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

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Abstract

This paper examines the impact of an economic shock and the government response on financial access for underserved consumers. Using foot traffic to consumer lenders as a proxy for loan demand, we find that the shelter-in-place order, new Covid-19 cases, and the government relief program (PEUC) are associated with a drop in visits to consumer lenders after controlled for the online borrowing and the supply of credit. Using natural experiments of the statewide shelter-in-place order and FPUC program, we find that the lockdown suppresses financially underserved consumers' access to credit, while the supplemental paychecks (FPUC) cushion their economic blow by further reducing visits to consumer lenders. We also find that regular unemployment insurance is less effective in reducing demand for consumer credit in financially underserved areas than in metropolitan areas. The demand for consumer credit is positively correlated with the average consumption level in an area. Lastly, we find differences in the impact of the government relief programs on visits to banks and visits to consumer lenders.

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1 Introduction

We know that financial development has a positive impact on economic growth and measures of welfare including reduction in inequality and poverty. However, aggregate measures of financial development do not capture the large variation in access to financial services (see Beck et al., 2009). 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 lenders (henceforth, consumer lenders). Though there is a well-developed literature on banks, we know little about what causes consumers to borrow from consumer lenders. There has been a debate about whether the access to consumer lenders is good or bad for consumers. Rather than addressing this debate, we ask a simpler question: what determines the demand for consumer credit? Specifically, we seek to identify the economic factors that drive demand for consumer credit. Such an understanding is a key first step towards evaluating the benefits of consumer lenders or other solutions for the underlying problems that steer consumers towards alternative forms of credit.

We consider the Covid-19 pandemic shock, 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 consumer lenders. Our measure of demand for consumer lenders is the foot traffic to physical locations of consumer lenders. We use novel detailed data of daily foot traffic to physical locations of consumer lenders and other businesses to measure variation in foot traffic across time and cross-sectionally, controlling for lender- and time-fixed effects. We relate the foot traffic to severity of the Covid-19 pandemic, the shelter-in-place restrictions, the unemployment rate, the insured unemployment rate, and local adoption of government relief programs on a weekly basis.

Financial services improve social welfare by allowing people to smooth consumption and share risks. At an aggregate level, access to financial credit promotes economic growth and stability by making households and businesses resilient to economic shocks. Businesses benefit from tapping sources of capital. Individual households are more willing to engage in productive but risky economic activity if they can share risks and disentangle income and consumption using savings products and credit from banks. However, traditional financial institutions are not accessible to many consumers. Alternative lenders complement mainstream banks by providing alternative loan products to underserved customers or in situations when bank credit is not available.[1] By connecting investors seeking alternative investment opportunities with those seeking credit but underserved by banks, alternative lenders may satisfy unmet credit demand of financially underserved consumers.

The total outstanding consumer credit in September 2020 was 4,161.3 billion U.S. dollars.[2] Depository institutions make up 40% of the total consumer credit, followed by the federal government at 33.4%, finance companies at 13.2%, credit union at 11.9%, and other lenders. Although banks hold the largest market share of the consumer lending market, banks' growth in terms of consumer credit was slowing before the outbreak of Covid-19. Consumer lenders such as finance companies extended 1.5% and 3.4% more consumer credit in the second and third quarters than in the first quarter of 2020, compared to negative growth rates of 3.8% and 3.3% for depository institutions.

Aggregate statistics do not reveal the inequity in access to credit across households with different incomes, education levels, races, and health conditions.[3] According to a 2019 survey conducted by the Federal Deposit Insurance Corporation, 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 sufficient credit history or high credit scores can more easily access bank credit than customers with stale or no credit history. The Consumer Finance Protection Bureau estimates that approximately 45 million Americans are credit invisible and lack access to mainstream banks.[4] Such limited access to credit is costly for households because they 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 curtail the development of the economy as the widening wealth gap restrains consumption and investment.[5]

[1]Alternative lenders may offer one or more form 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).

[2]Consumer credit statistical release, https://www.federalreserve.gov/releases/g19/current/

[3]2019 FDIC Survey, https://www.fdic.gov/analysis/household-survey/2019report.pdf

[4]CFPB report in 2016, https://files.consumerfinance.gov/f/documents/201612_cfpb_credit_invisible_policy_report.pdf

[5]McKinsey 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. https://www.mckinsey.com/industries/public-and-social-sector/our-insights/the-economic-impact-of-closing-the-racial-wealth-gap

Consumer lenders can serve underserved consumers by providing loans to high-risk consumers that fail to get loans from mainstream banks. Consumers can borrow without collateral from payday lenders, or they can borrow at peer-to-peer platforms. Although banks offer convenience and flexibility through the branch banking system, emerging consumer lenders, such as the online lending platforms, are beginning to utilize alternative data (soft 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).

One reason that banks may be unwilling to lend to underserved consumers either because lending to these consumers is not economically feasible. That is, 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. Another reason could be that frictions in the lending process make introduce costs that make bank lending to underserved consumers unviable. In this case, consumer lenders with different business models, mitigate the frictions, reduce costs, and offer credit to underserved consumers and improve welfare. Thus, whether consumer lenders are good or bad for the consumers depends on the frictions that prevent banks from extending credit to the underserved.

Borrowers seeking credit from consumer lenders are more likely to be lower-income or those with lower financial cushion. 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 the low-income, non-white households, and households with children (Monte, 2020; Ganong et al., 2020) from massive lay-offs and reduced working hours. We hypothesize that low-income families that lack easy access to traditional commercial banks may find themselves in a more difficult position after the negative impact of Covid-19 and their demand for credit from non-bank consumer lenders may increase. However, the government relief programs during the pandemic may have tempered this demand for credit. Understanding these demand patterns serves two purposes. It helps in understanding the economic factors that drive borrowers to borrow from consumer lenders. It also helps us understand the impact of economic shocks and of the government's response in the form of relief programs on the financially underserved consumers.

Demand and supply of aggregate credit, much of it through traditional banks, has been studies extensively. The focus of this literature has been on understanding aggregate consumer behavior and its macroeconomic consequences. Since consumer decisions are assumed to be rational and reflecting their circumstances and preferences, these studies help understand macroeconomic patterns but are not necessarily informative about access to credit and its welfare implications. Moreover, aggregate data doesn't reveal heterogeneity in access to credit.

Recent literature has examined credit provided by alternative lenders. For example, 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 in females, unmarried, non-whites, young, lower-income, unemployed, and those with high-school only education. Most commonly stated uses of alternative credit are basic living expenses, making up for lost income, or purchase or repair of house, car, or appliance. Common reasons stated for using an alternative lender than a traditional bank are ease or speed, unavailability of small-dollar loans from banks, and inability to get a loan from a bank. Variation in lending laws across time and across states has been used to examine the impact of supply of credit by consumer lenders. However, we still do not understand the determinants of the demand for credit from consumer lenders.

We investigate the demand for consumer lending by examining the relationship between macroeconomic and epidemiological variables and foot traffic to consumer lenders. We examine (i) how a health shock and government relief programs affect demand for credit, (ii) how different relief programs interact in influencing demand for credit, (iii) the differential impact of unemployment on demand for credit in underserved and metropolitan areas, (iv) how shift to online lending varies across underserved and metropolitan areas, (v) how demand for credit fro consumer lender depends on average consumption, and (vi) the differential impact of unemployment on demand for credit from banks and consumer lenders. We use weekly visitor data to brick-and-mortar locations of consumer lenders as a useful tool for understanding the demand for credit from consumer lenders at a granular level. Similar data has been used by other studies to measure business activity: [6] Although it is not easy to disentangle the demand and supply-side changes under a mix of influences, we argue that foot traffic changes throw more light on the demand-side than on the supply-side as most consumer lenders were considered essential businesses and remained open in the pandemic. This argument is consistent with our measure of credit supply: the average open rate for consumer lenders is 98.5%.

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 fully recover to the pre-pandemic level in most states. Three factors may contribute to the drop in overall foot traffic to consumer lenders. First, the statewide shelter-in-place order restricts mobility and consequently affects most businesses (Cronin and Evans, 2020; Chao and Zimmermann, 2020; Farboodi et al., 2020), including consumer lending. Second, a surge in new cases and death (Maloney and Taskin, 2020) deters people's willingness to visit consumer lenders in person and thus brings down the number of visits. Third, the federally funded relief programs (Karger and Rajan, 2020; Gallagher et al., 2020) support financially distressed households promptly so that people find less need for borrowing.

Our evidence supports all three factors. We find that the shelter-in-place order, the number of new cases, and the relief programs are statistically significant in explaining the foot traffic to consumer lenders. We attempt to control for the supply of credit, online demand for credit, and the number of devices tracked in Safegraph data. We also control for the insured unemployment rate and the unemployment rate.

The first question we address is whether government unemployment programs lower demand for credit from consumer lenders. Our results show that the demand for credit from consumers lenders decreases following increase in the number of consumers registered in the regular unemployment insurance (the insured unemployment rate) and in the continued claims rate for PEUC (Pandemic Emergency Unemployment Compensation). We interpret these results to

[6] Williams (2020a), Williams (2020b) use foot traffic data to measure the economic activity across industries in Wisconsin and find that storefront visits decline is positively correlated with reduced sales and business shutdown. 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 some industries that imposed restrictions, such as restaurant dine-in ban, which have a spillover effect on complementary industries (Cronin and Evans, 2020). Foot traffic data also shed light on demands for goods and services. Walmsley et al. (2020) estimate the pent-up demand comparing the current foot traffic level to that in the pre-pandemic time 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) work.

mean that the relief programs alleviate the financial distress faced by consumers that rely on consumer lenders for credit.

We next examine whether this impact of the relief programs on demand for credit from consumer lenders varies across time. Our sample period coincides with two experiments: one is the end of the shelter-in-place restrictions in most states at the end of May 2020 and the other is the expiration of the 600 dollars weekly supplemental compensation (FPUC) on 31 July, 2020. We find that the impact of PEUC on the demand for credit from consumer lenders does not change with the shelter-in-place restrictions. This suggests that the decline in demand for credit associated with the shelter-in-place restrictions is uncorrelated with the eligibility for PEUC program. That is, health concerns or travel restrictions may be the driving forces behind the reduction in demand rather than a lower need for credit.

We also find that the reduction in the demand for credit associated with the PEUC program is greater in the period when the unemployed receive the 600 dollars supplemental compensation. This suggests a complementarity between the two benefits in reducing the demand for credit from consumer lenders rather than a situation in which one benefit program diminishes the effectiveness of the other program in reducing the need for consumers to borrow from consumer lenders.

The second question relates to how an economic shock affects demand for consumer credit in different areas. Since the impact of the pandemic and the access to traditional banks is uneven across communities, we examine whether the impact of the economic shocks and government relief programs on the demand for consumer credit vary in financially underserved communities and in metropolitan areas. We find that the marginal impact of unemployment on the demand for consumer lenders is greater in financially underserved areas and lower in metropolitan areas. While we are unable to explain the average impact of unemployment on the demand for consumer credit due to the multiple channels through which unemployment can affect the demand for consumer credit, our results show that the overall effect of unemployment on financial well-being of households is more adverse in financially underserved areas and less adverse in metropolitan areas.

We also show that greater access to internet results in a greater reduction in the demand for credit from consumer lenders during shelter-in-place restrictions. This suggests that some demand for credit from consumer lenders may be shifting from brick-and-mortar lenders to online lenders. However, our evidence suggests that the marginal impact of internet access on the shift from brick-and-mortar lenders to online lenders is weaker in financially underserved areas and is stronger in metropolitan areas. One interpretation can be that those with better internet access in financially underserved areas are already relying on online lenders and the shelter-in-place restriction did little to change their behavior. However, those living in metropolitan areas may have preferred brick-and-mortar lenders in normal times due to ease of physical travel but switched to online lenders when shelter-in-place restrictions were imposed.

We also examine how the demand for consumer credit relates to the average local consumption level. Using debit card transaction data, we find that consumer credit demand is positively correlated with the consumption level in an area. This result complements Chetty et al. (2020), who find that low-income workers in affluent communities are hit harder by the pandemic than their low-income peers in other areas. The result suggests that the problem of inadequate access to financial services is not confined to areas with high poverty.

To control for omitted factors that may impact consumer's decision to travel, we use visits to other brands as control variables. Not surprisingly, we find that the visits to consumer lenders are positively correlated with visits to other brands. Furthermore, we find that the demand for consumer credit is more sensitive to essentials and grocery store visits than the demand for shelter-in-place orders.

Another factor that may influence visits to consumer lenders is the travel distance, which gains weight on people's choosing lenders during the pandemic. Not surprisingly, we find that an increase in median travel distance to consumer lenders is related to an increase in visits to local consumer lenders relative to distant consumer lenders during the shelter-in-place order. Moreover, mobility and the poverty level contribute to customer migration from local to faraway lenders.

