WINNERS AND LOSERS OF MARKETPLACE LENDING: EVIDENCE FROM BORROWER CREDIT DYNAMICS*

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Abstract

We study whether marketplace lending (MPL) platforms benefit borrowers by analyzing monthly credit bureau data for participants on a major platform. We find that credit card balances are halved following MPL origination, which elevates credit scores. Compared to similar non-borrowers in the same ZIP (or ZIP+4), MPL-induced debt consolidation raises the probability of crossing *ad-hoc* lending market credit score thresholds for borrowers, which spurs additional lending from banks, and higher aggregate indebtedness. Consequently, credit card defaults spike, especially for subprime borrowers. Our results highlight how MPLs trigger information cascades to banks through credit scores, which leaves some borrowers worse off.

Keywords: FinTech, Marketplace Lending, Consumer Credit, Credit Cards, Defaults, Subprime Borrowers

JEL Classification Codes: D12, D14, G21, G23, O30, O33

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I. Introduction

Consumer lending accounts for a significant share of the U.S. economy, accounting for \$3.6 trillion as of 2017. Banks are the primary providers of credit to most consumers. As financial intermediaries, banks specialize in the screening and monitoring of borrowers and enjoy economies of scale in reducing information asymmetries in the credit market. However, significant frictions remain in the credit market[1], especially for applicants who are more reliant on soft information. In addition, despite ultra-low short-term interest rates over the last several years, the interest rates charged on credit cards and personal loans are high, even for applicants of high credit quality (Stango and Zinman, 2009).

As a result of these imperfections in the credit market, several financial technology innovators have entered the credit markets in the last decade, including marketplace lending (MPL) platforms that specialize in peer-to-peer (P2P) lending.[2] These MPLs facilitate lending by directly connecting small businesses and individual borrowers with investors through online platforms. MPLs attempt to differentiate themselves from traditional banks through the use of non-traditional data and alternative algorithms and they engage in different interest rate pricing schemes. These FinTech players, while still a very small segment of the market, have grown rapidly in terms of lending volume.[3] In this paper, we analyze whether borrowers on these MPL platforms benefit from their unsecured consumer lending.

Specifically, we aim to address the following issues in this paper. First, given that MPLs typically do not have mechanisms in place to monitor the actual usage of borrowed funds, we analyze whether the stated aim of debt consolidation is misreported on loan applications. Second, using comprehensive credit bureau data, we create cohorts of MPL borrowers matched to non-MPL borrowers in the same ZIP code (or ZIP+4) who have identical credit dynamics. We then analyze whether MPL borrowing impacts the borrower's credit scores, subsequent credit availability from traditional lenders, and their credit utilization. Third, we conduct a cross-sectional analysis of the subsequent credit dynamics and default experiences of borrowers. This analysis is an attempt to identify the underlying mechanisms that drive some of the potential benefits or costs for MPL borrowers.

[1]For example, information asymmetry results in imperfect pooling of borrowers of varying credit risk (Leland and Pyle, 1977) or even credit rationing (Stiglitz and Weiss, 1981).

[2]Other contributors may be changes in consumer attitudes and technology (such as easier availability of alternative consumer data, improvements in machine learning, and cheaper cloud processing). Also, over time, in contrast to the original focus on retail peer lenders, MPL platforms seem to increasingly rely on institutional capital.

[3]Lending Club, a major marketplace lender has disbursed around \$31 billion in loans over the last decade, with a sixfold increase in MPL loan origination from 2013 to 2015. See `https://bit.ly/2E6hsuN`

As a first step, we study the characteristics of individuals who borrow on a major MPL platform. We use anonymized individual-level data, complete with rich dynamics at the year-month level and with narrow geographic information, which are made available to us by a credit bureau. Using this data, we identify approximately one million borrowers on the platform in the month immediately before MPL loan origination, and we compare these borrowers to a nationally representative 5% random sample of the U.S. population. Our findings suggest that MPL borrowers are more financially constrained relative to the average adult in the U.S. These borrowers have twice as many credit cards and over twice the average credit card debt relative to the national average. Most tellingly, their credit utilization ratio is 69%, which is over twice the national average of 30%. Additionally, MPL borrowers have average credit scores that are more than 20 points below the national average and a striking 80 points below the U.S. homeowners' average.

