The Effects of Price Caps on Open-End Loans: Evidence from the 2015 Expansion of the Military Lending Act

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ABSTRACT

States and the federal government have imposed caps on the annual percentage rates (APRs) of some credit products to protect consumers from high-cost lending. While most policy initiatives have been restricted to closed-end credit products—such as payday loans—there is increasing interest in expanding such caps to open-end products—such as credit cards. Even though APR capping might reduce the cost of credit for some borrowers, there may be unintended consequences for consumers whose credit histories disqualify them from cheaper loan products. We evaluate the effect of a 36% APR cap on open-end credit products for members of the military community, which was a primary component of the 2015 expansion of the Military Lending Act (MLA). We do not find evidence that subprime residents of military communities improved their credit health outcomes after the MLA expansion. Using secondary data analysis, we show that a 36% cap on open-end credit products does affect most subprime borrowers. We conclude that the currently proposed APR caps of 36% on open-end loans are an ineffective way to improve subprime consumers' financial well-being.

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I. Introduction

To protect consumers from high-cost lending, many government entities have imposed restrictions on interest rates and loan fees for credit products. Most initiatives focus on imposing annual percentage rate (APR) caps on closed-end loans, such as payday loans and motor vehicle title loans. For closed-end loans, the amount borrowed and the repayment period are set at the outset. As of 2021, 45 states and DC cap rates for $500, six-month installment loans (NCLC 2022).

While most policy initiatives have been restricted to closed-end credit products, there is increasing political interest in extending APR caps to open-end loan products, such as credit cards.[1] For open-end credit, the amount borrowed is not set in advance, and the repayment period depends on the timing of the borrower's use of the line of credit. Open-end products are considerably more popular than closed-end products: about 84% of US adults reported having a credit card in 2021, while only 2% reported taking out a payday loan in the past 12 months (Federal Reserve 2022).

To evaluate the effect of extending APR caps to open-end products, we investigate the impacts of 2015 expansion of Military Lending Act (MLA) on the financial health of military community residents. In 2006, Congress passed the MLA, which aims to protect active-duty military members and their families from high-cost credit products. One of the most salient components of the MLA was to limit the APR to 36% on payday loans and other closed-end products. In 2015, the Department of Defense significantly expanded the MLA's coverage to include most open-end credit products (DoD 2015).[2] Both active-duty military members and their families are protected under MLA and its expansion.

Using unique credit bureau panel data from 2013 to 2021, this research examines the effects of the 2015 MLA expansion on the credit health of military service members and their families. Although we cannot directly identify whether a consumer in the credit data is an active-duty military member, we can use zip codes of residence to identify consumers who are most likely to be servicemen and women or members of a military family.

[1] Veterans and Consumers Fair Credit Act, S. 2508, 117th Cong., 1st Sess. (2021–22), https://www.congress.gov/bill/117th-congress/senate-bill/2508/text.

[2] Additional credit products subject to the 36% APR cap after the 2015 MLA expansion include credit cards and overdraft lines of credit but exclude home equity loans.

First, in the 2015 data we identify subprime consumers living in military communities.[3] We define military communities as zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces.[4] We focus on subprime consumers because this population is more likely to be affected by the APR cap. Second, we find a suitable comparison group of subprime residents in non-military communities in 2015 with similar ages and credit health histories as those in the treatment group. Third, using an event-study approach, we compare credit health outcomes between our treatment and comparison groups for each year before and after the policy expansion. We evaluate the impact of the MLA expansion on open-end credit access, delinquency rates, and credit scores.

We find no significant effect of the 2015 MLA expansion on access to open-end credit for subprime residents of military communities. In other words, the 36% APR cap on open-end credit products did not prevent most subprime military consumers from owning a credit card and had no effect on their credit card limit. We also found no evidence that the MLA expansion decreased the delinquency rate on revolving loan products, which includes most open-end credit products. Finally, we do not find evidence that the MLA expansion had an impact on credit scores—a financial health composite measure—of subprime military families many years after its implementation. Overall, we find very little evidence that the imposition of a 36% cap on open-end products created meaningful changes in the financial health of subprime consumers in the military. Even among subprime consumers—where the policy should have the highest impact—we find little evidence of any credit health improvement.

We apply a couple of robustness checks to our findings. First, we explore an alternative definition of a military community based on zip codes within military bases in the US. Second, instead of following military community residents in 2015 over time, we look at the outcomes of military communities before and after the 2015 expansion. The benefit of this later approach is to account for the credit health of members who join the military after the MLA expansion—although it could be contaminated by endogenous decisions of subprime

[3] Subprime consumers are those with a Vantage score between 300 and 600. There are 1,932 subprime consumers living in military communities in 2015, which represent about 32% of all consumers in those locations.
[4] Using this definition, we classify 146 zip codes as military communities in 2015.

consumers to join the military. The results of these robustness checks are generally consistent with our preferred specification, and we find little evidence that the 2015 MLA expansion improved the credit health of subprime residents of military communities.

To better understand the lack of effects of the MLA expansion on the financial health of military families, we use complementary credit bureau data on estimated APRs for revolving loans of military community residents in February 2022.[5] We find that very few subprime residents of military communities have revolving loans near the 36% cap. In 2022, the average APR on revolving loans of subprime residents of military communities was 17%, and very few consumers had loans around the 36% cap. In addition, APR rates for open-end products tend to be substantially lower than 36%, even for the subprime population in non-military communities, with only 1% of subprime consumers having a revolving loan with an APR greater than 36%. This finding is consistent with publicly available data showing that an average APR on credit cards for subprime consumers is substantially lower than the 36% APR cap (CFPB 2021).

Finally, we also explore the heterogeneous effects of the MLA expansion across subgroups of consumers in military communities. We fail to find evidence that capping the APR of open-end credit products had a positive impact on credit health outcomes in any of the subgroups. If anything, we find suggestive evidence that deep subprime members of the military might have lost access to credit cards without improvements on their credit health after the expansion.[6] While estimated with less precision due to smaller sample size, we find that deep subprime residents of military communities are 7 percentage points less likely to have a credit card after the MLA expansion and have a $1,422 lower credit card limit than those in the comparison group after 2015. This finding suggest that lenders might find some deep subprime consumers too risky for receiving an open-end loan below the 36% cap.

This paper contributes to a large body of literature on the effect of APR caps on families' financial well-being. Virtually all previous literature has focused on the effect of APR caps and prohibition on closed-end credit products, such as payday loans. Evidence is mixed on the benefits of APR caps for such products. On one hand, evidence shows that state APR

[5] Revolving loans incorporate most open-end credit products such as credit cards. We only have access to estimated APR data after 2021.
[6] Deep subprime consumers are those with a Vantage score between 300 and 499. Deep subprime consumers represent about 4% of consumers living in military communities in 2015.

caps on payday loans led consumers to shift to other forms of high-interest credit (Zinman 2010; Bhutta, Goldin, and Homonoff 2016) and are not effective at reducing delinquency on mainstream credit products (Desai and Elliehausen 2017) or bankruptcy (Dasgupta and Mason 2020). Experimental evidence also suggests that banning payday loans reduces economic wellbeing because borrowers are not naïve about their ability to repay their high-cost loans (Allcott et al. 2022). On the other hand, some other evidence shows that access to payday products leads to an increased difficulty for consumers to pay mortgage, rent, and utility bills (Melzer 2011) and that APR caps and prohibition did not lead consumers to use other alternative financial service products (McKernan, Ratcliffe, and Kuehn 2013).[7]

Evidence on the benefits of the 2006 MLA cap on closed-end credits for military families is also mixed. Carter and Skimmyhorn (2017) find no substantial improvement in credit health and labor market outcomes of active-duty members after the MLA's implementation in 2006. If anything, access to payday loans before the MLA reduced the probability of an involuntary separation and improved credit outcomes in some subgroups. On the other hand, Galperin and Mauricio (2016) find that after the MLA implementation in 2006, military community residents substituted short-term costly credit with less expensive credit card borrowing.

This paper advances the literature in a few ways. First, the evidence on benefits of APR caps for credit products is mixed. This paper adds to this literature by showing that capping open-end loans at 36% APR is at best ineffective and at worst detrimental to deep subprime consumers. Second, it expands our knowledge about the effectiveness of credit protection rules in improving military families' financial well-being. Many military families are in financial distress, with nearly 60% of active-duty family members reporting stress because of their financial situation during the pandemic (Strong et al. 2020). Finally, to the best of our knowledge, no study has documented the impact of interest rate caps on a broader set of open-end credit products—such as credit cards—on financial well-being. As a result, this study not only offers unique insights on whether cost restrictions on open-end credit products

[7] Studies exploiting discontinuity of access to payday lending also present more mixed results. Bhutta et al. (2015) find no evidence that access to payday lending affects credit scores. On the other hand, Skiba and Tobacman (2019) find that access to payday loans increases personal bankruptcy rates by a factor of two.

have sufficiently benefited military families, but also informs the current debate on whether such protections should be extended to other underserved populations.[8]

II. Conceptual Framework

Introducing a cap on the interest rates of credit products might affect families' financial health in a few different ways. On one hand, APR capping reduces the cost of credit for some borrowers. At lower rates, consumers might be able to borrow more in case of an emergency, such as job loss or unexpected medical care. In addition, by spending less money on interest rates and fees, families have more resources for paying their bills on time and improving their financial health in the long run.

On the other hand, APR capping might prevent some consumers from accessing credit products. Some lenders might find consumers with a bad credit history too risky at the APR cap level. Without access to credit, families might be unable to pay bills on time, which has a negative effect on long-term credit health. It is also possible that high-risk consumers might need to switch to other suboptimal types of credit products that are not subject to the APR cap.