Lastly, we compare whether the pandemic and the government programs impact visits to consumer lenders and banks differently. We find that unemployment has a different effect on foot traffic to banks and to consumer lenders. A higher unemployment rate is associated with a larger ratio of the number of visits to consumer lenders to the number of visits to banks. However, we find opposite effects of the two relief programs, PUA and PEUC. An increase in the rate of PUA claims increases the ratio of the number of visits to consumer lenders to the number of visits to banks while an increase in the rate of PEUC claims has the opposite effect. We are unable to explain these individual effects but the results suggest that the economic factors driving the demand for bank credit are different from the factors driving the demand for credit from consumer lenders.

To show the reliability of our measure of demand for credit from consumer lenders, we address two concerns. One is the lack of supply-side data about consumer lending activities. The other one is the insufficiency of demand-side data to reflect the change that people choose the online platforms instead of the physical stores for borrowing. For the former concern, we construct the "supply rate" variable, which is the average proportion of the number of devices staying at a consumer lender for more than five minutes to the total number of devices observed at that location in a Census Block Group (CBG). For the latter concern, we include the county-level internet access data and the Google Trend Index in each state to control for people's online borrowing behavior. Our results continue to hold when we include these control variables. Our results are also robust to replacing the shelter-in-place variable with a social distancing index.

The remainder of the paper is organized as follows. Section 2 describes the data. Section 3 reports the impacts of the economic shock and government relief programs on foot traffic to consumer lenders. Section 4 concludes. All Figures are in an Appendix.

2 Literature

In the section, we provide theoretical arguments motivating our hypothesis that demand for consumer credit is higher during an economic shock in which consumers' income is adversely affected. The credit demand is more pronounced among low-income households with limited access to credit from mainstream banks. The hypothesis involves consumer lending and household borrowing decisions.

2.1 Consumer Lending

Consumer lending refers to credit supply in cash and holding from non-depositary financial institutions. As an alternative financing option, consumer lending is characterized by short-term, high liquidity, and no collateral. In most cases, the recipients of consumer credit are denied by 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 tilt toward those who have a thin margin between income and expenses, face fluctuating income, lack financial literacy, and fail to make sound financial decisions (Campbell et al., 2012).

Empirical research on the welfare effects of access to consumer credit is mixed. Compared to banks charging relatively higher fees for services, consumer lenders provide financially constrained households with cheaper credit (Morgan et al., 2012) to help them smooth consumption and invest in risky products (Barr, 2004; Zinman, 2010). The feature of an unsecured basis allows consumers to keep the earnings in liquid format to weather unpredicted shocks (Morse, 2011) and build long-term assets (Elliehausen and Lawrence, 2001). Restricting access to consumer lending deteriorates consumers' financial condition as limited substitutions make consumers turn to suboptimal credit choices (Zinman, 2010).

Contrary to the welfare-enhancing view about consumer credit, the critique of "debt trap" can be traced in literature as well. Skiba and Tobacman (2008) investigate the financial hardship after accessing consumer credit and find that consumers' financial condition regarding the number of bankruptcy filings worsens. Using the proximity to the nearest state that allows payday loans as a measure of the access to consumer credit, Melzer (2011) shows that payday loan availability results in delaying important payments, such as medical and utility bills.

There are also papers that find a null effect of consumer credit accessibility on financial well-being. Using the gap in payday loans approval rates to investigate the effect of payday loans on creditworthiness, Bhutta et al. (2015) 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 further shortfall.

Many studies use a shock to consumer credit supply in a state as a natural experiment to compare the consumer outcomes within the state (counties faraway from and adjacent to bordering states without bans, see works done by Morgan and Strain, 2008, Morgan et al., 2012) or between neighboring states (Zinman, 2010) to mitigate the omitted variables concern. Carrell and Zinman (2014) add on another source of variation using nationwide Air Force assignment which is unlikely to correlate with law changes on social programs and find a negative link between payday loan access and workplace productivity. By taking a field experiment in which the payday lender randomly extend credit to marginal borrowers who cannot meet the underwriting criteria, Karlan and Zinman (2010) find an value-enhancing role of liberalized credit access on consumers' overall well-being. Morse (2011) uses a natural disaster in California as an exogenous shock to examine the welfare effects of payday loans. The finding reveals that payday loans raise consumer welfare by reducing foreclosures and small property crimes.

2.2 Household Borrowing Decisions

The decision of households to get a loan depends on both demand and supply factors. On the demand side, consumers' financial health and self-sufficiency (employment) alleviate the craving for loans. On the supply side, the lending capacity of intermediaries and the affordability of a loan segment consumers with considerably different costs.

For households, the borrowing decisions are intertwined with income, consumption, and saving. One of the most prominent theories in this field is the life cycle hypothesis (LCH is revisited and elaborated more on Modigliani, 1986). Modigliani and Brumberg (1954) demonstrate that households maximize the utility by allocating resources to consume over life. In other words, the consumption depends on the sum of liquid assets and borrowings instead of the current income level. Therefore, households with an outstanding debt balance are supposed to reduce consumption when the borrowing becomes more expensive (see cross-country evidence provided by Crook, 2003). Brissimis et al. (2014) analyze the relationship between demand and supply of credit in Greece's liberalization period when banks can freely extend credit to households. They find that the 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 usuary law in Italy which caps interest rates charged on borrowers and find a negative elasticity of credit demand to interest rates.

If the 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) posit the asymmetry that high-income individuals are more sensitive to price changes but less sensitive to maturity changes, suggesting a differential effect of liquidity constraints on consumers with different risk profiles. Alan and Loranth (2013) use a lender's randomized price experiment to approximate the credit demand elasticity to an interest rate increase and find that the majority of the subprime borrowers are insensitive to the shock, causing a rapid debt accumulation.

There are two puzzles regarding the debt holdings. The first puzzle is that economic growth does not reduce the overall households' debts. 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. The second puzzle is that households at the low decile of the income distribution possess less debt than the high decile group. Gropp et al. (1997) show that the deleveraging and higher cost of financing automobiles among low-asset households relates to the state bankruptcy exemption level and attached insurance coverage. In high bankruptcy exemption states, lenders are conservative in making loans to risky borrowers because they suffer greater losses when those borrowers utilize the strategic bankruptcy to repay less.

The heterogeneity in households' debt holdings is more pronounced in the face of economic shocks. Most households reduce their consumption spending during uncertain times (Brissimis et al., 2014), consistent with the permanent income theory. It indicates that households will adjust consumption only when they consider shocks leave a long-term impact on income (Hall and Mishkin, 1982). However, the reduction is greater among less risky borrowers (Horvath et al., 2021). 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). Moreover, the credit card balance decreases less for riskier borrowers who encounter a greater unpredictability in future mortgage payments. Those results can be interpreted as a lower default cost (Maggio et al., 2017) and more selective credit access for riskier consumers (Gropp et al., 2014).

How rational a consumer can approach a loan relies on her financial literacy and cognition. The lack of financial literacy is likely to cause overindebtedness because illiterate participants make poor financial decisions that incur avoidable charges (Lusardi and Tufano, 2015), focus more on institutions' brand names than on fees and return (Hastings and Tejeda-Ashton, 2008), and ignore the punitive price of credit risks, namely the high APR (Disney and Gathergood, 2013; Ausubel, 1991). The life circle theory also assumes that individuals can undertake economic calculations to plan for saving and consumption expenditures. In the last decade, many papers examine other household decisions that require financial literacy, such as retirement planning (Lusardi and Mitchell, 2006; van Rooij et al., 2012), investment participation and outcomes (Gaudecker, 2015; van Rooij et al., 2012), mortgage selection (Fornero et al., 2011), and school choices (Hastings and Weinstein, 2008).

Financial literacy can partly, but not fully, contribute to the cognition bias. The difference between the two sources of irrationality is that the former causes the ignorance of potential costs, while the latter leads to the underestimation of risks. Stango and Zinman (2009) find payment/APR bias toward the short-term (but not long-term) installment loans. They argue that the value-induced memory and regulations on lender practices mitigate the bias in the long run. They further investigate the relationship between payment/APR bias and lenders' price discrimination comparing household bias before and after the "Truth in Lending Act" (Stango and Zinman, 2011). The results show that the degree of bias positively relates to the interest rate, explaining lenders' shrouding behavior. Suppose the quality of a household's financial decision is negatively associated with education, income, and wealth, then popularizing financial knowledge, promoting information transparency, and lowering the entry barriers of getting loans could decrease disparities across socioeconomic groups (Bertrand and Morse, 2011; Barr, 2004; Bernheim and Garrett, 1996). Innovative methods that improve repayment outcomes, such as group lending, may serve as a double-edged sword on broadening access to consumers and thus, require a comprehensive costs and benefits calculation under different circumstances. (Karlan, 2005; Karlan and Gine, 2007)

3 Data

3.1 Foot Traffic Data

We use foot traffic data to consumer lenders as a measure of demand for credit from non-bank financial intermediaries. There are some advantages of this measure. The high-frequency of this data allows a more precise detection of how demand for credit changes in response to changing Covid-19 conditions or government relief programs. Compared to loan transaction data, the foot traffic is more likely to represent the demand rather than the supply of credit.

Some disadvantages of this measure are that we do not observe all visits to consumer lenders and do not know the purpose of the visit. We do not expect limitations to significantly impact conclusions of our analyses, based on changes in the number of visits rather than an absolute number of visits.

We obtain the foot traffic data from the firm SafeGraph. SafeGraph provides aggregated, anonymized, privacy-safe data on a range of spatial behaviors of more than 45 million mobile devices in the United States.[7] We use two datasets in their free “Covid-19 Dataset”. One is the “Core Places” dataset that contains location information and category about 3.5 million Point of Interest (POIs) in the U.S.. The other one is the “Weekly Patterns” dataset that includes aggregated GPS-identified visits to POIs with the exact known location at hourly frequency. We use the “Core Places” data to identify consumer lenders as points of interests that are categorized as nondepository credit intermediaries and obtain the data on the visits to these consumer lenders from “Weekly Pattern” data. While our analysis focuses on consumer lenders, we also use foot traffic data to banks and some other businesses as control variables in some analyses. We extract information about a consumer lender’s location, the number of visitors and visits to the consumer lender, other brands visited by those visitors within the same week, visitors’ home Census Block Group (CBGs), median travel distance, and dwell time.

The SafeGraph data is based on cell phones and may under-represent the population that is less likely to own phones. However, the SafeGraph data are representative at the county level along with many demographic dimensions (Squire, 2019). We also note that SafeGraph does not provide individual-level information, so the foot traffic data gauge the extent and trend of consumer lending activities rather than measure individual consumer behaviors. Our data covers 520,143 observations with 13,165 locations across 50 states between January 2019 and December 2020.

3.2 Economic Data

Our primary measures for economic condition are unemployment-related data. The unemployment rate and the insured unemployment rate represent the proportion of the unemployed

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

workers in the labor forces and the percentage of the continued claims in total insured employment, respectively. To relieve the concern of multicollinearity on the unemployment rate and the insured unemployment rate, we subtract the latter from the former. The insured unemployment rate is weekly, while the unemployment rate is monthly.

Unemployment Insurance in the U.S. is a joint state-federal program that provides temporary financial assistance to unemployed workers. Each state sets its own additional requirements for eligibility, benefit amounts, and length of time benefits can be paid. Benefits are typically paid for a maximum of 26 weeks, but extended benefits may be available during times of high unemployment.

The regular unemployment insurance program was supplemented by the CARES Act passed in April 2020 with several measures to provide relief to the unemployed and others adversely affected by the pandemic. We focus on three of these programs. Pandemic Unemployment Assistance (PUA) program was designed to provide payment through March 14, 2021, to those not traditionally eligible for unemployment benefits, such as self-employed, who are unable to work as a direct result of the pandemic. Pandemic Emergency Unemployment Compensation (PEUC) was designed to provide an additional 13 weeks of unemployment benefits through December 31, 2020, to help those who remain unemployed after weeks of state unemployment benefits are no longer available. Federal Pandemic Unemployment Compensation (FPUC) program was designed to pay an additional $600 per week up to July 31, 2020, to individuals who are eligible for state unemployment insurance or relief programs (PUA and PEUC).[8]

We add economic variables related to Covid-19 relief programs, including Pandemic Unemployment Assistance continued claims rate and Pandemic Emergency Unemployment Compensation continued claims rate. The continued claims rate for PUA is the number of PUA recipients within that week scaled by the total labor force. The same scaling factor is applied to continued claims for PEUC. The number of continued claims measures the ongoing unemployment by counting claims receiving unemployment benefits.

We also include detailed transaction data at the ZIP Code level from the firm Facteus. Facteus has partnered with banks and creates a synthetic version of transaction data from debit cards. The data contains the transaction date, cardholder ZIP Code, number of cards,

[8]FPUC program has been reauthorized and provides extra $300 per week for the unemployed in the period December 26, 2020 and March 14, 2021. However our data do not cover that period.

number of transactions, and the total spending in dollars. Data are only available until August 2020 and are skewed toward the young population because the debit cards come primarily from "virtual banks" whose customers are typically millennials.

