	(0.050)
$unemployment.rate$	-1.135^{***}
	(0.082)
$PUA.CC.rate$	0.026
	(0.024)
$PEUC.CC.rate$	-0.978^{***}
	(0.272)
geo_div	-0.007
	(0.009)
$geo_div \times SIP$	0.050^{***}
	(0.006)
$geo_div \times ln(\#case+1)$	0.007^{***}
	(0.001)
$geo_div \times unemployment.rate$	-0.228^{***}
	(0.082)
Controls	Yes
Week Fixed Effect	Yes
Location Fixed Effect	Yes
Observations	351,322
Adjusted R^2	0.790

Table 4: **Robustness Check: Online Lending**

To address the concern that the results in Table 2 are driven by switching to online loans, we examine whether foot traffic to consumer lenders without online lending services is significantly lower than foot traffic to consumer lenders with online loans during the travel restrictions. We create three dummy variables representing keywords "online loan," "online application," and "apply online." The dummy takes the value one if the keyword occurs on consumer lenders' websites, otherwise it is zero. The dependent variable and other independent/control variables are the same as the variables in Table 2. In all regressions, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	ln(#visitors to consumer lenders)		
	online loan	***online application***	***apply online***
	(1)	(2)	(3)
SIP	-0.048^{***}	-0.032^{***}	-0.034^{***}
	(0.007)	(0.007)	(0.007)
$ln(\#case+1)$	-0.027^{***}	-0.027^{***}	-0.027^{***}
	(0.001)	(0.001)	(0.001)
$insured.rate$	-0.481^{***}	-0.490^{***}	-0.489^{***}
	(0.057)	(0.057)	(0.057)
$PUA.CC.rate$	0.003	0.003	0.003
	(0.028)	(0.028)	(0.028)
$PEUC.CC.rate$	-0.449	-0.460	-0.458
	(0.300)	(0.300)	(0.300)
$dum \times SIP$	0.071^{***}	0.015^{**}	0.022^{***}
	(0.007)	(0.008)	(0.007)
Controls	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes
Observations	257,514	257,514	257,514
Adjusted R^2	0.782	0.782	0.782

Table 5: **Robustness Check: Willingness to Travel**

This table shows the result of the robustness test in which we we incorporate visits to other brands as a control measure to account for the willingness to travel. The dependent variable is the natural logarithm of foot traffic to consumer lenders in location i and week t. In each state, we choose three brands that witnessed the most visits in 2019 and record the number of visitors who visit the consumer lenders in the same week. For space considerations, we only show the results of Walmart, Dollar General, and McDonald's. The coefficients of other non-reported brands are all positive and statistically significant. The numbers of visitors to other brands are in natural logarithm. The dependent variable and independent variable are the same as the variables in Table 2. The control variables are the unemployment rate, Google Trends Index for state s and, and the supply rate of credit in CBG c. In all regressions, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	ln(#visitors to consumer lenders)
	(1)
SIP	-0.026^{***}
	(0.004)
$ln(\#case+1)$	-0.025^{***}
	(0.001)
$insured.rate$	-0.203^{***}
	(0.036)
$PUA.CC.rate$	-0.091^{***}
	(0.018)
$PEUC.CC.rate$	-1.115^{***}
	(0.217)
$Walmart$	0.100^{***}
	(0.001)
$Dollar.General$	0.073^{***}
	(0.001)
$McDonald's$	0.072^{***}
	(0.001)
Week Fixed Effect	Yes
Location Fixed Effect	Yes
Observations	452,152
Adjusted R^2	0.839

Table 6: **Robustness Check: Alternative Measure of Activity Restrictions**
We formulate an alternative metric for activity restriction, termed the social distancing index (*SDI*). This index is computed as the average daily ratio of the number of devices staying at home during the daytime in week t to the total number of devices residing in the same CBG in week t. We replace the number of new COVID-19 cases and the shelter-in-place dummy with the social distancing index and repeat the analysis in Table 2. The independent and control variables are the same as the variables in Table 2, except we exclude the number of new COVID-19 cases. In all regressions, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	ln(#visitors to consumer lenders)		
	(1)	(2)	(3)
SDI	−0.470***	−0.249***	−0.202***
	(0.017)	(0.013)	(0.014)
insured.rate	−0.507***	−0.274***	−0.456***
	(0.068)	(0.046)	(0.049)
PUA.CC.rate	−0.642***	−0.220***	0.010
	(0.037)	(0.022)	(0.024)
PEUC.CC.rate	−3.266***	−1.268***	−0.842***
	(0.152)	(0.115)	(0.272)
Controls	No	No	Yes
Week Fixed Effect	No	Yes	Yes
Location Fixed Effect	No	Yes	Yes
Observations	398,823	398,823	351,225
Adjusted R^2	0.007	0.768	0.791