Among the loan applicants on MPL platforms in the U.S., more than 70% state that their primary reason for requesting funds is "expensive debt consolidation" to pay off more expensive debt and replace it with monthly amortized payments. This is consistent with MPL users being more financially constrained. However, MPL platforms have no mechanism in place to ensure that borrowed funds are used consistently with the reasons stated on applications. Despite their non-verifiability, however, Michels (2012) documents that the reasons stated on MPL loan applications affect both the probability of receiving funding as well as the rates charged on disbursed funds. Moreover, given the unsecured nature of P2P lending, investors face the risks of both falsification on loan applications as well as potential borrower defaults. Thus, the prevalence of strategic misreporting on MPL loan applications is an important unanswered question that our rich credit dynamics allow us to answer.

Our results suggest that misreporting on MPL loan applications is rare: Borrowers seem to use MPL funds for debt consolidation purposes as evidenced by the significant decrease in their credit utilization ratios immediately after receiving the MPL loans. More importantly, these borrowers consolidate only their most expensive debt: credit cards. We do not observe a significant incidence of inefficient consolidation of auto, mortgage, or student loans. We observe that credit card balances drop by approximately 47% in the quarter of MPL loan origination relative to pre-origination levels. This consolidation activity is also reflected in utilization ratios, which drop by approximately 12% in the quarter of MPL loan origination. The average credit score rises by nearly 3% in the quarter of MPL loan origination.

How long do these credit profile improvements last? Our evidence suggests that it depends on the actions of borrowers following MPL-induced debt consolidation. We find that in the quarter after MPL loan origination, borrowers revert to racking up their credit card debt. Three quarters after loan origination, MPL borrowers carry as much credit card debt as they did before origination. First, this indicates that MPL loans provide only temporary debt relief. These loans do not change the fundamental credit behavior of borrowers who are deeply indebted and financially constrained. Second, these borrowers do not actually reduce their aggregate indebtedness through MPL-induced credit card debt consolidation; rather, expensive credit card debt is simply transferred to a separate installment account, which is charged a relatively lower rate. Thus, when these borrowers resume their accumulation of credit card debt after consolidation, they in fact become more indebted (in an aggregate sense), since they are now faced with paying down both borrowed MPL funds and their newly accrued credit card debt.

More strikingly, increased credit card consumption after MPL loan origination is aided by an increase in credit card limits from traditional banking intermediaries. It appears that, influenced by the temporary consolidation-induced drop in utilization ratios, some banks extend additional credit to these borrowers at a greater rate in the months following MPL loan origination.[4] This allows MPL borrowers to consume on credit cards at pre-origination levels, while still maintaining utilization ratios below pre-origination levels.

We find that the probability of credit card default is 10 to 13 times higher one year after MPL loan origination relative to pre-origination levels. This is consistent with the idea that increased levels of debt positively correlate with the risk of default. Taken together, our findings suggest that the cascading of information from an MPL platform to a banking intermediary results in potentially inefficient extension of credit and higher defaults among borrowers who are already financially weaker. It is also important to note that while default probabilities on credit cards rise sharply following MPL loan origination, defaults on the MPL loan itself are not common. It appears that when these borrowers encounter financial distress after origination, they focus on repaying MPL loans at the expense of loans made by traditional banks.

A potential concern with our approach is that our results may be driven by certain omitted variables that are specific to the MPL borrower and independent of the origination of the MPL loan. However, our results show that MPL borrowers do consolidate credit after MPL loan origination, but they default at a higher rate later. So, an omitted borrower-specific variable is unlikely to explain both our ex ante and our ex post results. Moreover, our findings show that MPL borrower credit scores are stable in the year leading up to MPL loan origination, and these scores only begin to fluctuate in the

[4] Broadly, our results indicate that increases in credit card limits are associated with increased credit card indebtedness, consistent with the findings of Gross and Souleles (2002).

quarter of origination. This indicates that any possible unaccounted factor that could explain our findings does not relate to information in the credit files of these borrowers. Some non-credit file factors, such as monthly income or changes in occupation, might explain one facet of our results. However, we confirm that our results are not driven by changes in job or income. Moreover, we control for both these factors in our empirical specifications to reduce concerns that omitted variables may be driving our results.