3.3 Socioeconomic and Epidemiological Data

To recognize financially underserved areas and metropolitan areas, we utilize the list of rural and underserved counties released in 2020 by the Consumer Financial Protection Bureau (CFPB) and the list of metropolitan/micropolitan areas released by the Census Bureau. After matching the Federal Information Processing Standards (FIPS) codes of consumer lenders with underserved areas and metropolitan areas, we find that 9.45% and 83% of observations in our unbalanced data are identified as underserved areas and metropolitan areas, respectively.

We collect demographic characteristics from the Census Bureau to calculate several indicators at the county level. These include car ownership, poverty level, renters-population percentage, internet access rate, and health insurance coverage.[9]

The epidemiological data consists of the number of daily Covid-19 new cases and deaths at a county level from the New York Times. We compile the schedules for state-level shelter-in-place orders using timelines from Keystone Strategy, ABC News, CNN, NPR, Littler, and the New York Times.[10] The shelter-in-place dummy is one if the state had a mandatory stay-at-home order in the week, otherwise it is zero.

Since the mandate statewide stay-at-home order ended in all states in June 2020, the shelter-in-place dummy may not adequately capture local activity restrictions imposed after the new wave of Covid-19 infections in fall 2020. To reflect the effect of local policies and the voluntary choice of staying at home, we construct a social distancing index using SafeGraph's "Social Distancing Metrics" dataset. The social distancing index is the weekly average proportion of

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

[10]ABCNews, https://abcNews.go.com/US/list-states-stay-home-order-lifts/story?id=70317035;
CNN, https://www.cnn.com/interactive/2020/us/states-reopen-coronavirus-trnd/;
NPR, https://www.npr.org/2020/05/01/847416108/west-coronavirus-related-restrictions-by-state;
Littler, https://www.littler.com/publication-press/publication/stay-top-stay-home-list-statewide;
The New York Times, https://www.nytimes.com/interactive/2020/us/coronavirus-stay-at-home-order.html.

tracking devices residing at home.[11] The variable ranges from zero to one, with one representing the strictest social distancing policy and zero being the least.

3.4 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 number of devices residing in the census block group (CBG) of the location during that week. We attempt to partially control for online access to financial services with two control variables that proxy for online traffic to consumer lenders: the state level Google Trends Index for keyword "Cash Loan" and the county level internet access.

To control the shock to the supply of credit, we construct the variable "supply_rate" based on the assumption that the store is closed if no observations stay there for more than five minutes. The "supply_rate" is the share of open stores in the CBG of the location during that week. The summary statistics are shown in Table 1.

4 Results

4.1 Baseline Results

We first summarize the timing of the events that are relevant to our analysis. The exponentially growing new cases of Covid-19 infections and deaths related to Covid-19 triggered the implementation of shelter-in-place (or stay-at-home) orders in most states in early March 2020. Figure 1 shows the timing of these orders. California was the first state to issue statewide mandatory shelter-in-place order, followed by 34 states in March. In April, another 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 stay-at-home order.

Figure 2 depicts foot traffic to consumer lenders for 50 states between January 2019 and December 2020. Less than half of 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

[11] Safegraph defines a device is completely at home if it does not leave home during the time period. The home is defined as the place where the device stays during the nighttime (6 pm- 7 am) for over six weeks.

Table 1: Summary Statistics

This table displays the summary statistics for the variables used in the paper. Panel A reports statistics on the dependent variable. Panel B reports statistics on the Non-pharmaceutical Interventions (NPIs) and the public health condition. Panel C reports statistics on the unemployment condition and unemployment benefits from the state insurance and Covid-19 related new federal programs. Panel D reports statistics on county-level demographics. Panel E reports other variables. Covid-19 related variables, including new weekly cases, new weekly deaths, PUA CC rate, and PEUC CC rate are filled with zero for weeks before their first documentations in 2020 to keep the complete data sample in the regression. Data sources are introduced in Section 2. The frequency and the unit of variables are clarified in parentheses. All observations are within the period from January 2019 to 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
#New weekly deaths	186,987	3,544.72	8,608.66	0.00	417.00	71,745.00
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 unemployment rate (weekly) - unemployment rate	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
Underserved areas dummy (CFPB)	520,143	0.09	0.29	0.00	0.00	1.00
Metropolitan areas dummy	520,143	0.83	0.37	0.00	1.00	1.00
Panel E: Consumption level (weekly/Zip-Code) & visits to other brands (weekly/location)						
$Total spending	449,767	224,539.30	247,607.90	5.03	160,248.20	7,729,970.00
$Spending per order	449,767	35.72	7.11	1.49	34.43	524.66
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 trend (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

number of visitors to consumer lenders when the stay-at-home order was first issued. Although the 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.

There are multiple channels through which the pandemic may have impacted the demand for credit. The pandemic led to a sharp surge in unemployment, exposing many people to an abrupt earning loss shock. Figure 3 shows the unemployment rate and the insured unemployment rate from January 2019 and December 2020. It shows that the unemployment rate increased drastically when the authority began tracing the Covid cases. It kept rising until it touched the peak in mid-May where the unemployment rate was nearly triple the pre-pandemic level. The insured unemployment rate trajectory is similar to that of the unemployment rate, indicating that a growing number of unemployed workers are receiving financial aid from the government.

Besides unemployment, people were furloughed, lost work hours, or were unable to run their businesses due to quarantine, travel restrictions, and school closures. The decline in income may partially have been offset by a decline in expenses while staying at home but expenses like rent, utilities, and food are less discretionary[12]. However, for many, the loss of income resulted in a significant financial shock. Those with little financial buffer are more likely to have experienced a need for credit. However, other factors could have resulted in a decline in the demand for credit. We have already mentioned one as the decline in expenses during the stay-at-home restrictions. The shelter-in-place order itself or the fear of Covid-19 infection may have prevented consumers from visiting consumer lenders.[13] Finally, the government relief measures may have offset the adverse impact of the pandemic, and in some cases, the relief may have been more than the loss of income. We discuss these relief programs next.

The CARES Act passed in April 2020 introduced multiple measures to relieve Americans from the adverse impact of the pandemic. We focus on the federally funded programs that supplemented the traditional state-based unemployment insurance. There are three main programs approved to provide financial aid for recent unemployed workers: Federal Pandemic Unemployment Compensation (FPUC), Pandemic Unemployment Assistance (PUA), and Pandemic Emergency Unemployment Compensation (PEUC). FPUC was designated for people who meet

[12]There were some government and private initiatives to relieve consumers' of the pressure to meet rent or utility obligations.

[13]Some consumers may have switched from physical visits to accessing credit online. Our data do not allow us to measure this activity, but we attempt to control for this shift as a robustness check.

the regular unemployment insurance (UI) requirements to obtain additional 600 dollars per week for up to 26 weeks until it expired on July 31, 2020. PEUC extended the unemployment benefits to another 13 weeks after regular UI benefits are exhausted, and it is available through March 14, 2021. In order to increase the ease of access to financial assistance, the Fed established PUA to help those who were ineligible for traditional UI, such as gig-workers, self-employed, independent contractors, and individuals with insufficient work history by directing minimum weekly benefit described in the Stafford Act Disaster Unemployment Assistance program. Figure 4 shows that the aggregate number of continued claims for PUA program is much larger than that for PEUC program. However, two numbers converge over time.

The different channels discussed above may each have an impact on demand for consumer credit. However, the relative impact of these channels is not likely to be the same for all consumers. For example, the 600 dollars a week payment is more likely to offset the loss of income from losing a low-paying job than the loss of income from losing a high-paying job. Our focus is on examining the demand for credit from non-bank consumer lenders. Borrowers from these lenders are typically denied credit from banks and are likely to have lower incomes, assets, or credit scores. We believe these results are useful given the paucity of research on behalf of this segment of the economy. However, our results cannot be generalized to the broader population or to demand for credit from banks.

We now attempt to disentangle the impact of the spread of the Covid-19 pandemic, the stay-in-place restrictions, and the government relief programs on foot traffic to consumer lenders. The dependent variable is the natural logarithm of foot traffic to consumer lenders. Independent variables include the shelter-in-place dummy, the number of new cases and deaths, insured unemployment rate, the unemployment rate, PUA continued claims rate, and PEUC continued claims rate. We report the result in column 1 of Table 2.

We include time and location fixed effects in all our regressions to control for heterogeneity across consumer lenders and omitted temporal factors. We include the logarithm of the number of devices residing in CBGs as a control variable to control for the changes in SafeGraph coverage over time. The statistically significant negative coefficient of the SIP dummy in column 1 of Table 2 shows that the stay-at-home order negatively impacts foot traffic to consumer lenders. The coefficients on new cases and deaths are negative and statistically significant, suggesting that people reduce visits to consumer lenders when the public health condition worsens. These results show that both the shelter-in-place order and the increase in infected cases/deaths are connected to the decline in foot traffic to consumer lenders.

The coefficient on the insured unemployment rate is negative and statistically significant, implying that consumers may find less need to borrow from consumer lenders when more laid-offs are provided with financial aid. The coefficient on the unemployment rate is negative and highly significant. This puzzling finding suggests that a higher unemployment rate is associated with fewer visits to consumer lenders. It contrasts with the expectation that visits to consumer lenders increase when more people are out of jobs. However, an opposing effect is that consumers lower their expectation of lifelong income, reduce consumption and demand for credit or save more. Lu and van der Klaauw (2021) present evidence about aggregate credit that is consistent with out finding. Another possible explanation is that the unemployment rate and insured unemployment rate are correlated but provide different insights into the labor market condition. Specifically, the unemployment rate is based on the total labor force and represents accumulated effects of economic conditions over a period of time, while the insured unemployment rate is based on the insured workforce and only considers the insured workforce through employers and reflects the concurrent labor market more promptly due to the weekly report scheme.[14] The correlation between the two variables makes it difficult to interpret individual coefficients.

In column 1 of Table 2, we include both PUA and PEUC continued claims rates, which reflect different unemployment populations, to explore the the influence of new relief programs on demand for credit. We expect a relatively more significant effect of PUA program on foot traffic to consumer lenders. Because PUA program covers the unemployed who do not previously have a stable income to build up a credit score and are less likely to get a loan from banks. However, we do not detect a significant relationship between PUA continued claims rate and foot traffic to consumer lenders. The regression results show that visits to consumer lenders is negatively impacted by PEUC continued claims rate. Given that PEUC program

[14] Burtless (1983) points out that both the definitions and measurements of the unemployment rate and insured unemployment rate are different. The insured unemployment rate excludes new entrants, most reentrants and job leavers, and job losers whose unemployment horizon is longer than 26 weeks, all of which are considered in the unemployment rate. Besides, the denominator of the insured unemployment rate is calculated as the average of insured employment in the preceding 18 months to 7 months time window, thus it will be bigger than current employment when there is a recession.

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

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

$$Y_{i,t} = \alpha + \beta X_{j/s,t} + Controls_{c/y,t} + \delta_t + \eta_i.$$

where $Y_{i,t}$ represents the natural logarithm of the number of visitors to consumer lender in location i and week t. $X_{j/s,t}$ are epidemiological and economic variables either at the county-level j, the number of new cases/deaths, or at the state-level s, the shelter-in-place dummy, the difference between the state insured unemployment rate and the unemployment rate, the unemployment rate, pandemic unemployment assistance continued claims rate (PUA.CC.rate), and pandemic emergency unemployment compensation continued claims rate (PEUC.CC.rate). The control variables are the number of device residing in census block group (CBG) c, the supply rate of credit in CBG c, the google trend index for state s, and the internet access in county j. All control variables are weekly, except the internet access rate. All variables have been standardized to have a mean of zero and a standard deviation of one. In all regressions, we control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	Dependent variable: ln(#visitors to consumer lenders)	
	(1)	(2)
SIP_dum	-0.008***	-0.007***
	(0.002)	(0.002)
$ln(\#case + 1)$	-0.105***	-0.083***
	(0.008)	(0.009)
$ln(\#death + 1)$	-0.015***	-0.027***
	(0.005)	(0.006)
$insured.rate - unemployment.rate$	-0.014***	-0.016***
	(0.001)	(0.001)
$unemployment.rate$	−0.041***	-0.048***
	(0.003)	(0.003)
$PUA.CC.rate$	0.002	0.003**
	(0.001)	(0.001)
$PEUC.CC.rate$	−0.011***	−0.019***
	(0.002)	(0.004)
$ln(\#devices\_residing)$	0.089***	0.084***
	(0.003)	(0.003)
gg_index		-0.001
		(0.002)
$supply\_rate$		0.022***
		(0.001)
$SIP\_dum \times internet\_access$		−0.005***
		(0.001)
Week Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
Observations	398,919	282,260
R^2	0.755	0.779
Adjusted R^2	0.749	0.773
Residual Std. Error	0.541 (df = 388560)	0.486 (df = 274394)

provides an extension of unemployment insurance upon the unemployed exhausted their 26 weeks benefits, it is possible that people who are out of jobs for a long time in the pandemic avail of this program and find less need to visit consumer lenders.