Table 7: **Visits to Consumer Lenders versus Banks**

This table shows the differential effect of an economic shock on two groups: visitors to consumer lenders and those visiting banks. The dependent variable is the weekly count of visitors in natural logarithm to either consumer lenders or banks. we introduce a dummy variable denoted as *bank*, assigned a value of one for foot traffic related to banks, and zero otherwise. We interact *bank* with other independent variables, which mirror those outlined in Table 2. Our control variables are the unemployment rate, the natural logarithm of the number of devices residing in CBG c, the credit supply rate in CBG c, and the Google Trend Index for the term "cash loans" within state s. In all regression, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	ln(#visitors)
	(1)
SIP	-0.040^{***}
	(0.008)
$ln(case+1)$	-0.029^{***}
	(0.001)
$insured.rate$	-0.408^{***}
	(0.063)
$PUA.CC.rate$	-0.030
	(0.030)
$PEUC.CC.rate$	-1.841^{***}
	(0.354)
$bank \times SIP$	0.011
	(0.008)
$bank \times ln(case+1)$	-0.013^{***}
	(0.001)
$bank \times insured.rate$	0.189^{***}
	(0.065)
$bank \times PUA.CC.rate$	0.132^{***}
	(0.031)
$bank \times PEUC.CC.rate$	1.826^{***}
	(0.356)
Controls	Yes
Week Fixed Effect	Yes
Location Fixed Effect	Yes
Observations	7,814,077
Adjusted R^2	0.803

Table 8: **Consumer Lending in Bank Deserts versus in Metropolitan Areas**

This table shows the differential effect of an economic shock on visits to consumer lenders in bank deserts and metropolitan areas. The dependent variable in Columns 1-2 is the natural logarithm of the number of visitors to consumer lenders in location i and week t. The bank desert dummy is one if the location i is in the Zip Code where the bank density is less than 0.02 or less than one-tenth of the mean, otherwise is zero. The metropolitan dummy is one if the location i is in the list of metropolitan/micropolitan statistical areas released by the Census Bureau, otherwise is zero. Other independent/control variables are same as the variables in Table 2. All variables are converted to the weekly frequency that matches the foot traffic data. In all regressions, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	ln(#visitors to consumer lenders)	
	area= bank deserts	***area= metropolitan areas***
	(1)	(2)
SIP	-0.026^{***}	0.012
	(0.006)	(0.008)
$ln(\#case+1)$	-0.024^{***}	-0.020^{***}
	(0.001)	(0.001)
$insured.rate$	-0.472^{***}	-0.051
	(0.053)	(0.093)
$PUA.CC.rate$	-0.008	0.052
	(0.027)	(0.075)
$PEUC.CC.rate$	-1.415^{***}	1.198^{**}
	(0.292)	(0.549)
$area \times SIP$	0.012	-0.048^{***}
	(0.009)	(0.007)
$area \times insured.rate$	0.080	-0.506^{***}
	(0.123)	(0.096)
$area \times PUA.CC.rate$	0.082	-0.008
	(0.064)	(0.077)
$area \times PEUC.CC.rate$	2.584^{***}	-2.602^{***}
	(0.695)	(0.585)
Controls	Yes	Yes
Week Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
Observations	332,285	351,322
Adjusted R^2	0.794	0.791

Table 9: **Foot Traffic in Different Time Periods**

This table presents results of comparing the effects of unemployment insurance and government relief programs before and during the pandemic, and when people receive supplemental paychecks of $600 per week. The dependent variable in Columns 1-3 is the natural logarithm of the number of visitors to consumer lender i and in week t. In Column 1, we subsample the weeks before the pandemic, which is the period between January 2019 and January 21, 2020 (the first documentation of COVID-19 cases). In Column 2, we expand to full sample and add COVID-19 related variables. We create a "pandemic" dummy that takes value one if the observation is in the week after Jan 22, 2020. We interact the dummy with the insured unemployment rate to see if there is a differential effect in the pandemic. In Column 3, we use the full sample and create a dummy variable "FPUC" that takes the value of one if the FPUC program is in effect, otherwise it is zero. The control variables are the same in Table 2. In all regressions, we include week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	ln(#visitors to consumer lenders)		
	Pre-pandemic	***Full Sample***	***FPUC***
	(1)	(2)	(3)
SIP		-0.021^{***}	-0.029^{***}
		(0.007)	(0.006)
$ln(\#case+1)$		-0.026^{***}	-0.023^{***}
		(0.001)	(0.001)
$PUA.CC.rate$		0.006	-0.101^{*}
		(0.024)	(0.054)
$PEUC.CC.rate$		-0.874^{***}	1.049^{**}
		(0.273)	(0.470)
$insured.rate$	-3.815^{***}	0.508^{***}	0.069
	(0.560)	(0.183)	(0.132)
$pandemic$		-0.038^{***}	
		(0.012)	
$pandemic \times insured.rate$		-1.098^{***}	
		(0.184)	
$FPUC \times insured.rate$			-0.608^{***}
			(0.137)
$FPUC \times PUA.CC.rate$			0.124^{**}
			(0.057)
$FPUC \times PEUC.CC.rate$			-2.702^{***}
			(0.541)
Controls	Yes	Yes	Yes
Week Fixed Effect	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes
Observations	227,523	351,322	351,322
Adjusted R^2	0.830	0.791	0.791