The overall effect of APR capping depends on the level of the cap and which products are subject to the cap. Lower-level APR caps applied to popular credit products will likely have a significant impact on families' lives. In contrast, high APR levels applied to less popular credit products might only have a small impact on families. Previous literature has evaluated the effect of a *relatively* lower-level APR cap on less popular products (e.g., Carter and Skimmyhorn 2017). Our study evaluates the effect of a *relatively* higher-level APR on a more popular product.[9]

III. The Military Lending Act

Enacted in 2006, the Military Lending Act (MLA) was implemented by the Department of Defense (DoD) to protect active-duty military members along with their spouses, children, and other qualifying dependents from select lending practices by capping the APR on closed-

[8] Veterans and Consumers Fair Credit Act, S. 2508, 117th Cong., 1st Sess. (2021–22), https://www.congress.gov/bill/117th-congress/senate-bill/2508/text.

[9] While the average APR of a $300 payday loan can be as high as 600% in states without APR caps (Center for Responsible Lending 2021), in Q2 2022 the average APR on credit card plans for all Americans was 15% (FED 2022).

end loans at 36% (NCUA 2021). The initial protections provided by the MLA only covered "narrowly defined payday loans, motor vehicle title loans, and tax refund anticipation loans with particular terms" (MLA Handbook 2016). For covered transactions, the MLA limits "the amount a creditor may charge, including interest, fees, and charges imposed for credit insurance, debt cancellation and suspension, and other credit-related ancillary products sold in connection with the transaction" (MLA Handbook 2016). The total cost of covered products must be "expressed through an annualized interest rate referred to as the Military Annual Percentage Rate (MAPR) which may not exceed 36%" (MLA Handbook 2016). Calculation of the MAPR is unique because it includes fees that are not counted as finance charges in traditional APR calculation under the Truth in Lending Act (TILA) and regulation Z (NCUA 2020).

In 2015, the MLA was expanded to include a wider range of credit products including credit cards, deposit advance products, overdraft lines of credit (not traditional overdraft services), and certain installment loans, except those intended to finance the purchase of a vehicle or personal property when the credit is secured by the product being purchased (MLA Handbook 2016). The 2015 expansion also modified MAPR to include additional fees and charges, modified the disclosures creditors must provide to borrowers, made changes to safe harbor provisions available to creditors, altered the prohibition on rolling over, renewing, or refinancing consumer credit, and implemented changes relating to enforcement mechanisms for MLA violations (MLA Handbook 2016).[10] Creditors were required to come into compliance by October 3, 2016, for most changes and October 3, 2017, for credit card accounts. The 2015 MLA expansion only applies to credit extended on or after the mandatory compliance dates (Sheldon 2016).

Creditors are allowed to use their own methods for determining if borrowers are covered by the MLA; however, creditors are only offered "safe harbor provisions" by the MLA if they check the status of borrowers through the DoD's Defense Manpower Data Center's (DMDC) database or a qualifying nationwide consumer reporting agency (NCUA 2020).

[10] In this study, we cannot distinguish between the effects of the various MLA provisions. Nonetheless, if disclosures and other protections included in the MLA expansion benefit consumers, then the APR cap likely imposes an even more adverse consequence on consumers than what this study suggests.

Any agreements made in violation of the MLA are considered void from inception (MLA Handbook 2016).

IV. Data

The primary data source for this study is the annual Urban Institute longitudinal credit bureau dataset from August 2013 to August 2021.[11] These data consist of a random 2% sample of all consumers from a major credit bureau each year (about 5.5 million adults in each pull). To keep the sample representative at the national level, the consumer panel is refreshed at each data pull.[12] The credit bureau data contain an array of information on consumer credit profiles, including the amount of debt and delinquencies related to credit cards, auto loans, mortgages, and foreclosures. The data also include consumer credit scores, which are a composite indicator of overall financial risk and a proxy for financial wellbeing. Finally, while the credit bureau dataset does not include information on gender or race/ethnicity of consumers, it includes the consumer's zip code of residence and age.

Although we cannot directly identify whether a consumer in the credit data is an active-duty military member, we can use zip codes of residence to identify consumers who are likely to be service members. In precise terms, the American Community Survey (ACS) provides information on the active-duty military population for each ZIP Code Tabulation Area (ZCTA) in the US. Using the ACS, we identify ZCTAs in 2015 where more than 50% of the employed population are active-duty members of the US Armed Forces, which we define as majority-military zip codes.[13] We identify 146 majority-military ZCTAs across the US and estimate that about 30% of all active-duty military members in the US live in those 146 ZCTAs. The consumers in the majority-military zip codes in 2015 are very likely to be active-duty service members or members of a military family (e.g., spouses) and therefore affected by the MLA expansion.

[11] Past work using the Urban Institute credit bureau data includes Caswell and Goddeeris (2020); Caswell and Waidmann (2019); and Braga, McKernan, and Hassani (2019).

[12] Consumers only leave the panel if they no longer have a credit record (e.g., due to being identified as deceased), but a nationally representative sample of consumers with new credit records is added to the panel at each new data pull.

[13] We access the 2011–15 5-year ZCTA-level ACS through the tidycensus package in R (Walker and Herman 2022).

As a robustness check, we also identify whether the consumer likely lives in a military installation using the 2015 national military installation shapefile from the US Census Bureau.[14] We conduct a spatial join between the military installation shapefile and the ZCTA shapefile to identify ZCTAs that overlap by 50% or more with a military installation. We identify 188 majority-military installation ZCTAs. Many of these ZCTAs are the same as those that are majority-military employed. Ninety percent of the majority-military employed ZCTAs are also majority-military installations.

With the ACS data, we retrieve information about the characteristics of the ZCTAs in which the consumers live. Because age is the only demographic information available in the credit bureau data, we rely on the ACS demographics of the ZCTAs to approximate information about the consumers (Table 1). We extract information about racial composition and health care coverage of the ZCTA. Next, we identify subprime consumers (those with Vantage scores of 600 or less) in the credit bureau data who live in one of the 146 majority-military zip codes in August 2015—about one year before the policy was implemented. We focus on subprime consumers because they are more likely to be affected by the MLA expansion.

About 32% of consumers living in military communities in 2015 are subprime consumer, which represent 1,932 individuals in our data. We then track these consumers from 2013 to 2021 to examine how their financial outcomes evolved before and after the 2015 expansion of the Military Lending Act. As a robustness check, instead of following individuals over time, we look at the outcomes of military communities (i.e., the 146-majority military employed ZCTAs) before and after the 2015 expansion. The benefit of this later approach is to account for the credit health of members who join the military after the MLA expansion, but it could have the potential endogeneity problem of riskier consumers joining the military as a response to the policy expansion.

[14] This approach is like the one used in Galperin and Mauricio (2016) to identify consumers in the credit bureau who are likely affected by the implementation of the 2006 MLA; also accessed through the tigris package in R (Walker 2016).

V. Empirical Method

We rely on an event-study research design, which assumes that those affected by the policy and the comparison group would have similar credit outcome trends in the absence of the MLA expansion. Using an event-study, we can compare the credit outcomes of consumers living in military zip codes in 2015 with a suitable comparison group for each year before and after the policy was expanded. We use 2015 as the baseline year, as components of the MLA expansion took effect in 2016 and 2017. We can identify the effects of the expansion on credit outcomes for military consumers for each year between 2016 and 2021, therefore capturing both shorter- and longer-term policy impacts.

A. Finding a Comparison Group

We use propensity score matching to construct a comparison group of non-military consumers. The goal is to find a group who looks like the subprime residents in military communities before the MLA expansion and therefore whose outcomes would likely trend similarly to those in military areas after 2015. Because we are using an event-study empirical strategy, differences in unobservable characteristics between the treatment and comparison groups might still exist after the matching, as long as these unobservable characteristics remain relatively constant over the years.

To find a comparison group, we first identify a group of subprime consumers in non-military zip codes that are similar in terms of age, credit score, credit limit, and whether they have a credit card open, debt in collection, and revolving debt in delinquency in 2015. The choice of these credit health baseline characteristics for the matching is justified by the fact that these are outcomes of interest for the study. We also match on the characteristics of the zip codes of residence in 2015 using ACS data, including the share of residents that are Black or Hispanic and that have health insurance.[15] We chose these local-level baseline characteristics because past work shows these are community characteristics that strongly predict consumers' credit health (Braga et al. 2019). Lastly, we also match based on the region of the US in which they live—the Midwest, Northeast, South, or West. Using 3:1

[15] For zip codes that are missing health insurance rates, we impute with the average for majority-military and non-military zip codes.

nearest-neighbor matching, we identify 1,932 people in the treatment group and 1,340 people in the comparison group (that are weighted to equal the 1,932 in the treatment group).