One weakness of our data is that we cannot capture the behavior of those consumers who access credit online. This channel may become more important during the pandemic due to restrictions on travel or voluntary decisions of individuals to avoid travel. In the absence of a measure for access to credit online, we use two control variables as proxies for online borrowing demand. One of these is the normalized volume of online searches on Google for cash loans. We get this data from Google Trend Index at a weekly frequency and a state level. The other proxy is internet access defined as the proportion of households in the county with internet access.

Another weakness of the data is that we do not know whether the decline in visits comes from the shock to the supply of credit. To address this concern, we include the "supply_rate" variable to control for changes in the supply of credit from storefront consumer lenders.

The results of regressions with these three control variables are shown in column 2 of Table 2. The coefficient on the interaction of the internet access and the shelter-in-place dummy is negative and statistically significant. We interpret this result to mean that while the foot traffic to consumer lenders decreases overall during shelter-in-place restrictions, the decline in demand was concentrated in locations where more consumers had access to the internet. The coefficient on PUA continued claims rate is positive and statistically significant (at the 0.05 level) after controlling for online searches. The other coefficients in column 2 are qualitatively similar to those in column 1 of Table 2. The results in column 2 show that the index for the search for "Cash Loans" is not a significant predictor of the foot traffic to consumer lenders.

Finally, we replace the shelter-in-place dummy and the number of new cases and death with the social distancing index and repeat the regressions in Table 2. The results are similar, as shown in Table 9 in an Appendix. That means the government order, together with the public health condition, is adequate to capture the unexplained reasons for changes in foot traffic to consumer lenders.

4.2 Comparing Foot Traffic in Different Periods

4.2.1 Before the Economic Shock

To investigate whether the economic shock distorts the effect of regular UI, we create a dummy variable to split the data into "pre-pandemic" and "during pandemic" periods. The "pandemic" dummy is one for weeks after January 21, 2020, which is the date of the first documentation of Covid-19 cases. We interact the economic variables in Table 2 with the time dummy and report the result in Table 3.

In column 1 of Table 3, we subset the data before January 21, 2020, and include variables that are recorded even before the pandemic. We find that both the insured unemployment rate and the unemployment rate negatively impact the foot traffic to consumer lenders in the usual time. That means the puzzling negative relationship between the unemployment rate and the number of visitors has existed even before the pandemic. However, the coefficient on the social distancing index is positive and statistically significant, suggesting that more people will visit consumer lenders when more people stay at home.

Then we include all data and interact economic variables with the time dummy. The results are reported in column 2 of Table 3. We find that the coefficients on the social distancing index and the insured unemployment rate flips the sign after expanding data. One possible explanation of the social distancing index changing the sign is that the index, as a measure of activity restrictions, is a relatively robust indicator of foot traffic to other places in the pandemic, including the consumer lenders. However, other omitted factors may influence people's decision to visit consumer lenders usually, resulting in a spurious positive relationship between the index and foot traffic.

Although the insured unemployment rate positively affects the number of visitors to consumer lenders, the coefficient on interaction term of the dummy and the insured unemployment rate is negative and statistically significant. That means a higher insured unemployment rate is associated with fewer visits to consumer lenders during the pandemic than at any other time. It indicates that those unemployment benefits significantly relieve the economic hardship imposed on the unemployed during the pandemic than before the pandemic.

What remains puzzling is that the coefficient on the interaction term of pandemic and the unemployment rate is negative and statistically significant. That is, the negative effect of the unemployment rate is magnified during the Covid-19. People living in areas with a higher unemployment rate are less likely to visit consumer lenders in the pandemic.

Since the newly funded unemployment programs may also account for the drop in foot traffic to consumer lenders, we include the PUA and PEUC continued claims rates in the regression, as shown in column 2 of Table 3. The results show that PEUC continued claims rate negatively affects the number of visitors to consumer lenders. Together with the negative interaction terms of the insured unemployment rate and the time dummy, we find that people in areas with a higher insured unemployment rate and PEUC continued claims rate are less likely to visit consumer lenders during the economic shock. It indicates that the extended unemployment benefits help people stay afloat by ensuring people continue getting paychecks.

To prove that our results are robust to different measures of activity restrictions, we replace the social distancing index with the shelter-in-place dummy, the number of new cases, and the number of new deaths. The results are reported in column 3 of Table 3. The coefficients of the insured unemployment rate and the interaction of the unemployment rate and the time dummy are insignificant. Other effects have not changed much.

4.2.2 During the Lockdown

The local and state shelter-in-place mandates have had a catastrophic impact on the economy and resulted in massive job losses, 40% of which are in low-income households[15]. As a result, the demand for consumer lenders may increase, but the restriction on movements prevents consumers from traveling to lenders. The results in Table 2 show the aggregate effects of these events. To isolate these effects, we now interact the shelter-in-place dummy with other independent variables from Table 2 to examine whether the demand for consumer credit to different shocks varies with different periods. We report the results in the first column of Table 4.

In column 1 of Table 4, we control factors that may influence foot traffic changes and include the week and location fixed effects. The results show that the coefficient on the interaction of shelter-in-place order and the unemployment rate is positive and statistically significant. It suggests that consumers are more likely to visit a lender if they get unemployed during the

[15] A survey conducted by the central bank shows that only 64% of those who lost their job or have diminished working hours are able to make ends meet. https://www.federalreserve.gov/publications/files/2019-report-economic-well-being-us-households-202005.pdf

Table 3: Economic Conditions surrounding the Shock and Foot Traffic
This table presents results of comparing effects of economic variables on foot traffic to consumer lenders before and during the pandemic. The dependent variable in columns 1-3 is the natural logarithm of the number of visitors in location i and week t. SDI is the social distancing index, an average ratio of devices residing at home to the total devices tracked at the time. We have two epidemiological variables, the number of new cases and the number of new deaths. Four economic variables are the difference between the insured unemployment rate and the unemployment rate, the unemployment rate, pandemic unemployment assistance continued claims rate (PUA.CC.rate), and pandemic emergency unemployment compensation continued claims rate (PEUC.CC.rate). The epidemiological variables are daily data and at the county level, while the economic variables are weekly data (except the unemployment rate is monthly data) and at the state level. All variables are described in Section 2. The control variables are the natural logarithm of the number of device residing in CBG c and week t, the supply rate of credit in CBG c and week t, and the google trend index in state s and week t. The data are split into two time periods: before the pandemic, which is the period January 2019 to January 21, 2020 (the first documentation of Covid-19 cases); during the pandemic, the period January 21, 2020 to December 2020. In column 1, we use the pre-pandemic data to investigate relationships between economic variables and foot traffic to consumer lenders in normal times. In column 2, we include all data and introduce the Covid-19 related unemployment programs and epidemiological variables to see if the effects in column 1 still hold. In column 3, we substitute the shelter-in-place order, the number of new cases/deaths for the social distancing index to prove that the results are persist after controlling for measures of activity restrictions. In all regressions, we standardize variables and include week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	Dependent variable: ln(#visitors to consumer lenders)		
	Pre-pandemic	***During pandemic***	
	(1)	(2)	(3)
SDI	0.004**	−0.017***	
	(0.002)	(0.001)	
SIP_dum			-0.005**
			(0.002)
$ln(\#case + 1)$			-0.093***
			(0.008)
$ln(\#death + 1)$			-0.026***
			(0.005)
$insured.rate - unemployment.rate$	-0.101***	0.019***	0.007
	(0.015)	(0.005)	(0.005)
$unemployment.rate$	-0.161***	-0.027***	-0.035***
	(0.023)	(0.009)	(0.009)
$ln(\#device\_residing)$	0.047***	0.096***	0.088***
	(0.004)	(0.003)	(0.003)
gg_index	-0.001	-0.001	-0.003*
	(0.002)	(0.001)	(0.001)
$supply\_rate$	0.040***	0.044***	0.044***
	(0.001)	(0.001)	(0.001)
$pandemic$		-0.030***	-0.011*
		(0.006)	(0.007)
$PUA.CC.rate$		0.0002	0.002
		(0.001)	(0.001)
$PEUC.CC.rate$		-0.007**	-0.010***
		(0.003)	(0.003)
$pandemic \times (insured.rate - unemployment.rate)$		−0.022***	−0.014***
		(0.003)	(0.003)
$pandemic \times unemployment.rate$		−0.022***	-0.004
		(0.006)	(0.006)
Week Fixed Effect	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes
Observations	227,488	351,225	351,322
R^2	0.815	0.777	0.778
Adjusted R^2	0.809	0.771	0.771
Residual Std. Error	0.448 (df = 220000)	0.486 (df = 341455)	0.485 (df = 341549)

lockdown. Coupled with the coefficient on the shelter-in-place order, our analysis shows that the shelter-in-place order reduces visits to consumer lenders in general but not so much in areas where the unemployment rate increases more.

Although the interpretation of the negative relationship between the unemployment rate and foot traffic to consumer lenders is difficult, the interaction term suggests that visits to consumer lenders are much more likely in high unemployment areas. That is, while visits to consumer lenders drop during the shelter-in-place order, those who need credit most, such as recently unemployed workers, continued to visit consumer lenders. The result indicates that the shelter-in-place order suppresses access to credit for those whose safety concerns outweigh their need for credit.

The results show that PEUC continued claims rate negatively affects the number of visitors to consumer lenders. That is, people are less likely to visit consumer lenders when a higher proportion of the unemployed in the area are receiving financial aid from the government. Such an effect is not stronger during the lockdown, suggesting that PEUC may not further alleviate the financial burdens of many unemployed in the shelter-in-place order. In other words, the cash received from the PEUC program does not have a much more significant impact on reducing visits to consumer lenders when visiting consumer lenders is challenging because of shelter-in-place restrictions. It suggests PEUC program may not have a greater positive impact when people had to quarantine. In addition, the coefficient on the interaction term of PUA continued claims rate and the shelter-in-place dummy is positive and statistically significant. The results show a cost of stay-at-home orders in the sense that visits to consumer lenders are more sensitive to their cash flows when there is no lockdown than when there is a lockdown.

Our analysis shows that the shelter-in-place order reduces foot traffic to consumer lenders, but this reduction is low for those with more adverse economic shocks. The reduction in foot traffic from those with less negative shocks implies that these consumers may be foregoing accessing financial credit that they would otherwise have availed of. This suggests an adverse impact of the shelter-in-place order on the social welfare of financially underserved consumers.

Table 4: Impacts of the Shelter-in-Place Order and Supplemental Unemployment Compensation on Demand for Consumer Lending

This table summarizes results of two experiments, the shelter-in-place order and the supplemental unemployment compensation (600 dollars/week). The dependent variable in columns 1-2 is the natural logarithm of the number of visitors in location i and week t. The SIP dummy is one if the visits are during the state mandatory stay-at-home order, otherwise is zero. The FPUC dummy is one if the supplemental compensation covers the week t, otherwise is zero. Other independent variables, the number of new cases/deaths, the difference between the insured unemployment rate and the unemployment rate, the unemployment rate, pandemic unemployment assistance continued claims rate (PUA.CC.rate), and pandemic emergency unemployment compensation continued claims rate (PEUC.CC.rate) are described in Section 2. The epidemiological variables and all economic variables are weekly (except that the unemployment rate is monthly) and state-level data. The control variables are the natural logarithm of the number of device residing in CBG c and week t, the supply rate of credit in CBG c and week t, and the google trend index in state s and week t. In all regressions, we standardize variables and control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	Dependent variable: ln(#visitors to consumer lenders)	
	dum=SIP	***dum=FPUC***
	(1)	(2)
SIP_dum	-0.010***	-0.008***
	(0.002)	(0.002)
$ln(\#case+1)$	-0.095***	-0.093***
	(0.008)	(0.008)
$ln(\#death+1)$	-0.025***	-0.028***
	(0.005)	(0.005)
$insured.rate - unemployment.rate$	-0.008***	-0.008**
	(0.002)	(0.003)
$unemployment.rate$	-0.049***	-0.071***
	(0.003)	(0.007)
$PUA.CC.rate$	0.001	0.004
	(0.001)	(0.003)
$PEUC.CC.rate$	-0.009***	0.003
	(0.003)	(0.005)
$dum \times insured\_unemployment.rate$	−0.003***	−0.003*
	(0.001)	(0.002)
$dum \times unemployment.rate$	0.003**	0.014***
	(0.001)	(0.003)
$dum \times PUA.CC.rate$	0.003***	-0.002
	(0.001)	(0.001)
$dum \times PEUC.CC.rate$	0.004	−0.011***
	(0.004)	(0.003)
$ln(\#device\_residing)$	0.088***	0.088***
	(0.003)	(0.003)
gg_index	-0.002	-0.002
	(0.001)	(0.001)
$supply\_rate$	0.044***	0.044***
	(0.001)	(0.001)
Week Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
Observations	351,322	351,322
R^2	0.778	0.778
Adjusted R^2	0.771	0.771
Residual Std. Error	0.485 (df = 341548)	0.485 (df = 341548)

4.2.3 Under the Supplemental Unemployment Program

In addition to state unemployment insurance, the FPUC program delivers an additional weekly payment of 600 dollars to unemployed workers. In most states, recipients of state unemployment insurance and relief programs' compensation were automatically added to the FPUC program. The combination of these two unemployment compensation programs was expected to replace 100% of wages for U.S. average workers. We expect fewer visits or more considerable foot traffic decline to the consumer lenders when unemployed workers receive the supplemental payment. We expect the demand for consumer credit to increase when FPUC expired.