Table 10: **Comparison of Local versus Distant Visits to Consumer Lenders**

The table shows the impact of an economic shock on visitors' preferences for consumer lenders. The dependent variable in Columns 1-2 is the difference of the natural logarithm of the number of local visitors and distant visitors to the consumer lender i in the week t. The visitor is counted as a local visitor if she visits the consumer lender in the same CBG c as her home, otherwise she is counted as a distant visitor. The distance from home is the median distance of visitors' homes to the consumer lender. The share of local visitors to banks is paired with the dependent variable by ZIP Code and represents the difference in the number of local visitors and distant visitors to banks. Control variables, the car-ownership rate, poverty level, internet access rate, health insurance coverage rate, and the share of renters are described in Section 4. In all regression, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	ln(#local_visitors_cl)-ln(#nearby_visitors_cl)	
	(1)	(2)
SIP	0.039**	0.754
	(0.020)	(0.545)
$ln(\#local_visitors_banks) - ln(\#nearby_visitors_banks)$	0.002	0.003
	(0.003)	(0.003)
$distance_from_home$	−0.232***	−0.241***
	(0.003)	(0.003)
$SIP \times distance_from_home$		0.029***
		(0.010)
$SIP \times workbycar$		−0.577***
		(0.140)
$SIP \times poverty$		−0.901**
		(0.449)
$SIP \times health_insurance_cov$		−0.373
		(0.250)
$SIP \times sharehome_perct$		0.164
		(0.939)
$SIP \times internet_access$		−0.083
		(0.489)
Week Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
Observations	162,036	115,860
Adjusted R^2	0.401	0.420

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Appendix A: Proofs

Proof of Proposition 1: Consider a shock that increases the deadweight cost of taking the loan by $\delta > 0$. First note that this has no impact on the interest rate for bank loans (see (3)). From (4), bank consumers will take a loan if $V_i \geq d_b + \delta + (1 - w_b)y_b$. Thus, the reduction in demand for bank loans is the measure of consumers with $d_b + (1 - w_b)y_b \leq V_i < d_b + \delta + (1 - w_b)y_b$. That is, consumers whose net benefit $b_i = V_i + L - d_b - w_b R_b L - (1 - w_b)y_b$ from loan is less than δ no longer take a loan when the deadweight cost of taking a loan increases by δ.

Credit-weak consumers also reduce the demand for loans due to an increase in deadweight costs. First we ignore any change in interest rate on loans offered by consumer lenders. From (6), a weak-credit consumer, consumer i, will take a loan if $V_i \geq d_c + \delta + w_i R_c L + (1 - w_i)y_c - L$. Thus, the reduction in demand for loans from consumer lenders is the measure of credit-weak consumers with $d_c + w_i R_c L + (1 - w_i)y_c - L \leq V_i < d_c + \delta + w_i R_c L + (1 - w_i)y_c - L$. That is, consumers whose net benefit $b_i = V_i + L - d_c w_i R_c L - (1 - w_i)y_c$ from loan is less than δ no longer take a loan when the deadweight cost of taking a loan increases by δ.

However, we now show that unlike banks loans, interest rate for loans from consumer lenders changes following a shock to the deadweight costs of loans. Differentiating (8) with

respect to deadweight cost d_c and replacing $d_c + wR_cL + (1-w)y_c - L$ with v:

$$\frac{\partial \bar{w}}{\partial d_c} = \frac{-\int_0^1 w f_c(v)\, g(w)\mathrm{d}w \int_0^1 \{1 - F_c(v)\}\, g(w)\mathrm{d}w + \int_0^1 w\, \{1 - F_c(v)\}\, g(w)\mathrm{d}w \int_0^1 f_c(v)\, g(w)\mathrm{d}w}{\left(\int_0^1 \{1 - F_c(v)\}\, g(w)\mathrm{d}w\right)^2}$$

$$< 0 \tag{13}$$

from Chebyshev's inequality (see Mitrinović and Vaić (1970) Theorem 10, p. 40) because v is increasing in w and $f_c(v)/(1 - F_c(v))$ is non-decreasing in v from Assumption 1. As $\bar{w}$ decreases, lenders increase R_c to maintain zero profit condition (9). This leads to a further decline in the demand for loans from credit-weak consumers (see (6)). □

Appendix B: Figures and Additional Tables

Figure F.1: **The Timing of Shelter-in-Place Orders across States**

The green and yellow circles represent the start and end date of mandatory state-wide shelter-in-place orders in 2020, respectively.