Table 2 shows that after matching, there are no meaningful differences between the treatment and comparison groups in terms of the baseline characteristics used in the matching (i.e., all effect sizes are less than 0.2). The treatment and comparison groups remain relatively balanced in their baseline characteristics even after accounting for the departure of some consumers from the panel by 2021 (Table A1).[16]

B. Empirical Strategy

With the matched treatment and comparison groups, we then track their credit outcomes from 2013 to 2021. We focus on three sets of primary outcomes: (1) an indicator for whether the consumer has access to a credit card and their credit card limit; (2) an indicator for whether the consumer has any form of delinquency of 60 days or more on a revolving loan (such as a credit card or personal lines of credit) and an indicator for whether the consumer has any debt in collections;[17] (3) average credit scores. We test whether after the 2015 MLA expansion active-duty military and their families lost access to some credit products while improving their ability to pay their bills on time.

a. Event Study

In the event-study, we compare the credit outcomes of the matched treatment and comparison groups for each year before and after the MLA expansion. The underlying assumption is that treatment and comparison groups would have parallel outcome trajectories in the absence of the MLA expansion.[18] The event study design allows us to assess whether the MLA expansion has an immediate or delayed effect and provides a test for the parallel-trend assumption. This feature of the model is important given the MLA expansion had provisions that took effect in both 2016 and 2017. We use the following event study model:

[16] Consumers only leave the panel if they no longer have a credit record (e.g., due to being identified as deceased).
[17] Revolving loans include most types of open-end credit products. Our dataset does not include information on credit card delinquency before 2018—therefore, we focus on revolving debt delinquency.
[18] A potential threat to the validity of the study is the implementation of other policies affecting only the military families after 2015. While we could not find any substantial changes in payments or benefits to military personnel during the period, such policies could potentially bias our estimation.

$$Y_{i,z,t} = \gamma_t + \beta Military_{i,z} + \sum_{\tau=-2}^{-1} \boldsymbol{\theta_\tau} Military_{i,z} 1(EY = \tau) + \sum_{\tau=1}^{6} \boldsymbol{\pi_\tau} Military_{i,z}(EY = \tau) + \epsilon_{i,z,t}$$

In this model, $Y_{i,z,t}$ is the outcome of consumer *i* residing in zip code *z*, in year *t*; γ_t include year fixed-effects; $Military_{i,z}$ indicates whether the consumer *i* was a resident of a military zip code in 2015; EY is the number of years since 2015; θ_τ is a pre-trend test for 2013 and 2014; and π_τ is the effect of MLA expansion for each year between 2016 and 2021. Standard errors are clustered at the zip code level.

b. Difference-in-Difference

Using a difference-in-difference model, we compare the credit outcomes of the matched treatment and comparison groups before and after the MLA policy expansion. The underlying assumption is once again that treatment and comparison groups would have parallel outcome trajectories in the absence of the MLA expansion. While we cannot estimate year-specific effects of the policy, by grouping pre- and post-treatment, the difference-in-difference model entails more power to estimate a small effect of the policy on credit outcomes. We use the following difference-in-difference model:

$$Y_{i,z,t} = \gamma_t + \alpha Military_{i,z} + \beta Military_{i,z} \times Post2015_t + \epsilon_{i,z,t}$$

In this model, $Y_{i,z,t}$ is the outcome of consumer *i* residing in zip code *z*, in year *t*; γ_t includes year fixed-effects; $Military_{i,z}$ indicates whether the consumer was a resident of a military zip code in 2015; $Post2015_t$ indicates whether the year is after the MLA expansion; and β is the effect of MLA expansion on outcome $Y_{i,z,t}$. Standard errors are again clustered at the zip code level. The pre–MLA expansion period is defined as 2013 to 2015 and the post-period is 2016 to 2021.

VI. Results

A. Main Results

Although some credit card companies might find subprime consumers too risky at a 36% APR cap, we do not find any evidence that the MLA expansion affected access to open-end credit for subprime residents of military communities. First, we investigate whether the MLA

had an impact on credit limits among credit card holders (Figure 1). Before 2016, subprime credit card holders in military communities had very similar credit limits to those in the comparison group ($2,566 and $2,636 in 2015 respectively, Panel A). Most importantly, our event study analysis shows that consumers in the two groups experienced a similar increase in credit card limits in the following years (Panel B). Using 2015 as our baseline year, we do not find the difference in average credit card limits between the military and comparison groups have statistically changed after the MLA expansion. In 2021, the average credit card limit for subprime card holders in military communities was $7,769 and $7,961 in the comparison group. This result is confirmed in the difference-in-difference model, where we find a small ($86) and not statistically significant decline in credit limits after the MLA expansion (Table 3).

We also investigate the MLA expansion's effect on the likelihood of a subprime consumer having a credit card (Figure 2). In 2015, 44% of consumers in the military group had a credit card in 2015 compared with 46% in the comparison group (Panel A). The consumers in the two groups experienced increasing access to credit cards in the following years, in part because they got older and improved their credit scores. But most importantly we do not see a difference in terms of trajectory of access to credit cards between the two groups (Panel B). In fact, 68% of consumers in the military group had a credit card in 2021 compared with 65% in the comparison group. We do not find the difference in the likelihood of access to a credit card between the military and comparison groups to have statistically changed after the MLA expansion. The difference-in-difference estimation confirms the small—1 percentage point increase—and not statistically significant result of the MLA on the likelihood of owning a credit card (Table 3). This result suggests that the 36% cap on open-end credit products did not prevent subprime residents of military communities from accessing a credit card.

Next, we investigate whether MLA expansion helped subprime residents of military communities pay their bills on time, such as their credit card bills. We do not find evidence that the MLA expansion decreased delinquency rates among subprime military residents on revolving loan products (Figure 3). In 2015, revolving loan holders in the comparison group were slightly more likely to have a delinquency in their loans than those in the military group—29.8% vs. 28.7%, respectively (Panel A). Nonetheless, in 2021 we find that subprime

holders of revolving loans were slightly more likely to have a delinquent revolving loan than those in the comparison group (10.8% vs. 9.6%, respectively). The difference-in-difference estimation confirms the small—1 percentage point increase—and not statistically significant effect of the MLA on revolving loan delinquency (Table 3).

We also did not find evidence that the MLA expansion decreased the likelihood of collections for subprime residents of military communities. The difference in collections in relation to the comparison group went from 78% vs. 79%, respectively, in 2015 to 64% vs. 60% in 2021 (Panel A). In the difference-in-difference estimation, we find that the MLA expansion was associated with a small 3 percentage point increase in collections for subprime members of military communities—although the effect is not statistically significant (Table 3).

Finally, we investigate the effect of the MLA expansion on average credit scores. The subprime residents of military communities had virtually the same average credit scores as those in the comparison group in the year before the MLA expansion (Figure 5). In fact, in August 2015 the average Vantage credit score of our treatment group was 539 versus 537 in the comparison group. We observe an improvement in credit scores for both the treatment and comparison groups after 2015. As both groups got older, they experienced an increase in their credit scores. Nonetheless, the average credit score of both groups experienced virtually the same trajectory over the six-year period. The difference-in-difference estimation confirms this result, as we do not find significant effects of the MLA expansion on credit scores (Table 3). In summary, the 36% APR cap on open-end products did not improve the credit health of subprime residents of military communities.

B. Robustness Checks

To validate our results, we conduct two robustness checks. First, we use an alternate "treatment" definition to examine whether the definition of military communities affects the findings. Our main definition of military communities is ZCTAs in which 50% or more of the employed population is a member of the armed forces. Our alternate treatment definition of military communities is ZCTAs in which 50% or more of the area overlaps with a military installation. With this treatment group, we then repeat the same procedures. We identify the consumers that live in majority-military installations in 2015 and use propensity score

matching to identify a similar comparison group. However, to achieve a better match, we needed to adjust some of the matching variables used in the analysis. The ACS characteristics of the share of the ZCTA that is Black or Hispanic and the share of the ZCTA with health insurance coverage are not included. We also conduct an exact match on region (Table A2). We then use the difference-in-difference model on the matched treatment and comparison consumers.

Consistent with the main specification, we do not find that subprime consumers living in military bases experience an increase in their credit card limit after the MLA expansion (Table 4). There is a small and not statistically significant effect of the policy on the credit card limit after 2015. We also do not find significant effects of the MLA expansion on revolving loan delinquency or collections. Finally, we do not find significant effects of the MLA expansion on credit scores. Overall, using this alternative measure of military community, we find little evidence that the MLA expansion improved the credit health of subprime residents of military communities.

Second, in our main specification, we identify subprime consumers living in military communities in 2015 and follow them over time. One potential restriction of this approach is that some of these consumers might leave the military in the coming years and therefore would not be subject to the MLA's protections. In addition, our analysis would not include people who join the military after 2015. These young consumers might be considered riskier by lenders and therefore subject to the MLA's protections. To address this issue, we apply a robustness check where we track the outcomes of the 146 military communities over time. In other words, we look at the outcomes of residents of military communities for each year before and after 2015—regardless of their military status in 2015.

There are two potential issues with this approach. First, the sample of military community residents could be affected by the endogenous decision of subprime consumers to join the military after 2015 in response to the MLA expansion. Consumers with a poor credit history might join the military to benefit from the MLA expansion's protections. Second, we can no longer restrict the sample to subprime consumers. Credit score is the outcome of interest of this study and therefore potentially affected by the MLA expansion.

With those caveats in mind, we first use propensity score matching to identify comparison zip codes similar to the 146 military zip codes in the treatment group. We use the

following 2015 credit bureau characteristics in the matching: average credit score, average credit card limit, share with a credit card, revolving delinquency rate, share with debt in collections, share of consumers within the different age groups. We also use the ACS characteristics on the share of the ZCTA that is Black or Hispanic and the share of the ZCTA with health insurance coverage above the national median. We do not conduct an exact match on region to obtain a more reasonable match, and we drop 15 zip codes in the treatment group for which we could not find good comparisons (Table A3). We then use the difference-in-difference model on the matched treatment and comparison zip codes weighting the analysis by number of consumers in each zip code.

Consistent with the main specification, we do not find evidence that consumers in military communities experience changes in their credit card limit or in the likelihood of having a credit card after the MLA expansion (Table 5). We also do not find significant effects of the MLA expansion on collections. However, in this specification, we do find some evidence of a decrease in revolving loan delinquency for people living in military communities, which is inconsistent with our other findings. This result is mostly by driven by a substantial decline in delinquency rates in 2021 for the consumers in military communities (from 6.4% in 2020 to 4.4% in 2021).[19] Finally, we do not find significant effects of the MLA expansion on credit scores.