To explore the influence of the government's enhanced financial support on demand for credit, we create a FPUC dummy which is one for period March 29, 2020, to July 31, 2020, otherwise is zero. We interact the FPUC dummy with other variables and report the results in the last column of Table 4.

Similar to results in column 1, column 2 of Table 4 shows that the negative impact of insured unemployment rate on foot traffic to consumer lenders is enhanced under FPUC. On the contrary, the negative relationship between the unemployment rate and foot traffic weakens when FPUC is in effect.

In column 2 of Table 4, the interaction term of PEUC continued claim rate and the FPUC dummy is negative and statistically significant. However, the coefficient on the PEUC continued claims rate itself is insignificant. That means the effect of PEUC is pronounced in decreasing foot traffic to consumer lenders when people can receive the extra 600 dollars cash. In the unreported regression, we replace the shelter-in-place dummy and the number of new cases/death with the social distancing index and find similar results. Adding FPUC to the relief programs further reduces the demand for credit after controlling for activity restrictions. In other words, FPUC enhances social welfare in the sense that the marginal effect of stimulus checks on demand for credit is as significant as expected.

4.3 Financially Underserved Areas versus Metropolitan Areas

Although the pandemic adversely affects people in general, the impact may vary across underserved areas and metropolitan areas.[16] Figure 5 plots average foot traffic to consumer lenders in underserved areas and metropolitan areas. Although foot traffic in the two types of areas shows a similar trend, the average number of visitors in the underserved areas increased relative to the number of visitors in the metropolitan areas in April 2020 and the difference persisted in the following months. We compare the demographics of underserved counties and metropolitan counties in our data [17]and find that the two types of areas are very similar in terms of the car ownership rate, the share of renters, poverty level, internet access, and the health insurance coverage. Our analysis is limited by the sample size of underserved areas in our data. Although 9% of observations are located in underserved counties (83% in metropolitan counties), only 4 counties can be matched to the demographic characteristics by FIPS from the Census Bureau. Nevertheless, we find that the poverty rate is slightly higher, internet access rate is lower, and car ownership rate is higher in underserved areas than in metropolitan areas.

We now examine how the impact of pandemic and relief programs varies across financially underserved areas and metropolitan areas. We create two dummy variables for underserved areas and metropolitan areas, interact the variables in Table 2 with these two dummies, and report regression results in Table 5. In the first column of Table 5, we exploit the differential impacts of an economic shock in underserved areas. The results show that the negative impacts of the insured unemployment rate and the unemployment rate are reduced in underserved areas. It implies that the regular unemployment program may not effectively cushion the economic blow in underserved areas. However, we notice that the coefficient on the interaction term of PUA continued claims rate and the underserved dummy is negative and statistically significant. It means if the state has a high PUA continued claims rate, people in underserved areas are less likely to visit consumer lenders. Combining the results, we speculate that traditional unemployment insurance may have a limited reach in underserved areas, either because people in these areas are less likely to be eligible for these programs or they may be less effective at

[16] In Alison Weingarden's FEDS research, the gap in unemployment rates and employment rates for metropolitan and non-metropolitan areas diverges over time. Mueller et al. use survey data to assess the impact of the Covid-19 pandemic on people living in rural areas and find that people are more likely to experience unemployment in rural areas than other places else. The results are consistent across many demographics.

[17] We use the term underserved for counties that are classified as rural or underserved by CFPB. We use the term metropolitan for counties that are labeled as metropolitan counties by the Census Bureau.

availing of these benefits due to lack of education, awareness, or resources.

In column 2 of Table 5, we repeat our prior analyses but change the underserved dummy to the metropolitan dummy. The results show that the negative relationship between the insured unemployment rate and the number of visitors to consumer lenders is stronger in metropolitan areas. So does the relationship between the unemployment rate and foot traffic. A metropolitan area with a higher insured unemployment rate and the unemployment rate will witness less foot traffic to consumer lenders. It implies that people living in metropolitan areas are better off from traditional unemployment insurance. We do not detect differential effects of PUA and PEUC programs on foot traffic to consumer lenders in metropolitan areas and other regions. However, the number of visitors is further reduced in metropolitan areas when people have greater access to the internet.

Overall, the evidence in this section indicates that the impact of economic shock has differential effects in underserved areas and metropolitan areas. Regular unemployment insurance does not reduce the demand for credit in underserved areas as much as in metropolitan areas. However, the demand for credit in underserved areas is sensitive to newly funded relief programs.

4.4 Other Factors that Affect Demand for Credit

4.4.1 Consumption level

Consumers seeking credit from consumer lenders due to financial hardship may also take other actions in response to the hardship. We use Facteus data to examine spending at the ZIP Code level. Figure 6 reveals a substantial jump in aggregate spending by credit cards during the pandemic. The first peak appeared at the end of February 2020, followed by the highest point in two years with a magnitude twice as big. The number of transactions tends to have a similar pattern with the aggregate spending at the CBG level, while it started increasing from April and reached the all-time high at the end of the month. The timing of the increase coincides with the relief programs' schedule. By enrolling in enhanced and expanded unemployment benefits programs, some unemployed people even have more disposable income to spend than they did

Table 5: Consumer Lending in Underserved Areas versus in Metropolitan Areas

This table shows the differential effect of economic shock on underserved areas and metropolitan aeras. 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 underserved areas dummy is one if the location i is in the list of rural and underserved areas released by the CFPB in 2020, otherwise is zero. The metropolitan areas 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 variables, the shelter-in-place order, the number of new cases/deaths, the difference between the insured unemployment rate and the unemployment rate, the unemployment rate, pandemic unemployment assistance continued claims rate (PUA.CC.rate) , and pandemic emergency unemployment compensation continued claims rate (PEUC.CC.rate) are described in Section 2. The control variables are the natural logarithm of the number of device residing in CBG c and week t, the supply rate of credit in CBG c and week t, and the internet access county j. All variables are standardized and converted to weekly frequency that matches the visitor pattern 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.

	Dependent variable: ln(#visitors to consumer lenders)	
	area= underserved areas	***area= metropolitan areas***
	(1)	(2)
SIP_dum	-0.005**	-0.006***
	(0.002)	(0.002)
$ln(\#case + 1)$	-0.095***	-0.095***
	(0.010)	(0.010)
$ln(\#death + 1)$	-0.013**	-0.010
	(0.006)	(0.006)
$ln(\#device\_residing)$	0.082***	0.082***
	(0.003)	(0.003)
$supply\_rate$	0.046***	0.046***
	(0.001)	(0.001)
$insured.rate - unemployment.rate$	-0.016***	-0.016***
	(0.002)	(0.002)
$unemployment.rate$	-0.039^{***}	-0.041^{***}
	(0.004)	(0.003)
$PUA.CC.rate$	-0.002	0.001
	(0.002)	(0.002)
$PEUC.CC.rate$	-0.015^{***}	-0.015^{***}
	(0.002)	(0.002)
$area \times SIP\_dum$	0.005	-0.002
	(0.004)	(0.002)
$area \times (insured.rate - unemployment.rate)$	0.007**	-0.005^{**}
	(0.003)	(0.002)
$area \times unemployment.rate$	0.013**	-0.008^{***}
	(0.005)	(0.003)
$area \times PUA.CC.rate$	-0.015^{**}	0.002
	(0.006)	(0.003)
$area \times PEUC.CC.rate$	-0.005	0.004
	(0.004)	(0.003)
$SIP\_dum \times internet\_access$	-0.005^{***}	-0.005^{***}
	(0.001)	(0.001)
$area \times SIP\_dum \times internet\_access$	0.005***	-0.004^{***}
	(0.001)	(0.001)
Week Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
Observations	319,955	319,955
R^2	0.757	0.757
Adjusted R^2	0.751	0.751
Residual Std. Error	0.505 (df = 311594)	0.505 (df = 311594)

before being laid off or furloughed.[18]

The average amount spent on each transaction rocketed to 51.55 dollars in the week starting from February 24, up from 33.02 dollars in the preceding week and maintained a level higher than that before the pandemic. These patterns may reflect "panic shopping," as more people stock up essentials more than they needed for the unforeseeable future and thus spend more for each order. The average spending per transaction exhibited fluctuates after April but eventually reached a low of 35.79 dollars in August, a 44% drop from the highest level during the pandemic. The significant drop in August coincides with the expiration date of the program that paid 600 dollars per week to several households. It suggests that the federally funded programs were an essential driving force of the consumption level.

The turning points of aggregate consumption coincide with foot traffic changes to consumer lenders, either aggregate at a state level (Figure 2) or at the underserved/metropolitan county level (Figure 5). To examine the effect of consumption level in a community on the demand for credit in the same community, we relate the total debit card spending and average spending per order to foot traffic to consumer lenders and report the results in the first two columns of Table 6. In column 1, the coefficient on total spending is positive and statistically significant. Since our regressions have location fixed effects, the coefficient suggests that the number of visits to consumer lenders increases when consumption in the ZIP code increases. The coefficient of spending per order is negative and statistically significant, indicating that people are less likely to visit consumer lenders when the average expenditure on each order is higher. The first result is consistent with the results in Chetty et al. (2020), who argue that low-income households encounter greater financial difficulties in wealthy ZIP Codes because a massive wave of layoffs comes from high-income households' reduced spending on small business. A high average spending per transaction may imply more extra cash at hand, thus less need to go to consumer lenders[19].

Our interpretation of the link between large total spending in the county with high foot

[18]The Congressional Budget Office approximates the supplemental payments enable financially distressed individuals and households to pay for rent, food, and even other supplies or entertainment. On the other hand, those expenditures help reduce the unemployment rate supporting 2.8 million jobs. https://www.cbo.gov/system/files/2020-06/56387-CBO-Grassley-Letter.pdf

[19]According to Harvard researchers, low-income families contribute a significant amount to the current economy, because they are more likely to immediately spend the money they received on essentials, while high-income households reduce spending sharply. Furthermore, people with low-income remain the same spending power as the pre-pandemic level. https://www.tracktherecovery.org/

traffic is that such customers of consumer lenders, who are usually low-income and with low credit scores, are sensitive to the economic shock and vulnerable to the recession. Therefore, we interact the shelter-in-place dummy with variables in column 1 to explore whether the mandatory business shutdown affects foot traffic to consumer lenders. The result is reported in column 2 of Table 6. The results show that the associations discussed above are enhanced during shelter-in-place orders. This is consistent with the idea that high-income households curtail their spending considerably on local and small businesses during shelter-in-place orders, leading to loss of income for low-income people. Our analysis clarifies that the economic shock detrimentally impacts underserved consumers living in affluent areas to a greater extent than low-income peers in other areas.

4.4.2 Foot Traffic to Other Brands

Our foot traffic measure has two drawbacks: it is impacted by a general change in people's willingness to travel and by the number of devices tracked by SafeGraph. However, both of these factors will impact travel to all businesses, not just consumer lenders. We, therefore, control for these factors by including visits to other brands as control variables. For each state, we identify the three brands that are most often visited by visitors to consumer lenders in year 2019 within the same week. There is a large overlap in these brands across states. For example, Walmart is one of the 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 three most visited brands for each state as control variables and report the results in the last two columns of Table 6. Due to the space consideration, we report three brands with the highest number of visits from visitors to consumer lenders in 2019: Walmart, Dollar General, and McDonald's. The results show that an increase in the number of visits to Walmart, Dollar General, and McDonald's is positively associated with a rise in visits to consumer lenders within the same week. Unreported results show that visits to all brands are positively related to the foot traffic to consume lenders.