We also verify that our observed results are not simply a manifestation of economic conditions local to the MPL borrower but instead are completely exogenous to the origination of the MPL loan itself. It is certainly possible that bank profitability estimates at the local regional level and time-varying trends may be driving some of our results. The higher credit card default rates can be driven entirely by negative regional economic shocks. However, we include (5-digit) ZIP code $\times$ year-quarter fixed effects to capture any regional time-varying trends. Hence, it is unlikely that any omitted borrower-specific variables that change at the time of the MPL loan are responsible for our results.

Finally, we address the issue that borrowing from MPL platforms is endogenous. We implement a modified k-nearest neighbors (kNN) algorithm to create cohorts of MPL borrowers matched to their geographically and socioeconomically proximate non-MPL borrowing neighbors. In our baseline matching approach, we match MPL borrowers to non-borrowers residing in the same (5-digit) ZIP code in calendar time. The average 5-digit ZIP code population in the U.S. is approximately 7,500 people[5], which enables the identification of such "neighbors" at a narrow geographic level.

Within each cohort, we ensure that MPL borrowers and their non-borrowing neighbors display identical credit dynamics during the time leading up to MPL loan origination by the borrowers. Thus, within each cohort, the only factor that differentiates an MPL borrower from her neighbor is the origination of the MPL loan itself. In additional robustness tests, we implement the kNN algorithm at the 9-digit ZIP code (ZIP+4) level, which limits our analysis to a smaller number of cohorts.[6] The origination of an MPL loan drastically alters the credit dynamics of the borrower when compared to her neighbors within the same cohort. This finding holds regardless of the matching approach used, and it holds despite the fact that the borrower and her cohort neighbor share identical trends in their credit profile characteristics in the year leading up to the MPL loan origination.

We also perform cross-sectional tests, and we study the credit behavior of subprime,

[5]Statistics on ZIP codes can be found at `https://www.zip-codes.com/zip-code-statistics.asp`.

[6]Summary statistics generated using the U.S. credit file suggest that the average and median population of 9-digit ZIP codes in the United States is under 10 people.

near-prime, and prime MPL borrowers. The subprime, near-prime, and prime segments account for 23%, 50%, and 27% of the MPL borrower base, respectively. We find that credit card debt consolidation activity is weakest (strongest) for the subprime (prime) segment.[7] Moreover, we find that the increase in traditional credit limits is concentrated among borrowers who were subprime or near-prime before MPL loan origination. Finally, our analysis of defaults reveals that the increase in default probabilities following MPL loan origination is largest (smallest) in the subprime (prime) segment. Moreover, even in the subprime segment, we find that financially distressed MPL borrowers choose to default on credit cards rather than defaulting on the MPL loan itself.

Next, we examine the factors driving the strong growth in credit limits on existing credit cards for subprime and near-prime MPL borrowers in the post-MPL loan origination period. Through cohort-level analysis, we document that, relative to their subprime neighbors, subprime MPL borrowers experience a 5.55% increase in their credit score in the quarter of MPL loan origination. This means that, relative to non-MPL borrowers, the credit score of a subprime MPL borrower is 34% more likely to exceed 620, which is the threshold between subprime and near-prime credit scores. Consequently, subprime MPL borrowers experience significantly stronger credit limit growth relative to their non-borrowing subprime neighbors. Similarly, relative to their near-prime non-MPL neighbors, the credit score of a near-prime MPL borrower is 30% more likely to exceed 680, which is the threshold between near-prime and prime credit scores. Subsequently, they also enjoy higher credit limit growth relative to their neighbors.

Taken together, our findings regarding credit limit extensions suggest that bank decisions are heavily influenced by the temporary increase in credit scores that MPL borrowers enjoy due to the debt consolidation activity induced by MPL loans. While we cannot altogether rule out the possibility that banks infer MPL borrower quality through information spillovers generated by MPL platforms (as described in the context of information cascades studied in Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992)), we document that such spillovers – if they occur at all – operate through the borrower's credit score. MPL loans also allow borrowers to transition across the thresholds between subprime and near-prime credit scores and between near-prime and prime credit scores. In this context, our findings are more consistent with Rajan, Seru, and Vig (2015), who document that bank lending decisions have become increasingly credit score-centric over the years. These findings are also in line with Agarwal, Chomsiseng-

[7]Our findings suggest that the subprime segment consolidates the least amount of credit card debt, and is the quickest to revert to consuming on credit cards. Broadly, this highlights the role of liquidity constraints, consistent with arguments posed in Gross and Souleles (2002) and Agarwal, Liu, and Souleles (2007).

phet, Mahoney, and Stroebel (2018), who find that banks' marginal propensity to lend is increasing in borrowers' credit scores.