VII. Who Is Affected by the 36%APR Cap on Open-End Credit Products?

To better understand why we do not observe substantial improvements in the credit health of residents of military communities after the MLA expansion, we turn to a secondary data on estimated APRs in February 2022 produced by our credit bureau data provider. [20] The data is based on a 4% sample of all consumers with a credit record in the country. While credit bureau agencies do not have access to APR information for specific loans, they are able to estimate APRs based on payment history, loan terms, and changes in debt amounts.[21]

[19] We are reluctant to attribute this decline to an effect of the MLA expansion because it happened only during the COVID-19 Pandemic.
[20] We do not have access to estimated APRs before 2021.
[21] The credit bureau data provider has done several validations of their estimated APRs. For example, they found that their estimated APRs explain 91% of variation in real APRs using May 2020 data.

For this study, we focus on the estimated APR for the revolving loan with the highest amount for each consumer in February 2022.[22]

First, we identify 668 subprime consumers living in a majority military zip codes for whom we have estimated APR rates for revolving loans. We find that very few of these consumers have a revolving loan with an APR near the 36% cap (Figure 6). In fact, the average APR for revolving loans of subprime consumers in the military is 17%. We also see very little evidence of bunching of loans around 36%, suggesting that the cap is not binding for most subprime consumers living in military communities in 2022.

Next, we identify 407,095 subprime consumers living in a non-majority military zip codes for whom we have estimated APR rates for revolving loans. We also find that very few of these consumers had a revolving loan with an APR above 36%. The average APR for subprime consumers in non-military communities is 22%, and only 3% of subprime consumers pay above the 36% cap for their revolving loans (Figure 7). This result is consistent with Federal Reserve data showing a 15% average APR on credit card plans for all Americans in Q2 2022 (Federal Reserve 2022) and Consumer Financial Protection Bureau (CFPB) data showing that, even for deep subprime consumers, the average APR on a credit card was lower than 25% in 2020 (CFPB 2021). This evidence suggests that a 36% APR on open-end credit products would not be binding for the overall population.

VIII. Subgroup Analysis

Because the MLA expansion may not affect all subprime consumers equally, we repeat the difference-in-difference analysis for select subgroups of consumers. Specifically, we look separately at the effects for consumers in 2015 who are young (ages 18 to 24), have deep subprime credit scores (Vantage scores less than 500), live in the South, and live in the West. Younger consumers with less credit history and consumers with deep subprime scores may be more likely impacted by the MLA expansion's APR cap.[23] We also examine the West and the South separately because they have the highest concentrations of military zip codes, and

[22] Data from the Federal Reserve (2022) show that average interest rates on credit cards have increased in the past 5 years.
[23] Deep subprime consumers represent about 4.4% of all consumers living in a military community in 2015.

those regions generally have different levels of financial well-being. We subset the consumers from the matched treatment and comparison groups used in the main analysis.[24]

We fail to find evidence that MLA expansion had a positive impact on the credit health outcomes of any subgroups we analyzed (Table 6). If anything, we find that deep subprime residents of military communities lost access to open-end credit after MLA expansion. They were 7 percentage points less likely to have a credit card after the MLA expansion and had a $1,422 lower credit card limit than those in the comparison group after 2015, although these effects are only marginally significant. In other words, although these are big effects, they are estimated with less precision and in smaller sample sizes. Nonetheless, this result is consistent with past work showing that the APR cap on closed-end credit loans had a negative impact on credit outcomes for a few consumers (Carter and Skimmyhorn 2017; Desai and Elliehausen 2017). We do not find any evidence that the MLA expansion had an impact on the delinquency rates or credit scores of consumers with deep subprime credit scores. We also do not find evidence that the MLA expansion affected the credit health outcomes of any other subgroup.

IX. Conclusion

Using 2013–2021 waves of credit bureau data, this study does not find evidence that the 2015 MLA expansion improved credit health outcomes of subprime residents of military communities. We find small and not statistically significant effect of the expansion on access to open-end credit for subprime residents of military communities. We also do not find evidence that MLA expansion decreased the delinquency rate on revolving loan products, which incorporate most open-end credit products. Finally, we do not find evidence that MLA expansion had an impact on credit scores of subprime military families many years after its implementation.

Using secondary data for February 2022, we find that very few subprime consumers have a revolving loan with an APR of 36% or above. This finding is consistent with publicly available data showing that the average APR on credit cards for subprime consumers is

[24] We do not conduct matching procedures for each of the subgroups separately. However, the difference-in-difference design helps account for any potential imbalances between the treatment and comparison groups at baseline.

below the 36% cap (CFPB 2021). Overall, a 36% APR cap on open-end credit products would not binding for most of the subprime population.

Finally, this study finds suggestive evidence that a smaller set of consumers—those with a deep subprime credit score and younger consumers—might be negatively affected by a 36% APR cap on open-end products. This result suggests that lenders might find them too risky at the 36% APR cap. This finding is consistent with past work showing that APR caps might have a negative impact on credit outcomes for a few consumers (Carter and Skimmyhorn 2017; Desai and Elliehausen 2017).

These findings add to the existing literature by providing empirical evidence on the effectiveness of a consumer protection policy designed to improve the financial well-being of military members, many of whom report high levels of financial distress. These findings also have broader implications beyond military communities. For years, state and federal policymakers have debated effective ways to improve financial outcomes for consumers. In recent decades, dozens of states have passed price caps on various forms of credit, and Congress is currently considering passing the Veterans and Consumers Fair Credit Act to extend the provisions of the Military Lending Act to all consumers. Our research suggests that extending a 36% APR cap to all forms of revolving credit products would unlikely improve credit outcomes for the majority of borrowers. In fact, a nationwide extension of this policy might have detrimental effects on the most vulnerable consumers by limiting their access to credit in times of need. Because there are high costs associated with regulatory enforcement—as well as political capital spent to pass legislation—efforts to enact and enforce such a policy could divert time and resources from more effective strategies to improve credit outcomes for consumers.

Given the mixed evidence base, more research is warranted to better understand how and when price caps may be effective. Such research could focus on understanding the conditions under which price caps affect borrowers' credit health, examining the right thresholds for such caps, and understanding the effects of price caps on distinct subgroups of consumers, especially the most vulnerable. Price caps in other markets, such as rent controls or prescription drug price ceilings, are not set in a fixed threshold and typically adjusted based on the state of the economy (NYC Gov n.d.; Cubanski, Neuman, and Freed 2022).

Further research could also assess the impact of alternative regulatory approaches to improve borrowing outcomes. For example, research from Colorado shows that a new law requiring that loans be paid back in affordable installments (Urahn et al. 2013) over a six-month period, rather than in a single lump sum, can lead to better outcomes for consumers. Other research suggests that carefully designed disclosures (Bertrand and Morse 2011) on the cumulative costs of loans can reduce some of the negative consequences of borrowing high-cost credit.

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Table 1 - Community Characteristics in 2015

Characteristics	Military Community	All Other Communities
% Black	14%	7%
% White	62%	78%
% Hispanic	15%	9%
Poverty Rate	9%	15%
% Homeowner	5%	73%
% Health Insurance Coverage	96%	87%
Median Earnings ($)	23,607	30,775
# Communities	146	32,479

Source: 2012–15 American Community Survey

Notes: A community is a ZCTA. A military community is a ZCTA where more than 50% of the employed population are active-duty members of the US Armed Forces.

Table 2 - Credit Health of Subprime Military Community Residents and Comparison Group in August 2015

Characteristic	Matched		Effect Size	*p*-value	All US
	Military Community	Comparison Group			
Vantage Score	539.1	537.3	-0.040	0.216	532.8
Deep Subprime	14%	16%			16%
Access to Open-End Credit					
Credit Card Limit ($)	2,566	2,636	0.010	0.764	1,529
Has Credit Card	44%	45%	0.036	0.257	22%
Delinquency					
Revolving Loan Delinquency (60+)	13%	13%	0.023	0.474	8%
Has Debt in Collections	78%	79%	0.034	0.290	86%
Other					
Age 18–24	28%	30%	0.030	0.357	12%
Age 25–39	44%	45%	0.022	0.497	33%
Age Missing	18%	13%	-0.152	0.000	20%
Zip Code Characteristics					
Share Black or Hispanic	32%	33%	0.022	0.503	38%
Share with Health Insurance	97%	97%	0.019	0.556	85%
Region of Residence					
Midwest (North Central)	9%	8%	-0.0322	0.318	21%
Northeast	3%	3%	-0.0158	0.624	9%
South	59%	66%	0.144	0.000	46%
West	29%	23%	-0.132	0.000	24%
Military Definition					
Share Employed Military	77%	3%			
# Individuals	1,932	1,340 (unweighted)			1,401,910

Sample: Subprime consumers in August 2015.
Notes: A military community is a ZCTA where more than 50% of the employed population are active-duty members of the US Armed Forces. Weighted means calculated for matched comparison units. Cohen's D effect size calculated for difference between matched treatment and comparison groups. *P*-value shown for results of *t*-test between matched treatment and comparison groups. All variables shown were matching variables, except for deep subprime.