To examine whether the impact of shelter-in-place had a differential impact on visits to consumer lenders and to other brands, we include the stay-at-home dummy and its interactions

Table 6: Consumption Level and Visits to Other Brands

This table shows the associations of the the number of visitors to consumer lenders with the spending power in location i as well as the other brands visits observed during the same week t. The dependent variable in columns 1-4 is the natural logarithm of the number of visitors to consumer lenders in location i and week t. The total spending is the aggregate dollar amount spent in Zip-Code z. The spending per order is the average dollar amount for each transaction. The shelter-in-place dummy is one if the week t is during the state mandatory stay-at-home order, otherwise is zero. 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 the same week as they visit those brands. 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 coefficients for interactions terms of other brands and SIP_dum are a mix of positive and negative numbers. The numbers of visitors to other brands are in natural logarithm. In all regressions, we standardize variables and control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	Dependent variable: ln(#visitors to consumer lenders)			
	(1)	(2)	(3)	(4)
$ln(\$tot\_spending)$	0.164***	0.155***		
	(0.008)	(0.008)		
$ln(\$spending/order)$	-0.031***	-0.029***		
	(0.002)	(0.002)		
SIP_dum		-0.009***		-0.011***
		(0.002)		(0.001)
$ln(\#device\_residing)$	0.110***	0.107***		
	(0.003)	(0.003)		
$SIP\_dum \times ln(\$tot\_spending)$		0.005***		
		(0.001)		
$SIP\_dum \times ln(\$spending/order)$		-0.012***		
		(0.001)		
$Walmart$			0.183***	0.183***
			(0.001)	(0.001)
$Dollar.General$			0.064***	0.064***
			(0.001)	(0.001)
$McDonald.s$			0.093***	0.093***
			(0.001)	(0.001)
$SIP\_dum \times Walmart$				-0.001
				(0.001)
$SIP\_dum \times Dollar.General$				0.003***
				(0.001)
$SIP\_dum \times McDonald.s$				-0.00003
				(0.001)
Week Fixed Effect	Yes	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes	Yes
Observations	349,200	349,200	520,119	520,119
R^2	0.776	0.776	0.808	0.808
Adjusted R^2	0.769	0.770	0.803	0.803
Residual Std. Error	0.487 (df = 339462)	0.487 (df = 339459)	0.443 (df = 506801)	0.443 (df = 506756)

with visits to other brands as control variables. The regression results in column 4 of Table 6 show that the shelter-in-place led to a greater reduction in visits to consumer lenders than that predicted by the reduction in visits to other stores. This may reflect the fact that during a shelter-in-place order, people are less likely to reduce travel to groceries and food stores than visits to consumer lenders. There are two possible explanations. One is that substitutes that do not require travel are less costly for consumer lenders than for stores like Walmart, Dollar General, and McDonald's. The other is that consumers experience a greater disutility from not visiting brands such as Walmart than from not visiting consumer lenders. We also find a statistically significant positive coefficient on the interaction of shelter-in-place dummy and visits to Dollar General. One interpretation is that visits to Dollar General are a stronger indicator of economic hardship during a shelter-in-place order and consequently better predict visits to consumer lenders.

4.4.3 Distance to Consumer Lenders

A shelter-in-place order is more likely to discourage visits from borrowers who have to travel a longer distance to get to a consumer lender. This may impact the composition of borrowers who visit consumer lenders during shelter-in-place restrictions. However, this effect may depend on factors that impact ease of travel, such as car ownership.

We define a visitor to a consumer lender to be local if she is from the same Census Block Group as the consumer lender. We perform a regression with the dependent variable on the proportion of local visits calculated as the log of the number of local visitors minus the log of the number of distant visitors. We include car ownership, internet access rate, health insurance coverage, percentage of renters, and poverty level to control for factors that may affect people's decision of choosing consumer lenders. We include the median distance to home (at location level) and the proportion of local visitors to banks in the ZIP Code as additional control variables. The results reported in column 1 of Table 7 show that the proportion of local visitors to consumer lenders increases during shelter-in-place restriction. This evidence suggests that the decline in visits to consumer lenders is not driven solely by supply effects as that would not explain a change in the composition of visitors.

We find that a greater median distance from visitors' home to the consumer lender is

Table 7: Impact of Economic Shock on Local versus Distant Visits to Consumer Lenders

The table shows the impact of an economic shock on visitors' preferences for consumer lenders. The dependent variables 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. The visitors is counted as a local visitor if she visits the consumer lender in the same CBG c as her home's, 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 of 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 to population are described in Section 2. In all regression, we standardize variables and control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	Dependent variable: ln(#local_visitors_CL)-ln(#nearby_visitors_CL)	
	(1)	(2)
SDI	0.016***	0.018***
	(0.004)	(0.005)
$ln(median\_distance)$	-0.296***	-0.307***
	(0.004)	(0.004)
$ln(\#local\_visitors\_bank) - ln(nearby\_visitors\_bank)$	0.004	0.005
	(0.004)	(0.005)
$ln(\$tot\_spending)$	-0.068***	-0.078***
	(0.020)	(0.024)
SIP_dum	0.013**	0.009
	(0.006)	(0.007)
$SIP\_dum \times ln(median\_distance)$	0.007***	0.011***
	(0.002)	(0.003)
$SIP\_dum \times \%workbycar$		-0.008***
		(0.003)
$SIP\_dum \times \%poverty$		-0.014**
		(0.007)
$SIP\_dum \times \%internet\_access$		-0.010
		(0.007)
$SIP\_dum \times \%health\_insurance$		-0.003
		(0.004)
$SIP\_dum \times \%renters$		0.005
		(0.004)
Week Fixed Effect	Yes	Yes
Location Fixed Effect	Yes	Yes
Observations	113,654	80,052
R^2	0.413	0.432
Adjusted R^2	0.389	0.410
Residual Std. Error	0.866 (df = 109340)	0.864 (df = 76963)

associated with a smaller proportion of local visitors to consumer lenders. This coefficient may represent a mechanical correlation from a change in composition of visitors. However, another possibility is that in locations where consumers travel farther, such as suburban areas, visitors are more likely to travel from other Census Block Groups than is areas where consumer lenders are located close to consumers. However, the positive and statistically significant coefficient on the interaction of the distance to home and the shelter-in-place order suggests even in suburban areas, share of local visitors to consumer lenders increases.

The statistically insignificant coefficient on the fraction of local visitors to banks shows that the shift towards local borrowers during shelter-in-place order is more pronounced in consumer lenders than in banks. This can partly be attributed to the different customer bases of those two kinds of credit intermediaries. In columns 1 and 2 of Table 7, we find that the total spending at ZIP-Code level negatively impacts the share of local visitors to consumer lenders. That means the difference between the local visitors and nearby visitors narrows when the local spending power is strong.

Lastly, we test the roles demographic characteristics play in the demand for credit. The results in column 2 of Table 7 show that higher car ownership rate and poverty rate are associated with a drop in the share of local visitors. The former association suggests that people with cars may have higher freedom of choosing consumer lenders without distance restrictions. The latter association suggests that the shift to local visitors during a shelter-in-place order is not present or weaker in areas with greater poverty. This could reflect the inability of distant borrowers to resort to alternatives because of a lack of alternatives to consumer lenders in areas with greater poverty.

4.4.4 Visits to Consumer Lenders versus Visits to Banks

We now compare the effect of economic shock and relief programs on consumers' demand for bank's products with consumer lenders' products. Banks tightened lending standards during the pandemic.[20] Banks and financial-technology firms revised lending criteria in response to

[20]Major shares of senior loan officers reported that their current levels of lending standards are tightened for all categories of consumer loans. Many banks tightened important terms on credit card loans, including credit limits and minimum credit scores requirements. https://www.federalreserve.gov/data/sloos/sloos-202007.htm

soaring default rates.[21] This may have resulted in some consumers switching from banks to consumer lenders to meet their financing needs.

To compare the changes in foot traffic to consumer lenders with the changes in foot traffic to banks, We now choose the dependent variable as the log of the number of visitors to consumer lenders minus the log of the number of visitors to banks in the same ZIP Code. The independent variables are the same in Table 2, along with the total spending at the ZIP Code level. The results are reported in Table 8.

The coefficients of the two measures of unemployment in column 1 show that higher unemployment or higher insured unemployment lead to an increase in foot traffic to consumer lenders relative to the foot traffic to banks. That is, a higher coverage of the unemployed through the unemployment insurance reduces visitors to banks more than it does to visitors to consumer lenders. The results imply that although financially underserved customers benefit from the government financial aids, but the influence of the assistance on reducing the demand for credit from consumer lenders is not as significant as that on demand for credit from banks.

The coefficient on the PUA continued claims rate is positive and statistically significant. This finding is contrary to our expectations. We assume that the recipients of PUA programs, which are gig workers, self-employed, and independent workers, are more likely to get a loan from consumer lenders than banks because of volatile incomes and low credit scores. Therefore, a higher PUA continued claims rate should decrease foot traffic to consumer lenders more than banks. A possible explanation is that the PUA statistic is aggregated at the state level, so it may not be able to explain switch behavior at the ZIP Code level.

We include the social distancing index in columns 1 of Table 8 to control for the variation in activity restrictions across counties. We find that social distancing requirements do not reduce the visits to consumer lenders as much as they reduce the visits to banks. Since the restrictions are same for consumers of banks and consumer lenders, this finding suggests that borrowers from consumer lenders are more likely to have needs that overweight their concerns arising from social distancing restrictions.

In column 2 of Table 8, we add total spending per card at the county level as a measure

[21] For example, JPMorgan Chase reported the net income down 69% in the first quarter. The provision for credit losses was $8.3 billion, up $6.8 billion from the previous year driven by reserve builds, which reflect deterioration in the micro-economic environment. https://www.jpmorganchase.com/content/dam/jpmc/jpmorgan-chase-and-co/investor-relations/documents/quarterly-earnings/2020/1st-quarter/1q20-earnings-press-release.pdf

of local economic condition. The results show that PEUC continued claims rate and total spending are negatively related to the difference between foot traffic to consumer lenders and banks. That is, the gap between foot traffic to consumer lenders and banks narrows when the PEUC covers a larger proportion of unemployed workers or when the spending power is higher in the community.

Finally, we replace the social distancing index with the shelter-in-place dummy and the number of new cases/deaths to do a robustness check, as shown in column 3 of Table 8. The coefficients have not changed much (except the unemployment rate becomes insignificant), indicating that economic effects of economic variables are consistent with different measures of activity restrictions.

Table 8: Comparison of Visits to Consumer Lenders versus Banks

This table shows the differential effect of economic shock on visitors to consumer lenders and those to banks. The dependent variable in columns 1-3 is the difference of the natural logarithm of the number of visitors to consumer lenders and the natural logarithm of the number of visitors to banks in the same CBG c. Independent variables, the social distancing index, the shelter-in-place dummy, the number of new cases/deaths, the insured unemployment rate, the unemployment rate, pandemic unemployment assistance continued claims rate (PUA.CC.rate), pandemic emergency unemployment compensation continued claims rate (PEUC.CC.rate), total spending in county j are described in Section 2. In all regression, we standardize variables and control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates the statistical significance at the 1% level.

	Dependent variable: ln(#visitors_CL)-ln(#visitors_bank)		
	(1)	(2)	(3)
SDI	0.011***	0.009***	
	(0.001)	(0.001)	
SIP_dum			0.003***
			(0.001)
$ln(\#case)$			0.062***
			(0.005)
$ln(\#death)$			0.015***
			(0.003)
$(insured.rate - unemployment.rate)$	0.006***	0.005***	0.002***
	(0.001)	(0.001)	(0.001)
$unemployment.rate$	0.025***	0.014***	-0.002
	(0.002)	(0.002)	(0.002)
$PUA.CC.rate$	0.005***	0.004***	0.002***
	(0.001)	(0.001)	(0.001)
$PEUC.CC.rate$	-0.002	-0.018^{***}	-0.014^{***}
	(0.001)	(0.003)	(0.002)
$ln(\$tot\_spending)$		-0.022^{***}	-0.019^{***}
		(0.005)	(0.004)
Week Fixed Effect	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes
Observations	383,180	336,747	434,963
R^2	0.856	0.873	0.874
Adjusted R^2	0.852	0.870	0.870
Residual Std. Error	0.385 (df = 373126)	0.361 (df = 327292)	0.361 (df = 422877)

5 Conclusion

We match unique foot traffic data that provides granular information on visitor patterns to macroeconomic and epidemiological data to examine how an economic shock and the government response impact underserved customers' demand for credit. After controlling for proxies for alternative online borrowing, supply of credit, and the change in sample size (number of devices) over time, we find that the statewide shelter-in-place order, surging new cases and death, and the Covid-19 related unemployment relief program (PEUC) are all associated with a significant drop in foot traffic to consumer lenders. The results are robust to different measures of activity restrictions.

A drop in foot traffic by itself cannot be used to determine the impact of these shocks on consumer welfare. However, additional tests show that the decline in foot traffic was greater for those more impacted by the shelter-in-place restrictions and the effect was weaker for foot traffic to banks. If a consumer's decision to visit a lender reflects a trade-off between the marginal benefit of accessing financing and the marginal cost of travel due to the pandemic and the restrictions, our results suggest that borrowers of consumer lenders are financially constrained and assign a greater marginal benefit to financing than bank consumers.