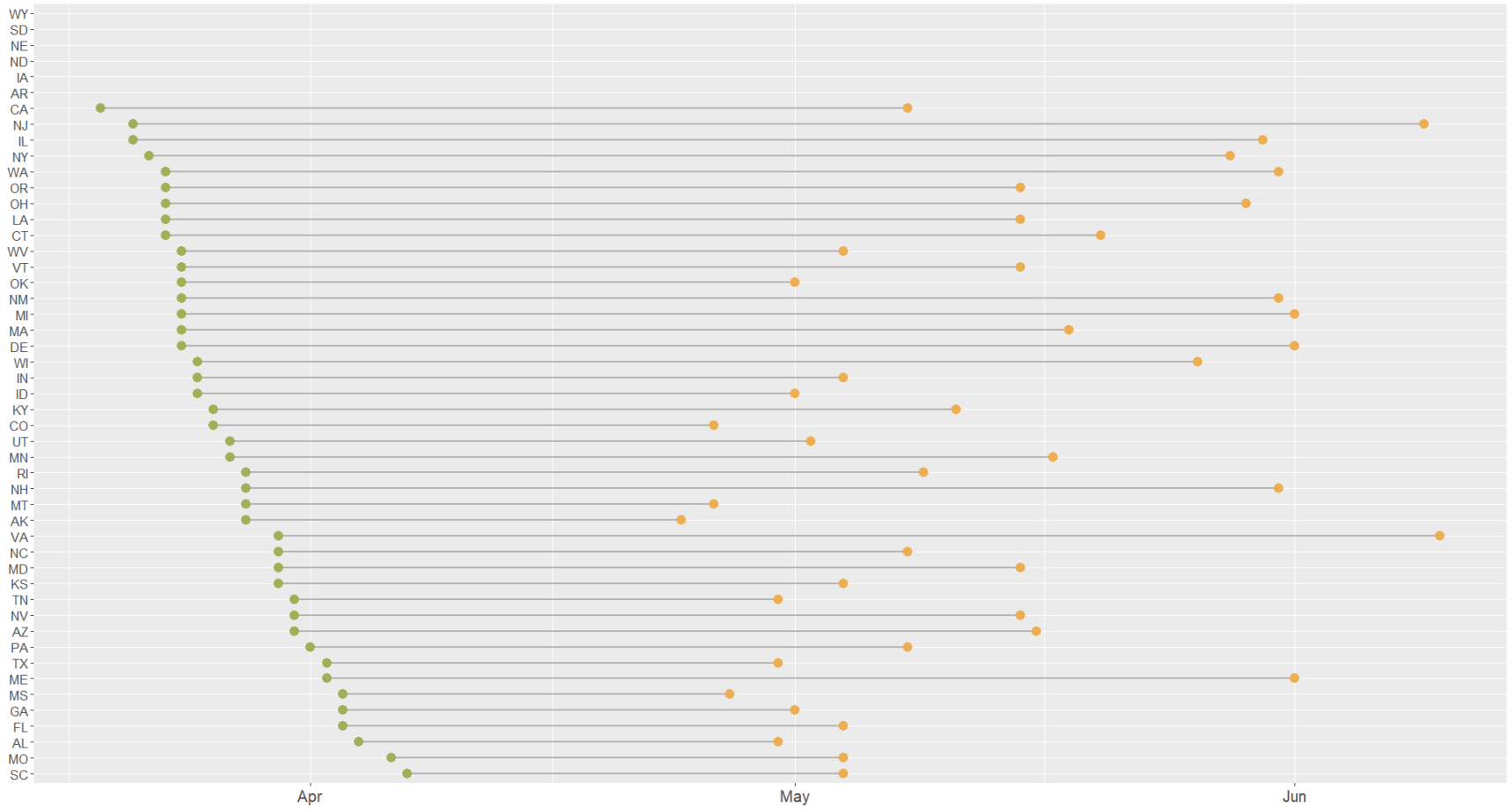


Figure F.2: **Aggregate Visits to Consumer Lenders by States**

The figure depicts aggregate weekly foot traffic to consumer lenders for 49 states between January 2019 and December 2020. The number of visitors is winsorized at 1% and 99%. The green and yellow lines represent the day of the first COVID-19 case and the start date of the shelter-in-place orders, respectively. There is insufficient data for Vermont.