Table 3 - The Effect of MLA Expansion on Credit Health - Difference-in-Difference Specification

Dependent Variable	Credit Card Limit	Owns a Credit Card	Revolving Loan Delinquency	Has Debt in Collections	Credit Score
Military x Post 2015	-85.97	0.01	0.01	0.03	-0.99
	(381.96)	(0.02)	(0.02)	(0.02)	(2.97)
Observations	24,628	24,628	12,257	24,628	24,628
Mean Outcome, Control Group in 2015	2,636	0.454	0.135	0.793	537.3

Sample: Subprime residents of military communities in 2015 and their comparison group. The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. All models include an indicator for living in a military community in 2015 and year-fixed effects. Standard errors reported in parentheses are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 4 - The Effect of the MLA Expansion on Credit Health - Difference-in-Difference Specification, Military Base Definition

Dependent Variable	Credit Card Limit	Owns a Credit Card	Revolving Loan Delinquency	Has Debt in Collections	Credit Score
Military x Post 2015	-54.9	0.002	0.01	-0.01	1.61
	(291.66)	(0.01)	(0.01)	(0.01)	(2.14)
Observations	46,516	46,516	22,607	46,516	46,516
Mean Outcome, Control Group in 2015	2,562	0.366	0.323	0.810	538.7

Sample: Subprime residents of military communities (military base definition) in 2015 and their comparison group. The military group includes subprime residents of zip codes in which 50% or more of the area overlaps with a military installation. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. All models include an indicator for living in a military community in 2015 and year-fixed effects. Standard errors reported in parentheses are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 5 - The Effect of MLA Expansion on Credit Health - Difference-in-Difference Specification, Following Military Communities Over Time

Dependent Variable	Credit Card Limit	Owns a Credit Card	Revolving Loan Delinquency	Has Debt in Collections	Credit Score
Military x Post 2015	-1,213	0.00885	-0.0123***	-0.00751	0.211
	(775.9)	(0.00958)	(0.00472)	(0.0112)	(3.022)
Observations	2,887	2,887	2,681	2,887	2,869
Mean Outcome, Control Group in 2015	15,957	0.579	0.0575	0.308	650.3

Sample: Military communities and their comparison group. The military communities are zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Comparison group communities are defined based on propensity score matching on 2015 characteristics. See section VI, D. for more details. All models include an indicator for military community in 2015 and year-fixed effects. Standard errors reported in parentheses are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1

Table 6 - The Effect of MLA Expansion on Credit Health - Difference-in-Difference Specification by Subgroup

Panel A - Ages 18 to 24

Dependent Variable	**Credit Card Limit**	**Owns a Credit Card**	**Revolving Loan Delinquency**	**Has Debt in Collections**	**Credit Score**
Military x Post 2015	47.62	-0.09	0.05	0.1	-3.58
	(538.67)	(0.03)	(0.04)	(0.03)	(6.54)
Observations	7,528	7,528	3,867	7,528	7,528
Mean Outcome, Control Group in 2015	1,329	0.423	0.321	0.713	529.7

Panel B - Deep Subprime

Dependent Variable	**Credit Card Limit**	**Owns a Credit Card**	**Revolving Loan Delinquency**	**Has Debt in Collections**	**Credit Score**
Military x Post 2015	-1,422.06*	-0.07*	0.004	0.03	-6.22
	(841.30)	(0.04)	(0.05)	(0.03)	(6.81)
Observations	4,128	4,128	1,780	4,128	4,128
Mean Outcome, Control Group in 2015	1,442	0.451	0.662	0.882	455.8

Panel C - Residents of the South Region

Dependent Variable	Credit Card Limit	Owns a Credit Card	Revolving Loan Delinquency	Has Debt in Collections	Credit Score
Military x Post 2015	106.62	0.001	0.01	0.005	1.16
	(522.76)	(0.02)	(0.03)	(0.02)	(3.63)
Observations	15,037	15,037	7,328	15,037	15,037
Mean Outcome, Control Group in 2015	2,544	0.429	0.328	0.793	533.5

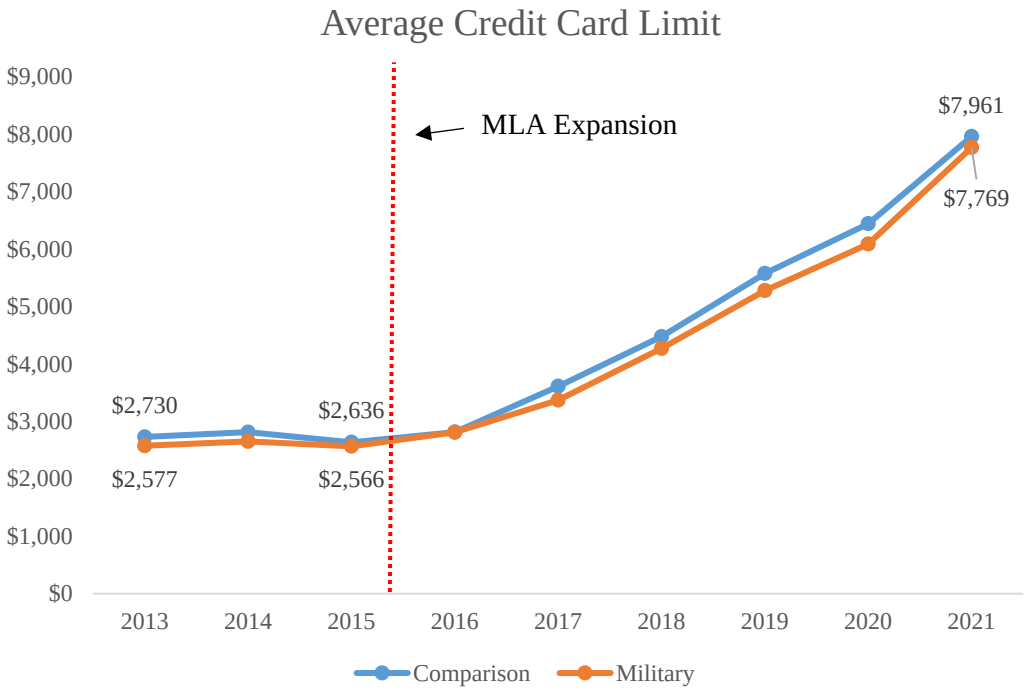
Panel D - Residents of the West Region

Dependent Variable	Credit Card Limit	Owns a Credit Card	Revolving Loan Delinquency	Has Debt in Collections	Credit Score
Military x Post 2015	-505.41	0.02	0.04	0.06*	-8.65
	(533.94)	(0.04)	(0.04)	(0.03)	(6.09)
Observations	6,626	6,626	3,461	6,626	6,626
Mean Outcome, Control Group in 2015	2,964	0.501	0.253	0.781	547.0

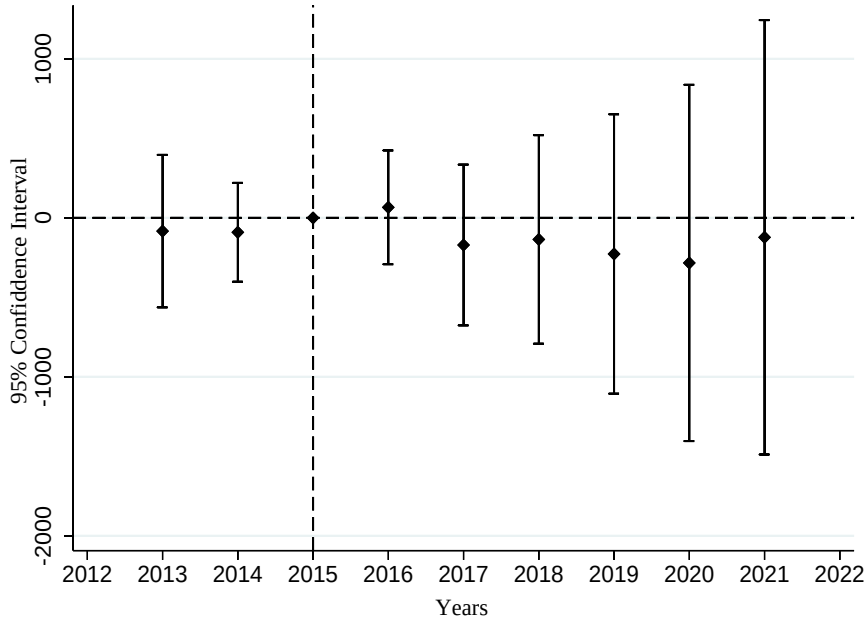
Sample: Subprime residents of military communities in 2015 and their comparison group. The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. All models include an indicator for living in a military community in 2015 and year-fixed effects. Standard errors reported in parentheses are clustered at the zip code level. *** p<0.01, ** p<0.05, * p<0.1

Figure 1 - The MLA Expansion Has No Effect on Credit Card Limits

Panel A - Average Credit Limit - Military and Comparison Group



Panel B - Event Study Estimates of the MLA Expansion on Credit Card Limit with 95% Confidence Intervals

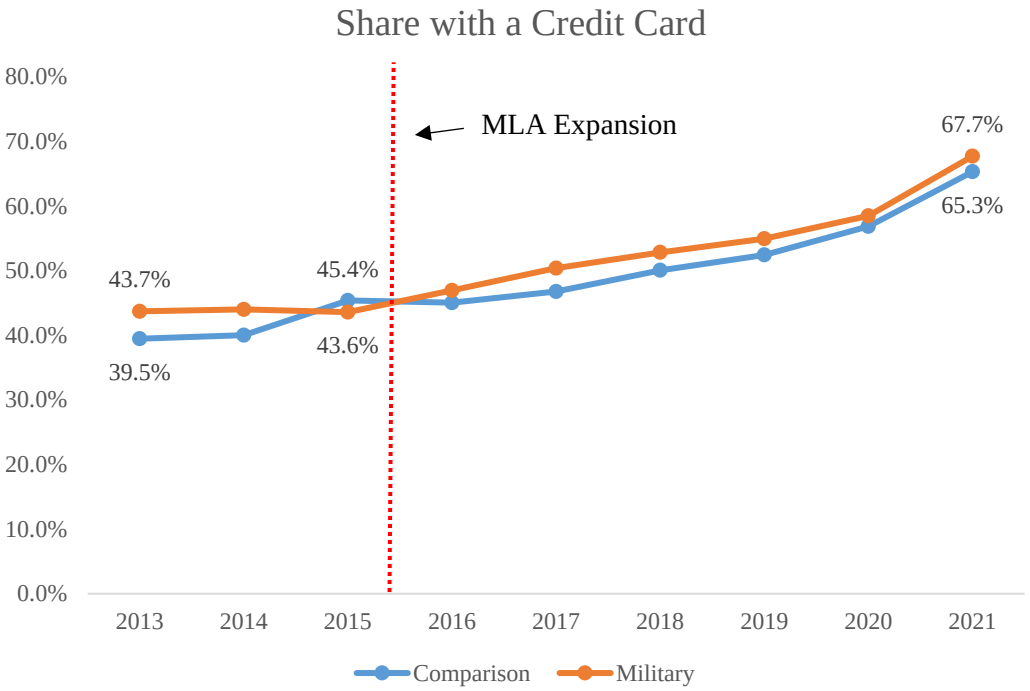


Source: Urban Institute credit bureau data.