We employ two natural experiments, the imposition of shelter-in-place orders across states and the FPUC program. Our results show that visits to consumer lenders increase with an increase in unemployment rate and an increase in PUA continued claims rate during the shelter-in-place order. These findings show that the demand for consumer lenders is highly sensitive to economic shocks and the relief programs.

Under FPUC, a higher unemployment rate and PEUC continued claims rate are related to decreased foot traffic to consumer lenders. Extending the relief programs by adding 600 dollars per week further reduces the demand for credit from consumer lenders in adversely impacted areas.

We also examine the differential effects of government order and responses in underserved areas and metropolitan areas and find the following results. First, the high insured unemployment rate and unemployment rate reduce more foot traffic in metropolitan areas than in underserved areas. Second, the effect of relief programs is larger during the lockdown in underserved areas than in metropolitan areas. Lastly, having greater internet access during the lockdown is important in decreasing the foot traffic to consumer lenders in metropolitan areas, but not in underserved areas. Our results also suggest that low-income households in affluent areas need more credit than low-income peers in other areas.

Our work sheds light on changes in consumers' behavior in response to an economic shock. Underserved consumers prefer to visit consumer lenders that require shorter travel during the shelter-in-place order. This behavior is more pronounced in borrowers from consumer lenders than in bank customers. Lacking resources, such as cars, is likely to leave consumers with fewer credit choices.

From a policy perspective, our results confirm that state unemployment programs and federally funded relief programs are effective in alleviating financial constraints facing consumers that lack access to traditional lenders. Identifying dynamics of differential impacts of an economic shock on demand for credit in different areas reveals implications on the design of government policies related to financial inclusion, local financial market development, and relief programs in the crisis.

Appendix

Table 9: Robustness Check: A Different Measure of Activity Restrictions

We use a different measure of activity restrictions by replacing the number of new cases/deaths and the shelter-in-place dummy by the social distancing index to estimate the baseline model:

$$Y_{i,t} = \alpha + \beta X_{j/s,t} + Controls_{c/y,t} + \delta_t + \eta_i.$$

where $Y_{i,t}$ represents the natural logarithm of the number of visitors to consumer lender in location i and week t. $X_{j/s,t}$ are several independent variables either at the county-level j, the social distancing index and the number of new cases/deaths in week t, or at the state-level s, the difference between the state insured unemployment rate and the unemployment rate, unemployment rate, pandemic unemployment assistance continued claims rate (PUA.CC.rate), and pandemic emergency unemployment compensation continued claims rate (PEUC.CC.rate). The control variables are the number of device residing in census block group (CBG) c and week t, the google trend index for state s and week t, and the internet access in county j and week t. In all regressions, we standardize variables and control for week and location fixed effects. Standard errors are reported in parentheses. *** indicates statistical significance at the 1% level.

	Dependent variable: ln(#visitors to consumer lenders)				
	(1)	(2)	(3)	(4)	(5)
SDI	-0.020***	-0.017***	-0.016***	-0.012***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$insured.rate - unemployment.rate$		-0.014***	-0.015***	-0.015***	-0.015***
		(0.001)	(0.001)	(0.001)	(0.001)
$unemployment.rate$		-0.059***	-0.058***	-0.060***	-0.059***
		(0.003)	(0.003)	(0.003)	(0.003)
$PUA.CC.rate$			-0.0003	0.002	0.002
			(0.001)	(0.001)	(0.001)
$PEUC.CC.rate$			-0.012***	-0.016***	-0.016***
			(0.001)	(0.004)	(0.004)
$ln(\#device\_residing)$	0.103***	0.095***	0.094***	0.091***	0.090***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SIP_dum				-0.009***	-0.009***
				(0.002)	(0.002)
gg_index				0.0003	0.0004
				(0.002)	(0.002)
$supply\_rate$					0.044***
					(0.001)
$SIP\_dum \times internet\_access$				-0.006^{***}	-0.007^{***}
				(0.001)	(0.001)
Week Fixed Effect	Yes	Yes	Yes	Yes	Yes
Location Fixed Effect	Yes	Yes	Yes	Yes	Yes
Observations	401,554	398,821	398,821	282,163	282,163
R^2	0.754	0.755	0.755	0.778	0.780
Adjusted R^2	0.747	0.748	0.748	0.772	0.774
Residual Std. Error	0.507 (df = 391185)	0.505 (df = 388467)	0.505 (df = 388465)	0.487 (df = 274300)	0.485 (df = 274299)

Figures

Figure 1: The Timing of Shelter-in-Place Orders across States
Figure 1 shows schedules of mandatory state-wide shelter-in-place (SIP) order across 50 states in U.S.. The purple and red circles represent the start and end date of SIP orders, respectively.

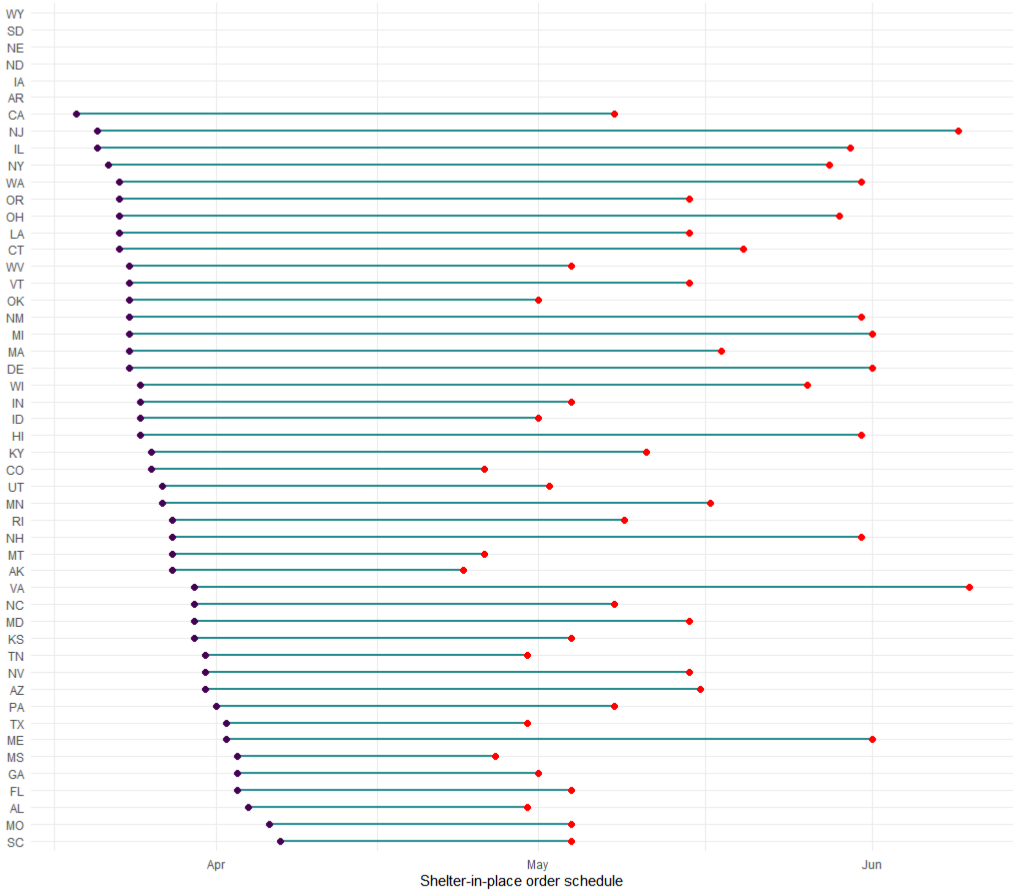


Figure 2: Aggregate Visits to Consumer Lenders in Different States

Figure 2 depicts aggregate foot traffic to consumer lenders for 50 states between January 2019 and December 2020. The number of visitors is winsorized at 1% and 99% within states. Two red dashed lines represent the day of the first Covid-19 case and the start date of the stay-at-home orders, respectively. There are no observations in Vermont in Figure 2, because of the winsorization of the limited values in that state

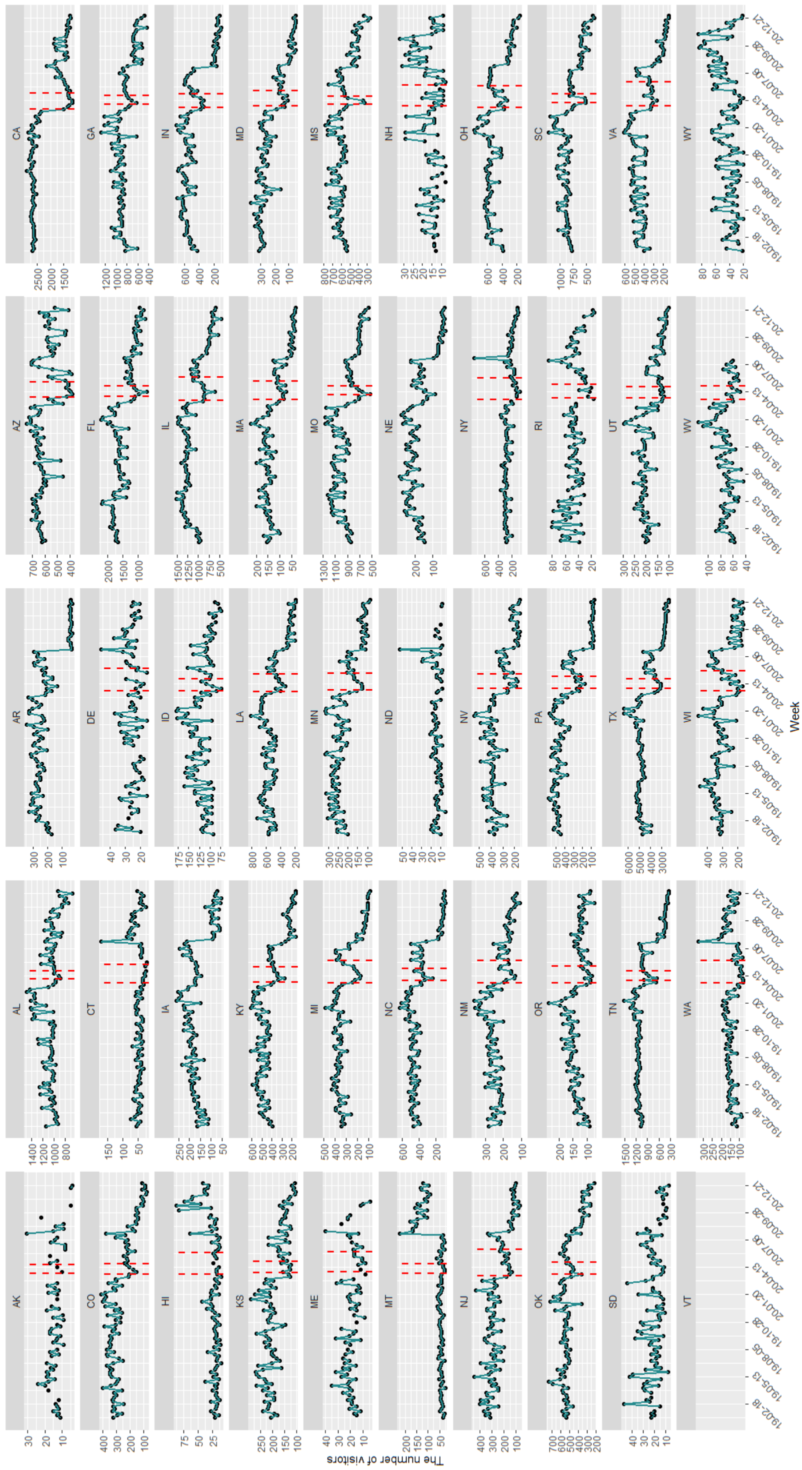


Figure 3: The Unemployment Rate and the Insured Unemployment Rate in the U.S.
Figure 3 shows the unemployment rate and the insured unemployment rate in the U.S. from January 2019 and December 2020. The purple circle is the value for a state during a week. The blue line is the average rate in 50 states over time with the 25th and 75th percentile corresponding to the blue color band for the 50% interval. Two red dashed lines represent the date of the first Covid-19 case and the earliest lockdown among states.