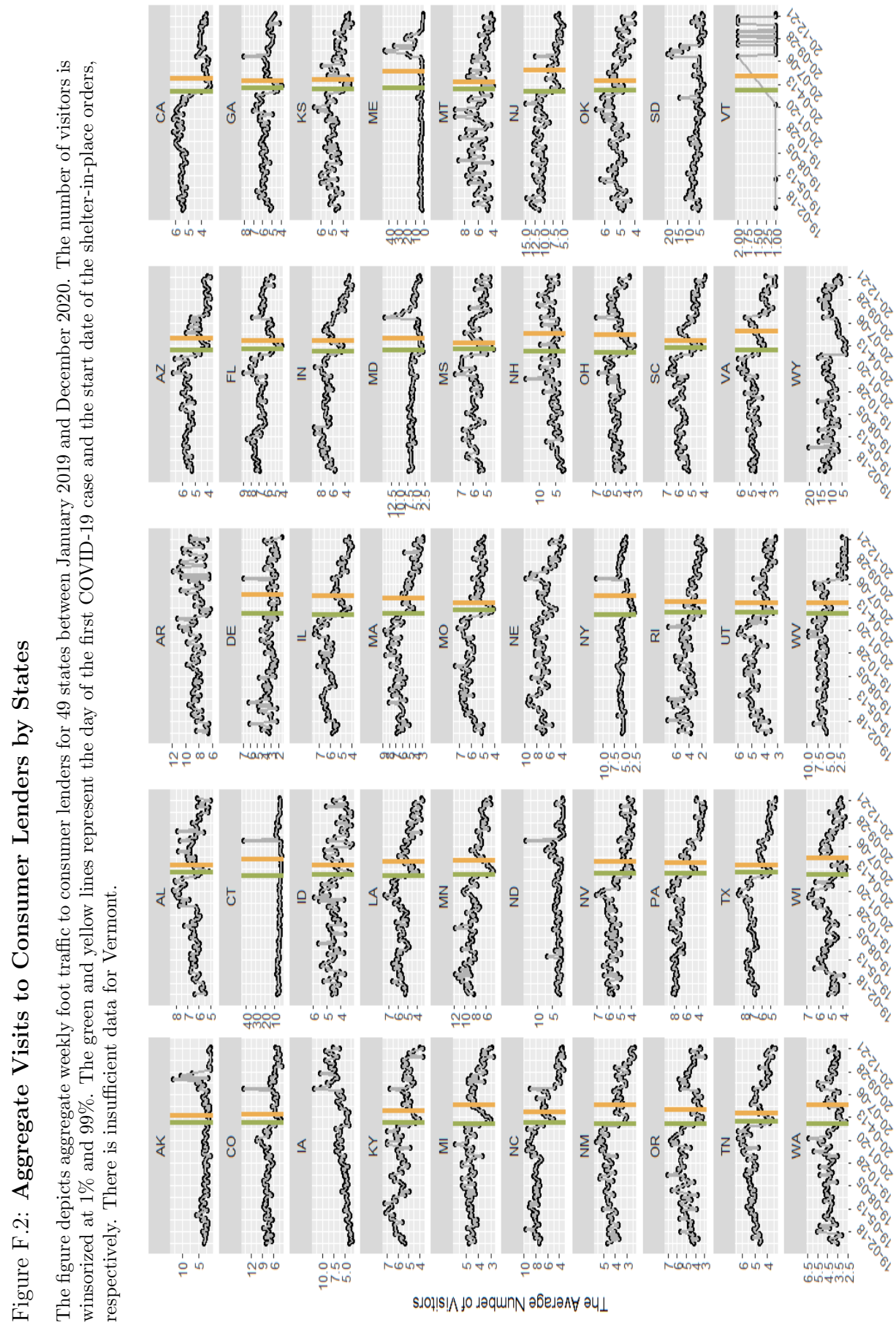


Figure F.3: **Government Programs for Unemployment Assistance**

The chart provides details on four unemployment relief programs: the state-funded Unemployment Insurance (UI) program , the Pandemic Unemployment Assistance (PUA) program , the Pandemic Emergency Unemployment Compensation (PEUC) program , and the Federal Pandemic Unemployment Compensation (FPUC) program.