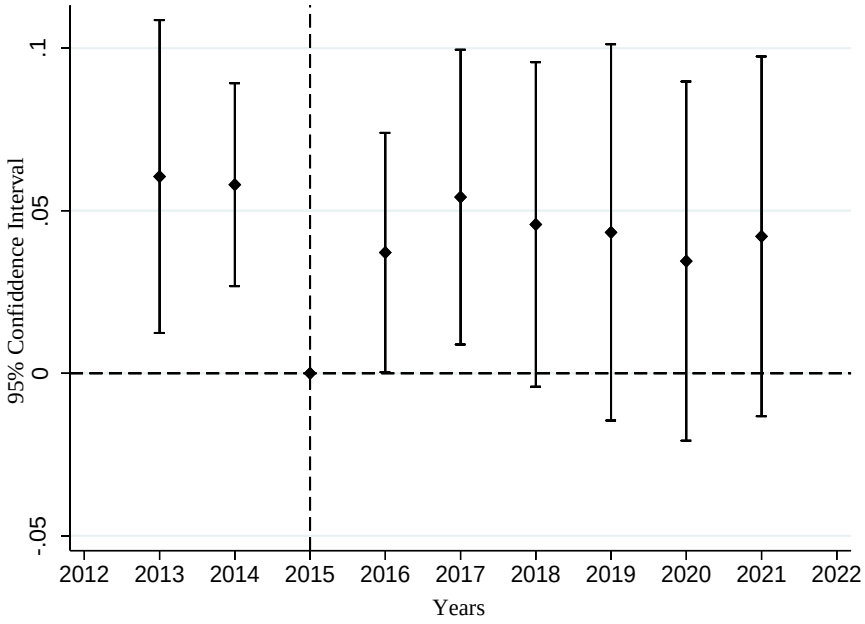
Notes: The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. 95% confidence intervals are based on standard errors clustered at the zip code level.

Figure 2 - The MLA Expansion Has No Effect on the Likelihood of Having a Credit Card

Panel A - Share Owning a Credit Card - Military and Comparison Group



Panel B - Event Study Estimates of the MLA Expansion on Owning a Credit Card with 95% Confidence Intervals

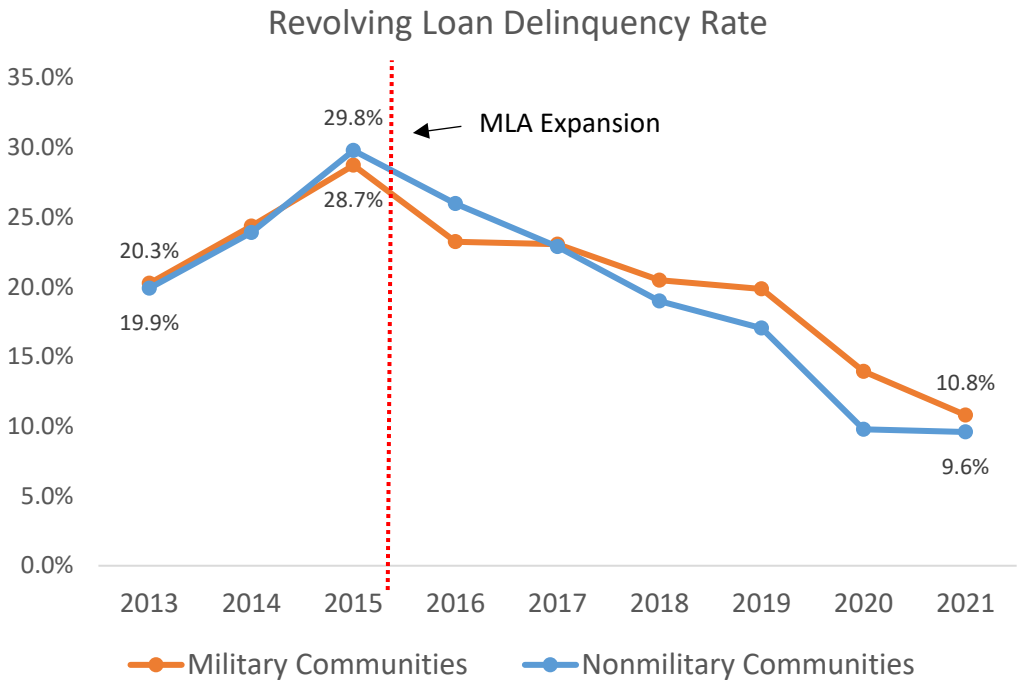


Source: Urban Institute credit bureau data.

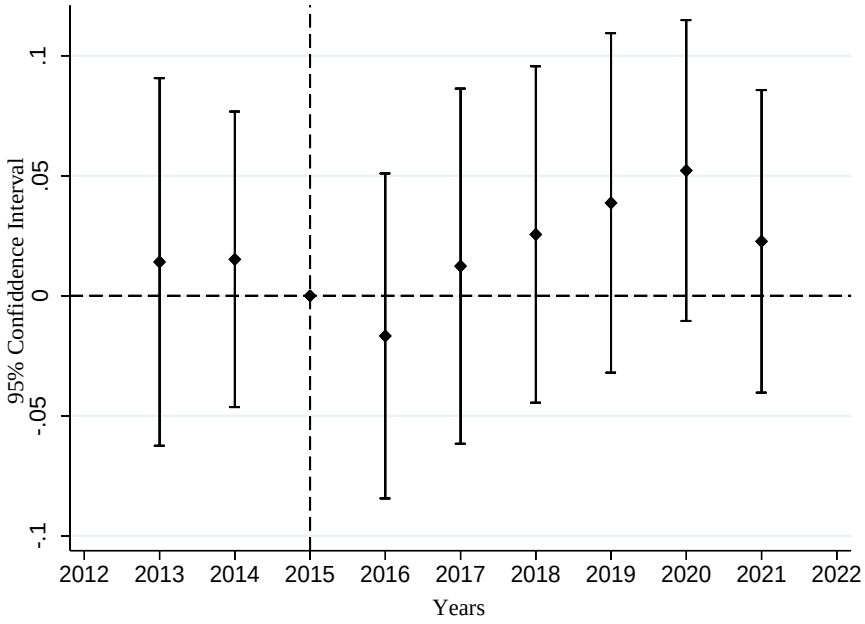
Notes: The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. 95% confidence intervals are based on standard errors clustered at the zip code level.

Figure 3 - The MLA Expansion Has No Effect on Credit Card Delinquency

Panel A - Revolving Loan Delinquency Rate (30+ days) - Military and Comparison Group



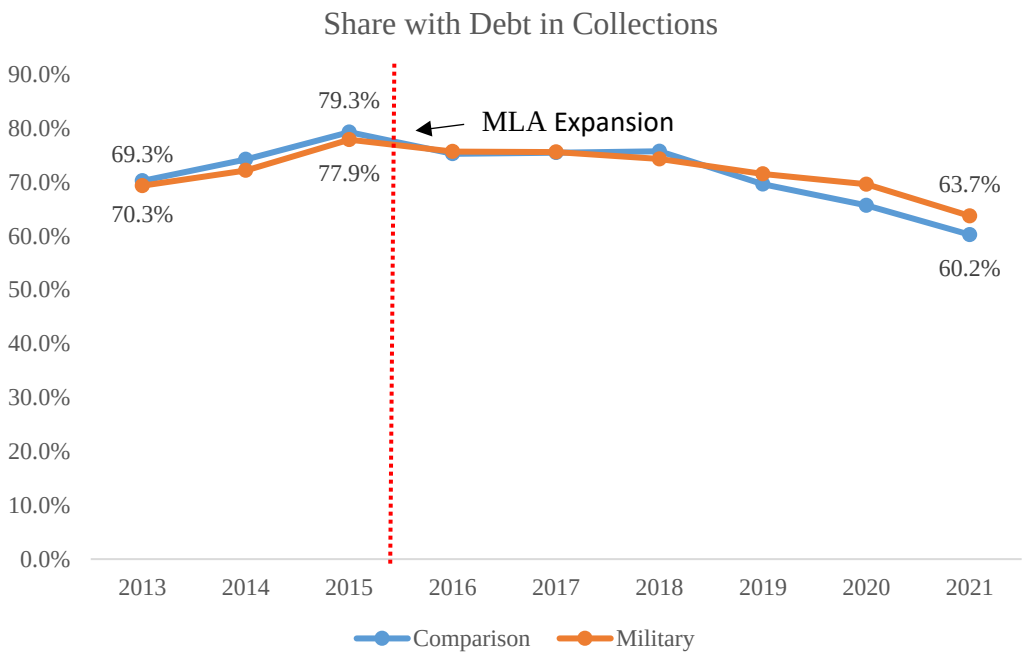
Panel B - Event Study Estimates of the MLA Expansion on Revolving Loan Delinquency with 95% Confidence Intervals