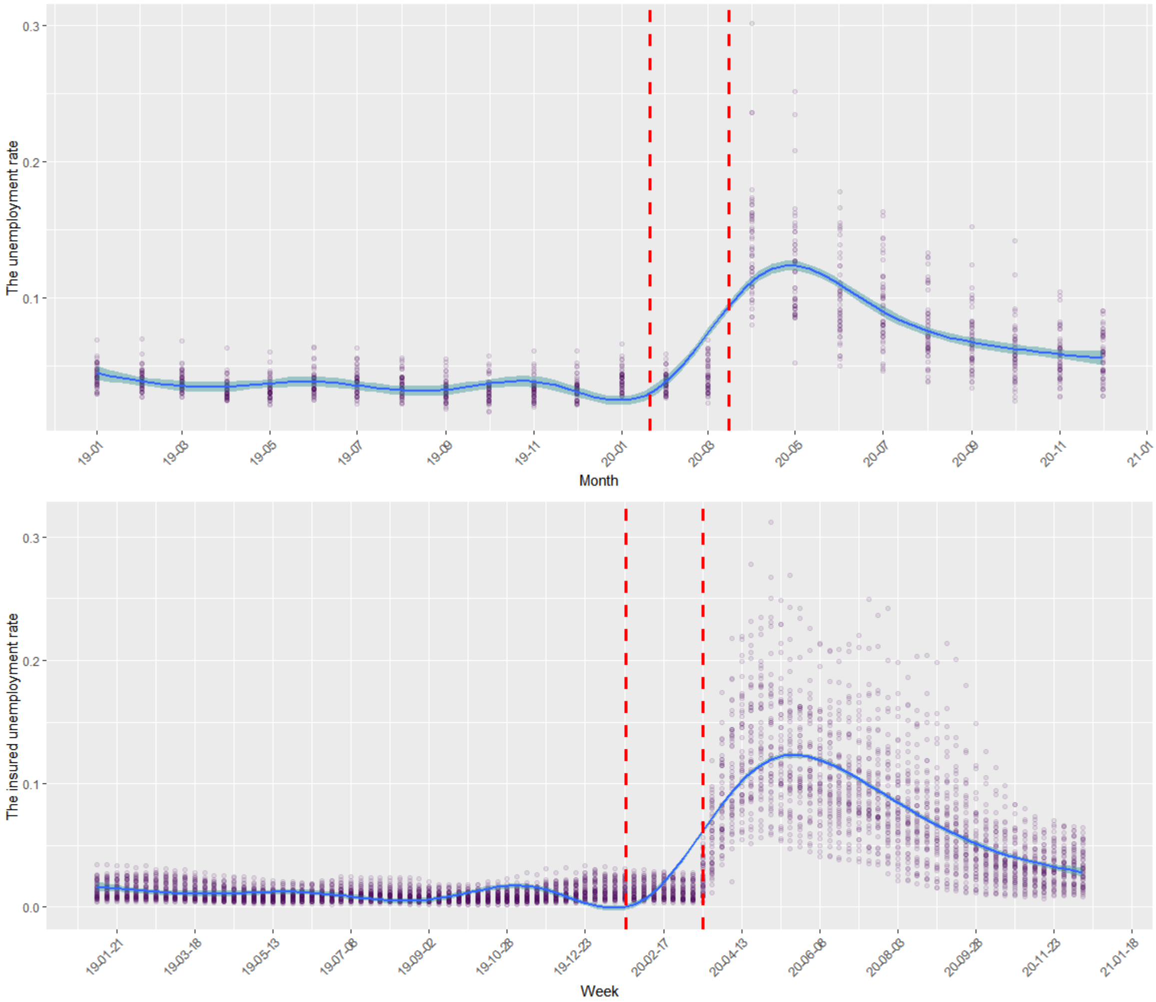


Figure 4: Aggregate Number of Continued Claims for Relief Programs

Figure 4 shows the aggregate continued claims for two relief programs by week. The documentation starts from the week ended on March 26, 2020 to the week ended on January 2, 2021.

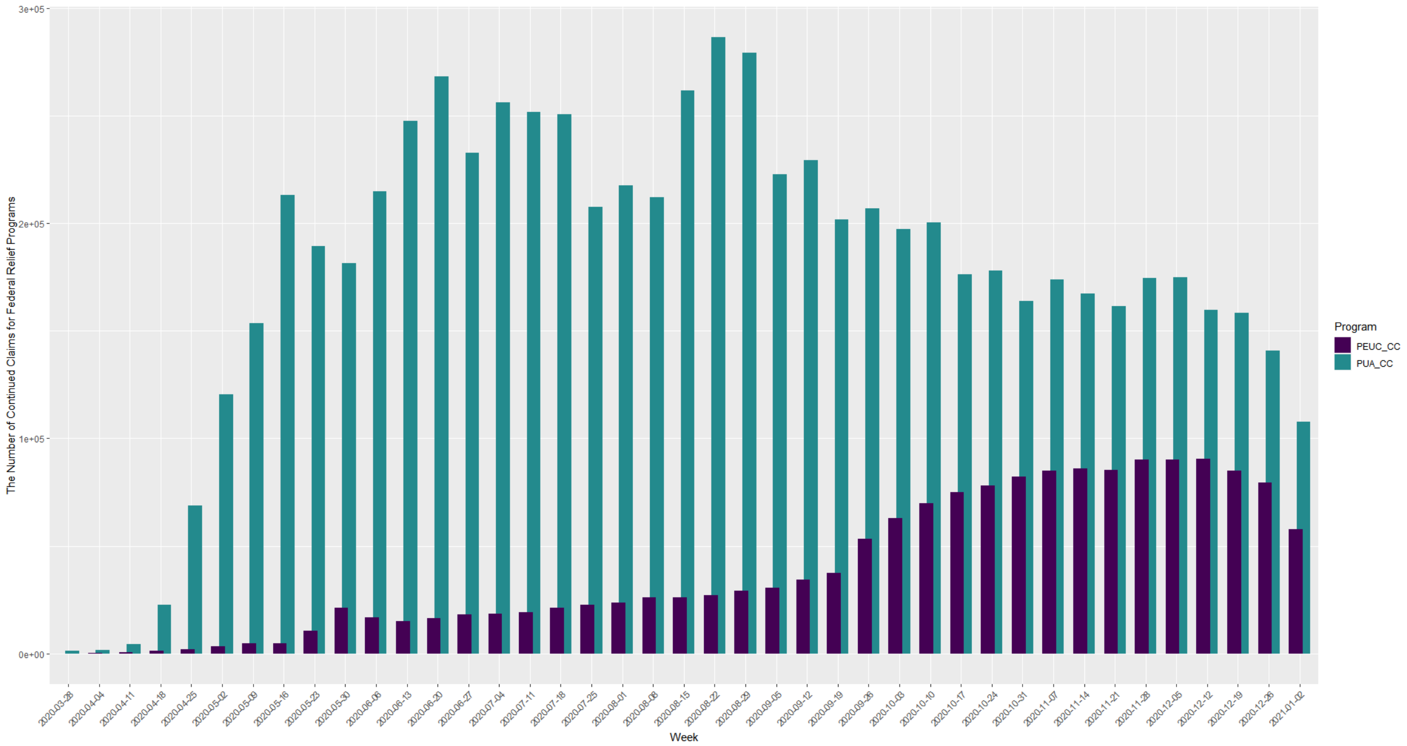


Figure 5: Foot Traffic to Consumer Lenders in Underserved Areas and in Metropolitan Areas

Figure 5 plots average foot traffic to consumer lenders in underserved areas and metropolitan areas on a weekly basis.

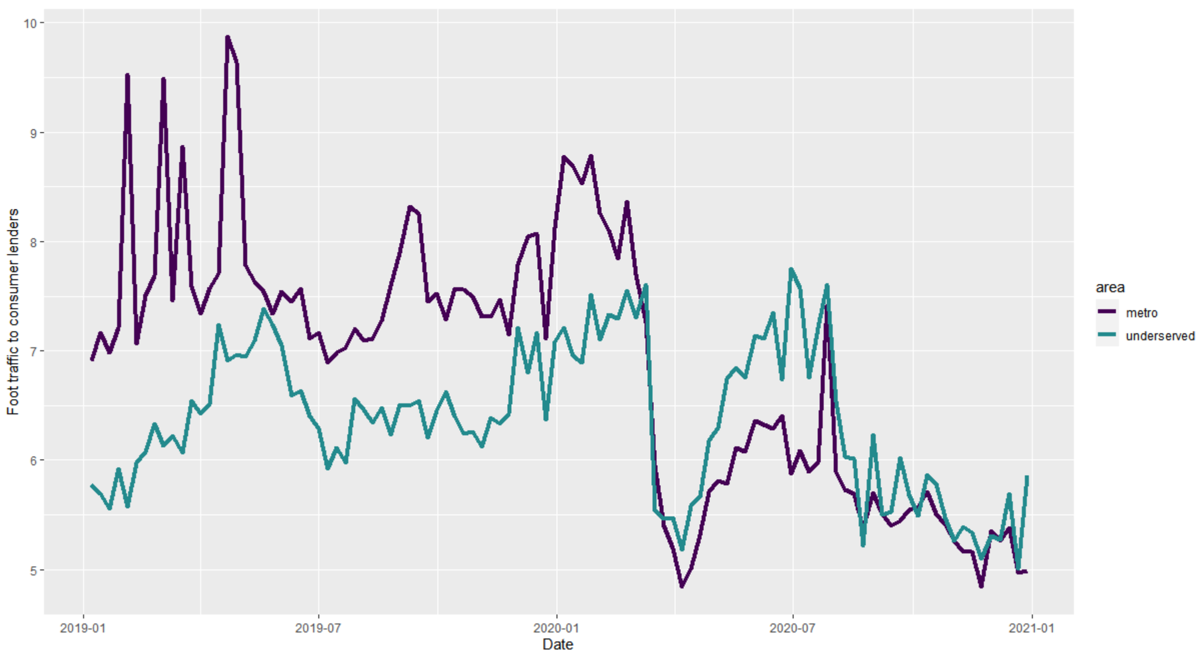
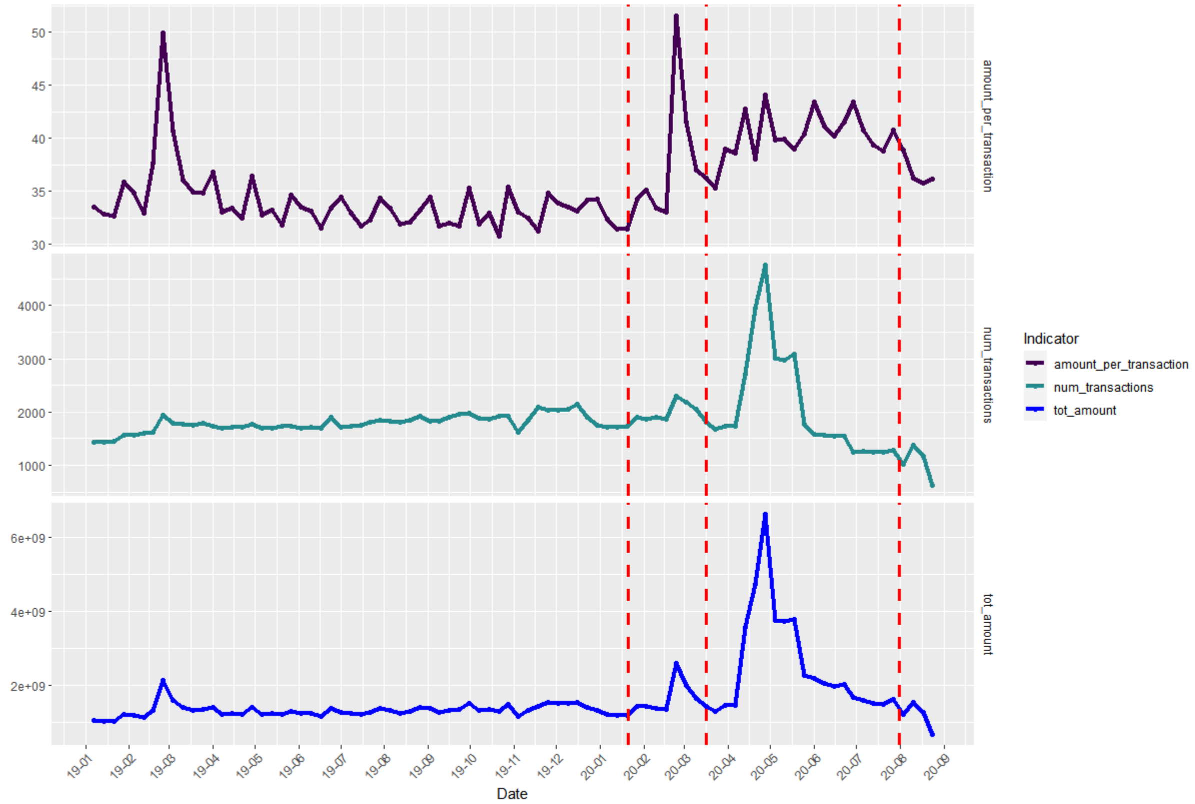


Figure 6: Consumption Level from Facteus Data

Figure 6 depicts the ZIP Code level spending per transaction, total number of transactions, and total spending on a weekly basis. Three red lines mark the onset of the pandemic, the beginning of the shelter-in-place order, and the end of the order, respectively.



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