Our paper relates to several strands of literature. First, it adds to the extant MPL literature on consumer credit, which has focused primarily on two areas. The first broad area deals with lending decisions within online lending platforms. Freedman and Jin (2011) and Lin, Prabhala, and Viswanathan (2013) show that online lenders utilize social networks and verifiable community relationships to overcome adverse selection. In a more recent paper, Hildebrand, Puri, and Rocholl (2016) document that group leader bids in the presence of origination fees alter the market's perception of the credit quality of the borrower. Moreover, Iyer et al. (2015) document that, relative to using credit scores alone, peer lenders are more accurate when predicting the borrowers' likelihood of defaulting on loans.[8] Finally, utilizing a panel of MPL platform investors, Paravisini, Rappoport, and Ravina (2016) document negative investor-specific wealth elasticities, and a positive relationship between relative risk aversion and investor wealth in the cross-section.[9]

A second strand of literature focuses on borrower-specific determinants of (a) the probability of funding success and (b) the interest rates charged on peer-financed loans in the consumer credit space, such as beauty (Ravina, 2012), age and race (Pope and Sydnor, 2011), appearance of trustworthiness (Duarte, Siegel, and Young, 2012), non-verifiable reasons on online MPL loan applications (Michels, 2012), and stereotypes (Hasan, He, and Lu, 2018).[10] In contrast, our paper focuses on the utilization of MPL funds and on some of the potential benefits or costs generated for MPL borrowers.

Our paper also contributes to the growing literature on the interaction between banking intermediaries and FinTech lenders. In the consumer credit space, Jagtiani and Lemieux (2017) show that MPL platforms have penetrated areas where bank branches have closed and areas that have highly concentrated banking markets. They argue in favor of credit expansion through financial technology to creditworthy borrowers who are not served by banks. On the opposite side, Wolfe and Yoo (2017) document that small, rural commercial banks lose lending volume to MPL platforms, which suggests

[8]Berg et al. (2018) also highlight the benefits of alternative data by documenting that customer creditworthiness, as judged through their "digital footprint" on a German E-Commerce website, produces information content which is superior to that of credit bureau scores.

[9]Hertzberg, Liberman, and Paravisini (2018) analyze MPL decisions from the perspective of borrowers, and document that MPL borrowers self-select into loans of differing maturities depending on their future ability to repay, i.e., on the basis of private information unavailable to lenders, and that this self-selection influences future default rates.

[10]In the mortgage setting, Bartlett et al. (2018) document that ethnicity plays a statistically and economically significant role in loan rejection rates. The authors note, however, that FinTech lenders are less likely to discriminate than traditional lenders.

nontrivial credit substitution. Buchak et al. (2017) document that shadow banks in the mortgage space gained a larger market share among less creditworthy borrowers, and these banks filled the gap left behind by credit contraction among traditional banks in areas where traditional lenders face more regulatory and capital constraints. Within this subset of shadow banks, FinTech lenders account for approximately 25% of shadow bank originations, serving more creditworthy borrowers. We contribute to this literature by documenting that traditional banks appear to utilize information generated by MPL platforms, albeit through borrowers' credit scores.

Two contemporary papers that closely relate to ours are Demyanyk, Loutskina, and Kolliner (2017) and Balyuk (2018). In contrast to one of our results, Demyanyk et al. (2017) suggest that MPL funds are not used for debt consolidation purposes. However, due to data constraints, their analysis is conducted at the individual-year level. On the other hand, access to rich credit bureau data allows us to track MPL borrowers in the months surrounding MPL loan origination. Our results show that most MPL-induced credit profile changes occur in the months immediately following MPL loan origination, and traditional lenders react to the MPL-induced credit card debt consolidation by providing more credit to these borrowers. The high granularity of our data also allows us to implement stringent specifications that track credit dynamics more accurately. Moreover, our cross-sectional results help us identify the subprime MPL borrower segment as being most susceptible to ex post credit card defaults.