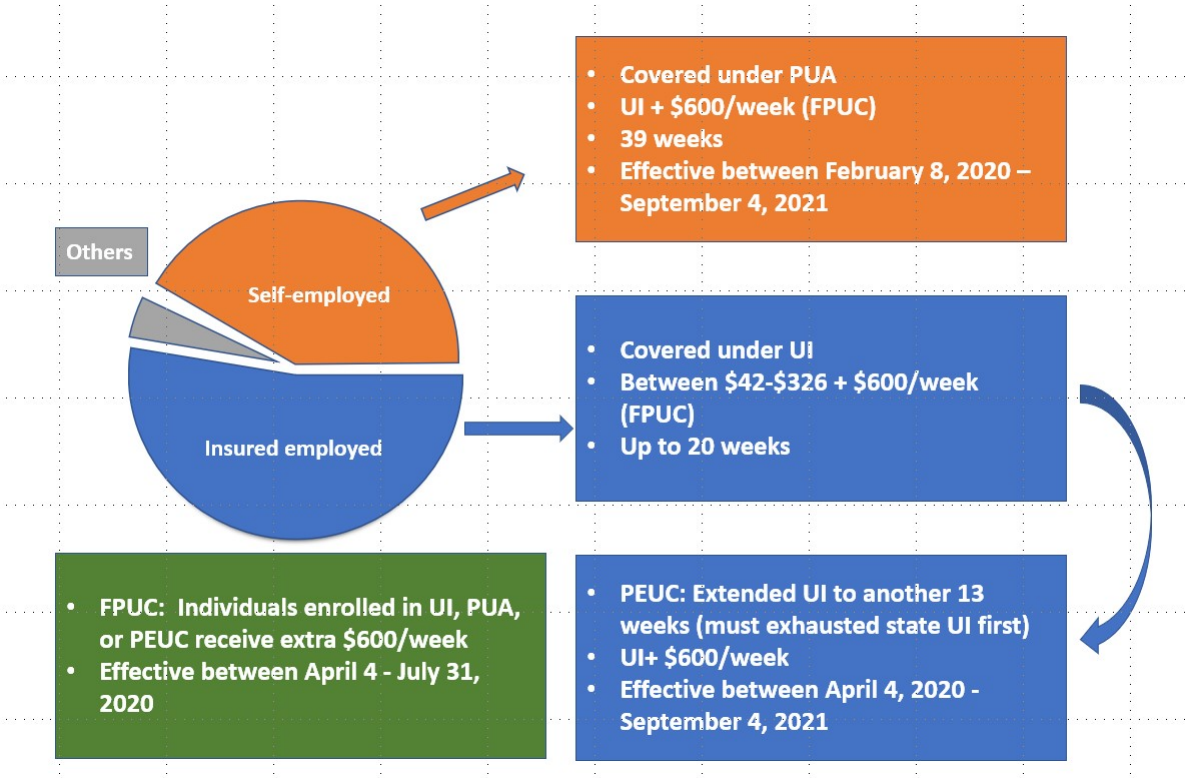


Figure F.4: **Aggregate Number of Continued Claims for Relief Programs**

The figure shows weekly continued claims for two relief programs from the week that ended on March 26, 2020 to the week that ended on January 2, 2021.