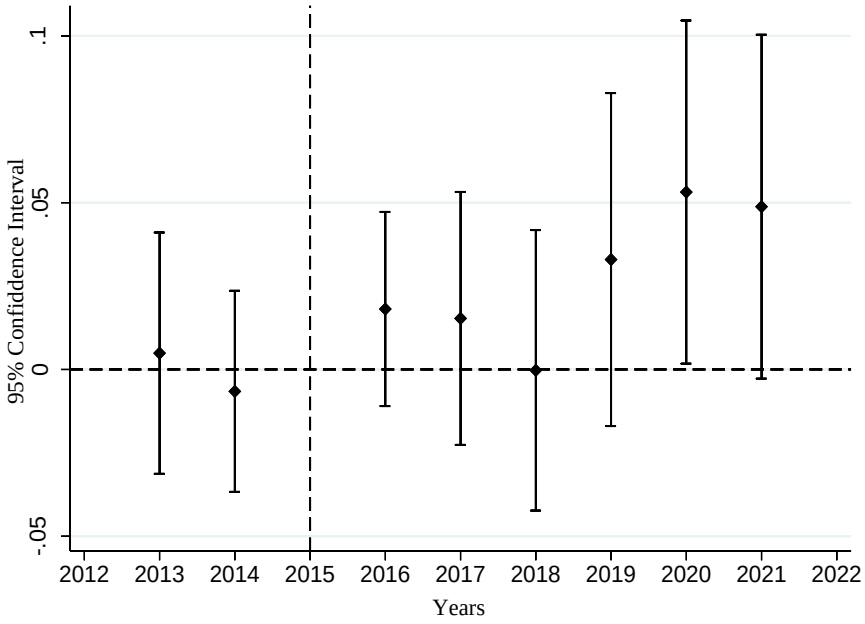
Source: Urban Institute credit bureau data. The sample is restricted to credit card holders.
Notes: The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. 95% confidence intervals are based on standard errors clustered at the zip code level.

Figure 4 - Subprime Residents of Military Communities Have Slightly Greater Collections Rates after the MLA Expansion

Panel A - Share with Debt in Collections - Military and Comparison Group



Panel B - Event Study Estimates of the MLA Expansion on Collections with 95% Confidence Intervals

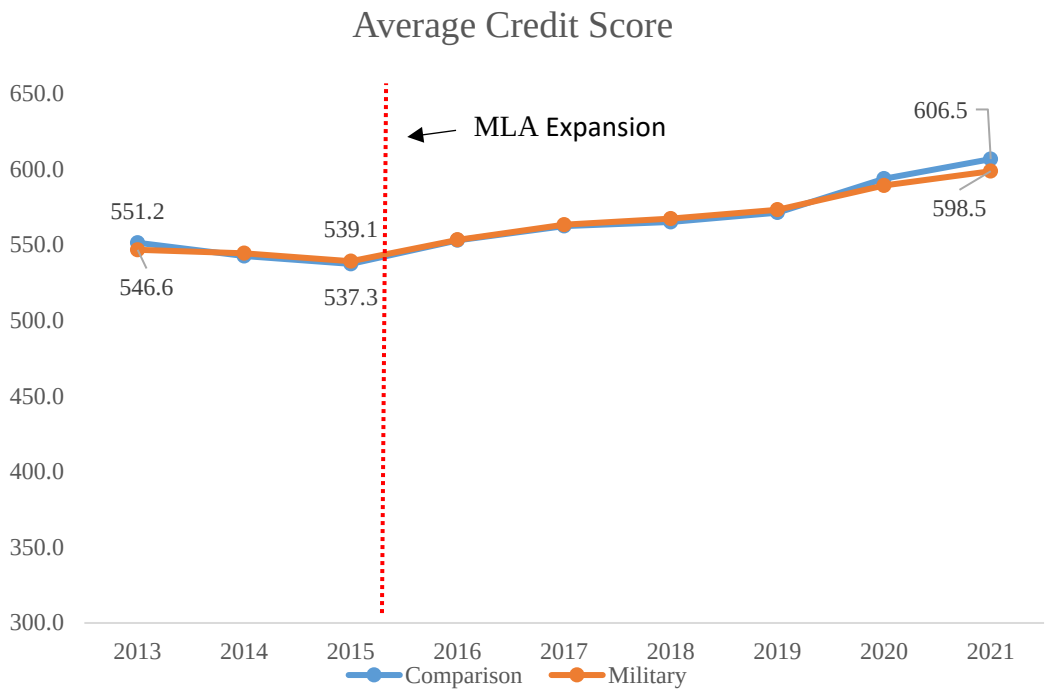


Source: Urban Institute credit bureau data.

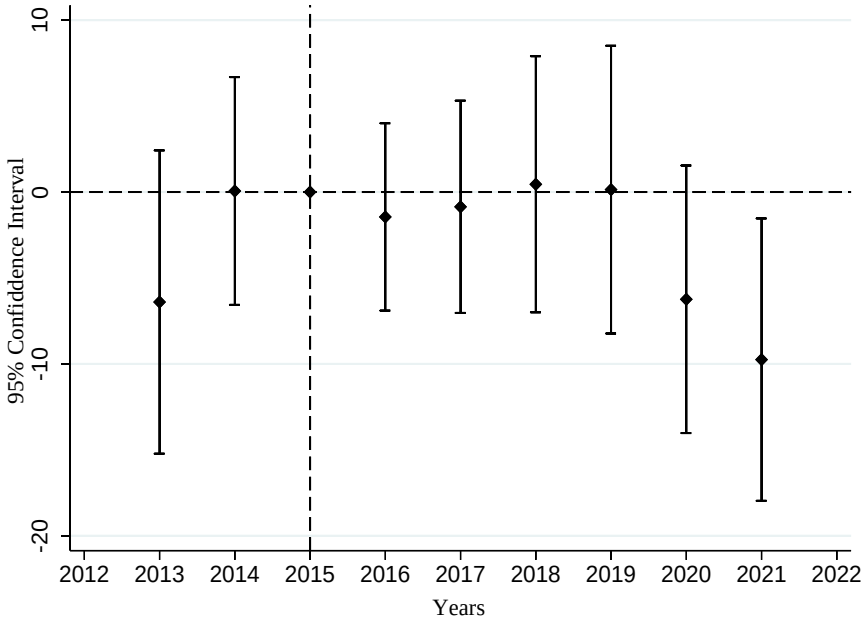
Notes: The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. 95% confidence intervals are based on standard errors clustered at the zip code level.

Figure 5 - The MLA Expansion Has No Effect on Credit Scores

Panel A - Average Credit Score - Military and Comparison Group



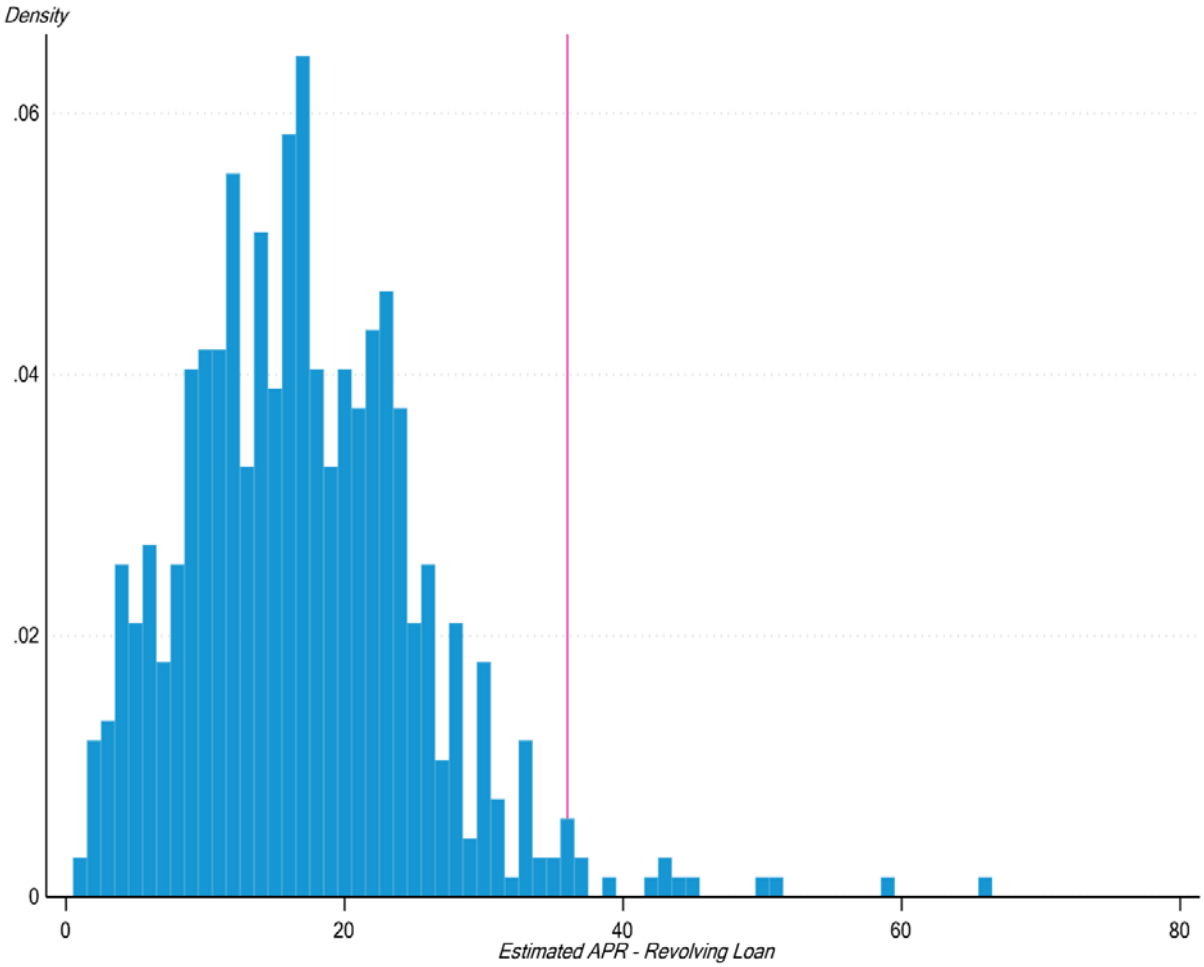
Panel B - Event Study Estimates of the MLA Expansion on Credit Scores with 95% Confidence Intervals



Source: Urban Institute credit bureau data.