Similar to one of our results, Balyuk (2018) also finds that credit limits on existing credit cards increase post-MPL loan origination, but finds no evidence that increased access to credit results in higher delinquencies. However, our results suggest that MPL loan-induced credit limit extensions are ex post inefficient for one-quarter of the borrowers, leading to overborrowing for subprime borrowers. Contrary to Balyuk (2018), but consistent with Demyanyk et al. (2017), we find a higher incidence of credit card defaults among MPL borrowers. In addition, our results strongly suggest that credit limit extension decisions are heavily influenced by the short-term improvements in credit scores induced by MPL activity, in line with the arguments made in Rajan, Seru, and Vig (2015). Moreover, due to data constraints, the analysis in Balyuk (2018) is limited to individuals who apply multiple times on MPL platforms, a small portion of the MPL borrowers; also, such individuals are only tracked at the time of MPL loan application. On the other hand, our analysis focuses on one-time MPL borrowers, who account for over 80% of all MPL borrowers. In addition, our data allow us to track these borrowers over time and compare them to their neighbors in the same ZIP (or ZIP+4) code with identical credit dynamics before the origination of the MPL loan.

The rest of the paper is organized as follows. In Section II, we provide institutional details on marketplace lending, and discuss our data sources. In Section III, we discuss our empirical methodology and describe identification challenges. In Section IV, we present our main findings and robustness tests. In Section V, we provide a discussion of our results and identify the winners and losers from MPL borrowing through examination of cross-sectional cuts. In Section V, we also discuss whether MPL loans alter the perceived creditworthiness of borrowers. We conclude in Section VI.

II. Institutional Background And Data Sources

A. Institutional Background Of Marketplace Lending

The mid-2000s witnessed the advent of peer-to-peer lending (P2P lending) or marketplace lending (MPL) as an alternative investment with the goal of revolutionizing the centuries-old traditional banking model. Marketplace lenders promote themselves as cutting out the "middle man" (intermediary banking institutions) and directly connecting individual borrowers and lenders. Banks and other credit agencies have historically been the primary source for personal loans, owing to their advantages over individual lenders in terms of information and diversification. Although banks have greater information generation capacity relative to individual lenders, individual borrowers are still more knowledgeable about their risk profiles than banks. This information asymmetry results in average pricing on credit instruments (similar to the pooling equilibrium considered in Akerlof (1970) and Leland and Pyle (1977)) as well as rationing of certain categories of borrowers (Stiglitz and Weiss, 1981). Average pricing is especially an issue, since high-credit-quality borrowers subsidize low-quality borrowers. In addition, marginal-quality borrowers are unable to differentiate themselves from low-quality borrowers, and end up being rationed out of the market.

MPLs have attempted to incorporate some of the advantages of banks while also overcoming some of their shortcomings. Individual investors are provided the option to partially fund loan listings, thus enabling them to diversify their peer-to-peer lending portfolios by co-investing in one loan with multiple other lenders. To assist investors, MPLs also provide borrower credit profile information that was previously available exclusively to banks, thus reducing information asymmetry between borrowers and lenders on such platforms.[11] Moreover, MPLs function completely online; thus, unlike banks, they do not incur the fixed investment costs of setting up and maintaining brick-and-mortar branches. Phillippon (2015) shows that the cost of traditional financial intermediaries in

[11]Such information includes FICO credit scores, past delinquencies, revolving credit balances, utilization ratios, monthly income, and the debt-to-income ratio of the loan applicant.

the United States has remained between 1.5–2% of intermediated assets over the last 30 years. However, a recent Lending Club (one of the largest MPL platforms in the United States) report shows that Lending Club carries a 60% lower operational cost than banks due to its electronic services.[12]

A.1. The Peer-to-Peer Loan Application Process

Prospective MPL borrwers are required to submit an online application, and this service is only available to individuals with a bank account. Thus, the unbanked population is not eligible for MPL loans. The borrower submits the requested loan amount, her annual income, and employment status. In addition, prospective borrowers also provide the intended purpose of the requested funds. Once the application is complete, the MPL platform makes a soft credit check into the borrower's credit history and pulls the borrower's credit score, debt, credit utilization ratios, the number of accounts under the borrower's name, and the outstanding balances on these accounts. Using both the self-reported data and the credit report, the lending platform develops an interest rate quote, which becomes the preset interest rate at which the loan will be provided if it is originated.