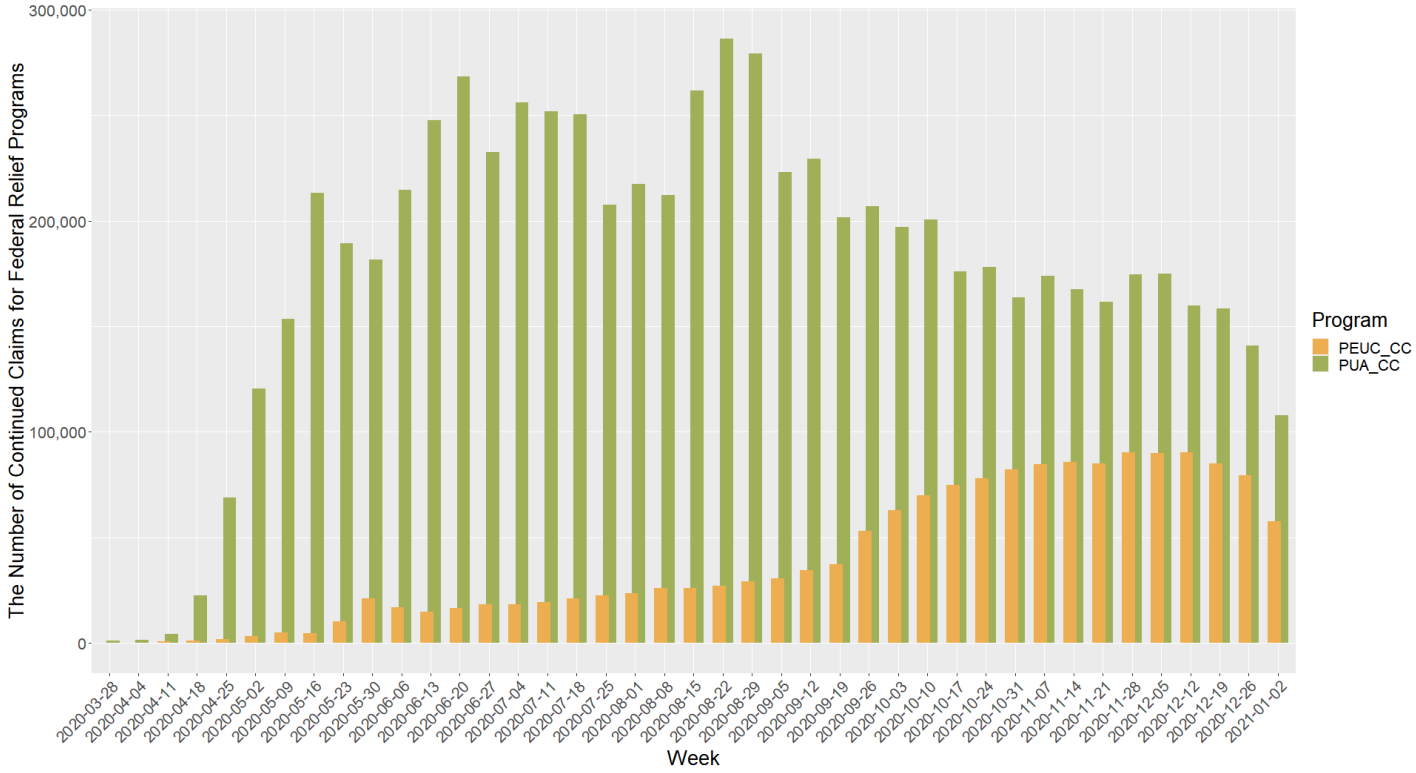


Table A.1: **Variable Definitions**

Variables	**Definition**
ln(#visitors to consumer lenders)	The natural logarithm of the number of visitors at a consumer lender's location i during week t.
SIP	A dummy variable that is one for weeks during the shelter-in-place orders; otherwise it is zero.
ln(#case+1)	The natural logarithm of the number of new COVID-19 cases in CBG b during week t
insured.rate	The difference between the ratio of total insured employees to the total labor force in a state and the corresponding unemployment rate on a monthly basis
PUA.CC.rate	The ratio of the weekly number of continued claims for the PUA program to the total labor force in a state
PEUC.CC.rate	The ratio of the weekly number of continued claims for the PEUC program to the total labor force in a state
unemployment.rate	The monthly state-level unemployment rate.
ln(#device residing)	The natural logarithm of the number of devices residing in the CBG of the location for that week
supply_rate	The ratio of consumer lenders remain open in the CBG of the location for that week
Google Trends	The state level Google Trend Index for the keyword "Cash Loan"
goe_div	A dummy variable that is one for consumer lenders whose location-based Herfindahl-Hirschman Index, calculated as the sum of the squared ratio of the number of locations in a county to the total number of locations in a given year, is greater than the median.
online loan	A dummy variable if consumer lender's website contains keyword "online loan"
online application	A dummy variable if consumer lender's website contains keyword "online application"
apply online	A dummy variable if consumer lender's website contains keyword "apply online"
SDI	The average proportion of devices residing at home CBG

Continue

Variables	Definition
bank	A dummy variable that is one if the location is a bank.
bank_desert	A dummy variable that indicates whether a consumer lender's location is in a Zip Code where the bank density is less than 0.02 or less than one-tenth of the mean
metropolitan areas	A dummy variable that indicates whether a consumer lender's location is in a Zip Code where the Census Beauru lists as metropolitan area
pandemic	A dummy variable that takes the value of one for weeks after January 21, 2020
FPUC	A dummy variable that takes the value of one for weeks between March 29, 2020 and July 31, 2020
ln(#local_visitors_cl)	The natural logarithm of the number of visitors who visit consumer lenders located in their respective home CBGs
ln(#nearby_visitors_cl)	The natural logarithm of the number of visitors who visit consumer lenders located outside their respective home CBGs
ln(#local_visitors_banks)	The natural logarithm of the number of visitors who visit banks located in their respective home CBGs
ln(#nearby_visitors_banks)	The natural logarithm of the number of visitors who visit banks located outside their respective home CBGs
distance _from_home	The median distance from the location to consumers' homes
workbycar	The fraction of individuals whose main transportation method is the car, truck, or van (drive alone)
poverty	The fraction of households with incomes no more than half of the federal poverty line in 2018
health_insurance_cov	The percentage of population covered by at least one insurance
sharehome_perc	The percentage of individuals who share the house/rooms with non-relatives
internet_access	The percentage of households with internet access

Table A.2: Comparison of Changes in Foot Traffic and Consumer Loans in Texas

This table presents the connection between our foot traffic data and credit demand, validating by a comparison of changes in foot traffic and changes in consumer loans issued in Texas during the year 2020. The data comprises the aggregate dollar amount and the count of payday loans and title loans originated by Metropolitan Statistical Area in Texas from 2019 to 2020, sourced from the Texas Office of Consumer Credit Commissioner. We compute the annual growth rate of consumer loans in both dollar amount and quantity. Then we use FIPS as an identifier to match this data with our foot traffic data. In Panel A, we sum up foot traffic to locations that were present in January 2019. In Panel B, as an alternative measure of credit demand, we compute the average weekly foot traffic per lender within a metropolitan area. In instances where there are gaps in observations between weeks with positive foot traffic, we make the assumption that foot traffic is zero during those intervening weeks.