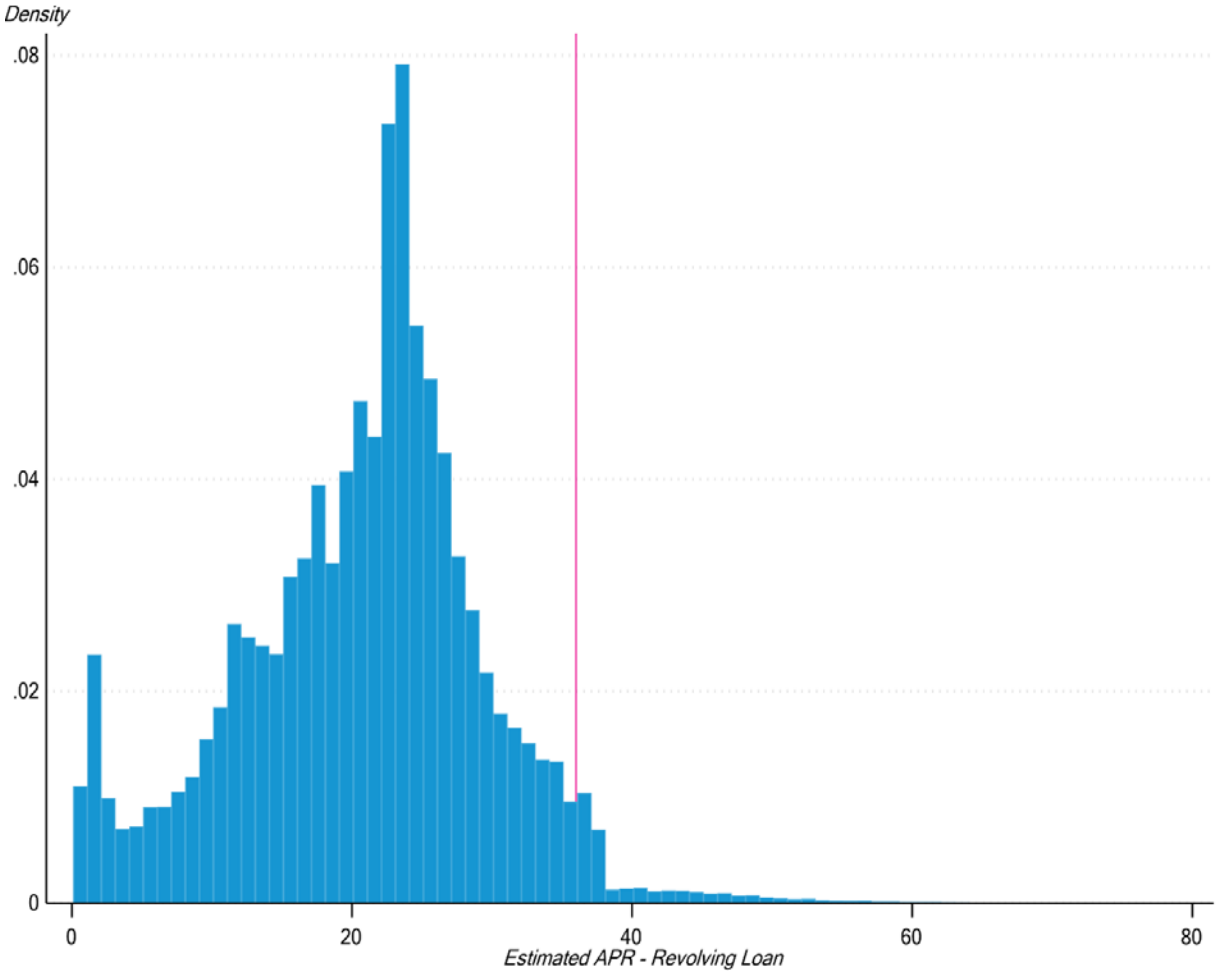
Notes: The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2015. Control group is defined based on propensity score matching on 2015 characteristics. See data and methods for more details. Subprime consumers have a Vantage score below 600. 95% confidence intervals are based on standard errors clustered at the zip code level.

Figure 6 - APR Distribution of Revolving Loans - Subprime Consumers in Military Communities in February 2022



Source: February 2022 APR estimates from the credit bureau data.
Notes: Red vertical line represents the 36% APR Cap. The military group includes subprime residents of zip codes where more than 50% of the employed population are active-duty members of the US Armed Forces in 2021. Subprime consumers have a Vantage scores below 600. Red vertical line represents 36% APR.

Figure 7 - APR Distribution of Revolving Loans - Subprime Consumers in Non-Military Communities in February 2022



Source: February 2022 APR estimates from the credit bureau data.
Notes: Red vertical line represents the 36% APR Cap. The non-military group includes subprime residents of zip codes where less than 50% of the employed population are active-duty members of the US Armed Forces in 2021. Subprime consumers have Vantage scores below 600. Red vertical line represents 36% APR.

Table A1 - Credit Health of Subprime Military Community Residents and Comparison Group in August 2015 that Appear in the 2021 Wave

Credit Health Metric	Military Community	Comparison Group	*p*-value
Vantage Score	537.07	535.75	0.479
Access to Open-End Credit			
Credit Card Limit ($)	3,182	3,024	0.710
Has Credit Card	55%	54%	0.698
Delinquency			
Revolving Loan Delinquency (60+)	15%	16%	0.751
Has Debt in Collections	76%	80%	0.038
Other			
Ages 18–24	36%	33%	0.611
Ages 25–39	53%	53%	0.252
Ages 40–64	11%	14%	0.017
Age Missing	0%	0%	0.624
Zip Code Characteristics			
Share Black or Hispanic	32%	32%	0.338
Share with Health Insurance	97%	97%	0.085
Region of Residence			
Midwest (North Central)	10%	9%	0.104
Northeast	3%	3%	0.344
South	59%	63%	0.000
West	28%	25%	0.000
# Individuals	1,453	1,537 (weighted)	

Note: *P*-value comes from weighted *t*-test between matched treatment and comparison units that appear in the 2021 wave.

Table A2 - Credit Health of Subprime Military Community Residents and Comparison Group in August 2015, Military Base definition

Characteristic	Matched		Effect Size	*p*-value	All US
	Military Community	Comparison Group			
Vantage Score	537.7	538.7	0.024	0.300	532.8
Access to Open-End Credit					
Credit Card Limit ($)	2,630	2,562	-0.008	0.730	1,528
Has Credit Card	37%	37%	-0.006	0.788	22%
Delinquency					
Revolving Loan Delinquency (60+)	12%	12%	0.014	0.559	8%
Has Debt in Collections	80%	81%	0.015	0.511	86%
Other					
Ages 18–24	22%	21%	-0.027	0.249	12%
Ages 25–39	41%	43%	0.027	0.252	33%
Age Missing	19%	19%	0.003	0.904	20%
Region of Residence					
Midwest (North Central)	6%	6%	0.000	NA	21%
Northeast	2%	2%	0.000	NA	9%
South	50%	50%	0.000	NA	46%
West	42%	42%	0.000	NA	24%
Military Definition					
Share Employed Military	48%	1%			0%
# Individuals	3,605	2,556 (unweighted)			1,400,267

Notes: Weighted means calculated for matched comparison units. Cohen's D effect size calculated for difference between matched treatment and comparison groups. *P*-value shown for results of weighted *t*-test between matched treatment and comparison groups. All variables shown were matching variables, except share military. An exact match was conducted on region.

Table A3 – Baseline Characteristics of Military Communities and Comparison Communities in August 2015, Zip Code Level Analysis

Characteristic	Matched		Effect Size	*p*-value
	Military Community	Comparison Group		
Vantage Score	644.5	643.9	0.006	0.943
Access to Open-end Credit				
Credit Card Limit ($)	9,988	12,705	0.166	0.068
Has Credit Card	57%	66%	0.290	0.001
Delinquency				
Revolving Loan Delinquency (60+)	6%	8%	0.091	0.291
Has Debt in Collections	27%	25%	0.061	0.493
Other				
Ages 18–24	36%	37%	0.028	0.769
Ages 25–39	34%	38%	0.098	0.274
Age Missing	14%	13%	0.069	0.459
Zip Code Characteristics				
Share Black or Hispanic	29%	27%	0.087	0.296
Share with Health Insurance above Median	69%	65%	0.091	0.398
#Communities	131	207		

Notes: Weighted means calculated for matched comparison units. Cohen's D effect size calculated for difference between matched treatment and comparison groups. *P*-value shown for results of weighted *t*-test between matched treatment and comparison groups. All variables shown were matching variables.