MPLs provide unsecured loans for successful loan applications. As mentioned earlier, prospective borrowers are required to provide the intended purpose of the borrowed funds. Reasons provided in the loan applications range from debt consolidation to medical bills to financing various kinds of conspicuous consumption. It is important to note, however, that MPLs do not have any mechanism in place to ensure that borrowed funds are used for the purpose stated in the loan application. Thus, it is unclear whether borrowers actually use loan funds for their stated purpose or they simply "game the system" to increase the probability of loan origination.[13]

B. Data And Descriptive Statistics

In this section, we discuss the sources used to construct our data, and we describe the data cleaning process. All the data sources described below are used purely for academic purposes and contain completely anonymized information made available to us through a credit bureau. In addition, we also provide summary statistics that compare the credit characteristics of MPL platform borrowers to a 5% random sample of the

[12]http://lendingmemo.com/wp-content/uploads/2013/08/1.pdf

[13]In the older model of MPL, investors were required to bid against one another on the basis of interest rates charged on MPL loans to prospective borrowers. In this older regime, Michels (2012) finds that providing a reason on the loan application significantly increases the probability of the loan being funded.

national population, and to a 33% random sample of homeowners in the United States.

B.1. Data Sources: Trades File

Through the credit bureau's trade line-level data, we have access to comprehensive records of the various lines of credit opened by every U.S. resident. These reported lines of credit span many domains such, as mortgage, auto, student loans, credit cards, personal/business loans, and utilities. Each credit line is associated with a bureau-generated individual key to identify the borrower. The MPL platform we consider for our analysis is one of the largest in the U.S. We first identify all individuals who have opened an installment trade on the MPL platform from 2011–2016.

In order to ensure the validity of the records, we consider only those MPL trade lines associated with non-missing start dates and positive balances at the time of loan origination. In addition, we require that MPL accounts with balances equal to zero are associated with non-missing closing dates. For our analysis, we focus only on one-time MPL platform borrowers from 2011–2016. Thus, we exclude individuals who have borrowed multiple times from the MPL, which reduces concerns of strategic borrower behavior and eliminates contamination from our analysis of post-loan origination credit behavior. Following our data cleaning process, we are left with approximately one million individuals who opened a single MPL-funded credit line from 2011–2016.

B.2. Data Sources: Attributes File

We use the credit bureau's attributes file to study the credit profile evolution of MPL platform borrowers in the months leading up to and following the origination of the MPL loan. The attributes files contains information on inquiries, balances, utilization ratios, and credit limits in the domains of mortgages, auto loans, student loans, and revolving credit (i.e., credit cards). This information is available in the form of monthly snapshots at the individual level.

We merge the attributes file with the MPL borrower data gathered from the trades file. We merge these data based on the individual identifier. For every MPL borrower, we merge in the inquiries, balances, utilization ratio, and credit limit information from the attributes file for the 25-month window centered on the month in which the MPL platform borrower originates the MPL loan. Next, we remove any individuals who have invalid information for any variables relevant to our analysis at any point in the 25-month window under consideration. For the subset of individuals with valid credit attributes, we winsorize the numerical variables at the 1% and 99% levels.

B.3. Data Sources: Scores File

The scores file provides us with data on individual credit scores at a monthly frequency. The MPL platform we study generates its interest rate quotes using FICO scores. However, FICO scores are owned by the Fair Issac Corporation and not by any of the credit reporting agencies (CRAs), so CRAs can incur significant fees by using FICO scores. Therefore, we use the Vantage 3.0 score, which is highly positively correlated with all three FICO scores.[14] We map every MPL borrower from the trades file to the scores file for the 25-month window centered on the month in which the MPL loan is originated. We exclude individuals with invalid Vantage 3.0 scores (i.e., below 300 or above 850) at any point from our analyses.

B.4. Data Sources: Demographics File

The Demographics file contains information on individual monthly income, occupation, education level, homeownership status, location, and various other socioeconomic measures. The data in this file are matched to MPL borrowers from the merged Trades-Attributes-Scores file on the basis of the individual key.[15]

The variables gathered from the Demographics file serve as control variables in our empirical analysis. Demographics data are only available starting from June, 2013. Thus, when conducting multivariate analysis, our sample is restricted to studying individuals who opened MPL trades between June 2013 and December 2016.