Panel A. Exclusively Include Locations Appeared in January 2019

	SafeGraph		Texas Office of Consumer Credit Commissioner	
MSA	#Visitors	$\triangle\#Visitors(\%)$	$\triangle\$ConsumerLoans(\%)$	$\triangle\#ConsumerLoans(\%)$
Austin-RoundRock-SanMarcos	5341	-30	-47	-40
Beaumont-Port Arthur	1386	-35	40	-38
Corpus Christi	5821	-27	-41	-38
Dallas-Fort Worth-Arlington	55622	-44	-51	-48
El Paso	4364	-32	-54	-47
Houston-The Woodlands-Sugar Land	37504	-42	-35	-36
Killeen-Temple	8431	-27	-45	-42
Laredo	5431	-45	-47	-38
Lubbock	2159	-20	-42	-38
McAllen-Edinburg-Mission	19285	-33	-51	-40
San Antonio-New Braunfels	31562	-30	-49	-42
Waco	2045	-38	-43	-41
Correlation between $\triangle\#Visitors(\%)$ and $\triangle\$ConsumerLoans(\%)$			0.37	
Correlation between $\triangle\#Visitors(\%)$ and $\triangle\#ConsumerLoans(\%)$			0.11	

Panel B. Filling Missing Weeks with Zeros

	SafeGraph		Texas Office of Consumer Credit Commissioner	
MSA	#Visitors	$\triangle\#Visitors(\%)$	$\triangle\$ConsumerLoans(\%)$	$\triangle\#ConsumerLoans(\%)$
Austin-RoundRock-SanMarcos	6.88	-11	-47	-40
Beaumont-Port Arthur	2.25	4	-40	-38
Corpus Christi	5.07	-5	-41	-38
Dallas-Fort Worth-Arlington	4.30	-29	-51	-48
El Paso	2.91	-13	-54	-47
Houston-The Woodlands-Sugar Land	4.18	-24	-35	-36
Killeen-Temple	5.64	-17	-45	-42
Laredo	5.55	-18	-47	-38
Lubbock	3.63	01	-42	-38
McAllen-Edinburg-Mission	9.23	-11	-51	-40
San Antonio-New Braunfels	5.99	-16	-49	-42
Waco	2.49	-15	-43	-41
Correlation between $\triangle\#Visitors(\%)$ and $\triangle\$ConsumerLoans(\%)$			0.26	
Correlation between $\triangle\#Visitors(\%)$ and $\triangle\#ConsumerLoans(\%)$			0.44	

Table A.3: **Fixed Credit Supply**

This table provides additional evidence against the main results outlined in Table 2 driving by the supply-side changes. In this analysis, we focus on consumer lenders operating multiple brick-and-mortar stores across counties, and compare the changes in foot traffic within the lender. The dependent variable is the weekly count of visitors in natural logarithm to consumer lenders. The independent variables are the same as the variables in Table 2. Our control variables are the unemployment rate, the natural logarithm of the number of devices residing in CBG b, the credit supply rate in CBG b, and the Google Trend Index for the term "cash loans" within state s. In all regression, we control for location fixed effects alongside interactive fixed effects associated with the consumer lender and the respective week. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	ln(#visitors to consumer lenders)	
	(1)	(2)
SIP	-0.023^{***}	-0.025^{***}
	(0.008)	(0.009)
$ln(case+1)$	-0.029^{***}	-0.022^{***}
	(0.001)	(0.001)
$insured.rate$	-0.256^{***}	-0.550^{***}
	(0.056)	(0.071)
$PUA.CC.rate$	-0.234^{***}	-0.034
	(0.029)	(0.035)
$PEUC.CC.rate$	-0.354^{***}	-0.183
	(0.119)	(0.345)
Controls	No	Yes
Location FE	Yes	Yes
Consumer lender×week FE	Yes	Yes
Observations	298,528	186,081
Adjusted R^2	0.735	0.775
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A.4: **Subsample of States that Prohibit Online Payday Lending**

This table presents the results of a robustness test designed to examine the sensitivity of storefront visits to online lending using foot traffic in states that prohibit online payday lending. These 7 states are Georgia, Iowa, Kentucky, Nebraska, New York, North Carolina, Ohio, Pennsylvania, Vermont, and West Virginia. The dependent variable is the weekly count of visitors in natural logarithm to consumer lenders. The independent variables are the same as the variables in Table 2. Our control variables are the unemployment rate, the natural logarithm of the number of devices residing in CBG b, and the credit supply rate in CBG b. In Column 1, we do not include control variables, while in Column 2, we incorporate these control variables. In all regression, we control for location and week fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	ln(#visitors to consumer lenders)	
	(1)	(2)
SIP	-0.049^{***}	-0.049^{***}
	(0.012)	(0.014)
$ln(case+1)$	-0.016^{***}	-0.012^{***}
	(0.002)	(0.002)
$insured.rate$	-0.298^{***}	0.069
	(0.107)	(0.130)
$PUA.CC.rate$	-0.266^{***}	-0.086
	(0.050)	(0.066)
$PEUC.CC.rate$	-1.449^{***}	-1.330^{**}
	(0.307)	(0.629)
Controls	No	Yes
Location FE	Yes	Yes
Week FE	Yes	Yes
Observations	72,613	50,739
Adjusted R^2	0.774	0.802
Note:	*p<0.1; **p<0.05; ***p<0.01	