B.5. Data Sources: Performance File

The Performance file keeps detailed records of the financial health of all individuals along broad trade lines, and these records are available at the monthly frequency. For our analysis, we define *default* as being 90 days past due on a required payment on an open credit line. We set an indicator variable equal to 1 starting from the month in which the individual is considered to be officially in default, and 0 otherwise. This measure is

[14]According to a Fall 2012 report, the Consumer Financial Protection Bureau (CFPB) found that for a large majority of consumers in the United States, the scores produced by different scoring models provided similar information about the relative creditworthiness of the consumers. That is, if a consumer had a good score from one scoring model, the same consumer was likely to receive a good score using an alternative scoring criteria. In fact, correlations across the results of scoring models were high, and generally over 90%. Source: `http://files.consumerfinance.gov/f/201209_Analysis_Differences_Consumer_Credit.pdf`

[15]Unlike the Attributes and Scores files, demographic information is available at the individual level every six weeks. Thus, for months in which we do not find a direct match between the Demographics file and the merged Trades-Attributes-Scores file, we impute the relevant variables using the most recently available Demographics archive.

then aggregated at the individual level across all open credit lines in four broad credit domains: *auto*, *mortgage*, *student debt*, and *credit cards*.

B.6. Descriptive Statistics

In this section, we compare the profile characteristics of all MPL borrowers at the time of MPL loan origination to a 5% random sample of the total U.S. population and to a 33% random sample of homeowners as identified in the credit file. The results presented in Table I help us identify whether the credit, income, and default risk profiles of MPL borrowers differ significantly from the average consumer in the U.S.

The results presented in Panel A highlight that MPL borrowers have more open trades compared to the national average and compared to the homeowners sample average. This difference is stark for open credit card trades; MPL borrowers have more than twice as many open trades in this domain relative to both the national average and the homeowners sample average. Moreover, MPL borrowers owe more than twice the national average in credit card debt, and they have credit utilization ratios over twice the national average and over twice the U.S. homeowners average. We find that MPL borrowers have significantly lower credit scores than both control samples, and this is consistent with higher indebtedness being positively linked to a higher probability of default. Finally, MPL borrowers have debt-to-income (DTI) ratios that are comparable to the U.S. homeowners sample despite having an average mortgage balance that is approximately $85,000 lower. This indicates that their high DTI ratios can be attributed to lower income and higher non-mortgage debt.

III. Empirical Methodology And Threats To Identification

In this section, we describe the basic empirical approach we undertake to examine MPL loan-induced changes in the credit profiles of MPL borrowers. We also discuss some potential threats to our identification and how we address the self-selection and endogeneity concerns inherent in any analysis of MPL borrowing.

A. Base Specification

We examine how the origination of MPL loans changes the credit profiles of MPL borrowers along two broad domains: credit balances and default risk. In addition, we also examine whether these individual-level responses are complemented by credit expansionary or contractionary activities on the part of traditional banking intermediaries. Similar to Agarwal, Pan, and Qian (2016) and Agarwal, Qian, and Zou (2017), our empirical strategy utilizes individual-level data available at a monthly frequency and also studies the 25-month period centered on the month in which the MPL loan is originated.

We use the following regression model to estimate the average credit profile characteristics at the quarterly level:

$$ln(Y_{i,t}) = \sum_{\tau \neq -1} \beta_\tau Quarter_{i,\tau} + \gamma \mathbf{X}_{i,t} + \alpha_i + \delta_{yq} + \epsilon_{i,t}. \tag{1}$$

Our analysis includes observations at the individual level at a monthly frequency. The variable τ indicates quarters relative to the quarter of MPL loan origination, $Quarter_0$. We construct $Quarter_0$ as months [0,+3] in relation to the month of MPL loan origination. We choose τ to vary from -4 to +3, with $\tau = -1$ serving as the omitted category. Thus, $Quarter_{-1}$ ($Quarter_{+1}$) refers to months [-3,-1] (months [+4,+6]) in relation to the month of MPL loan origination. All other quarter indicators are defined in an analogous manner. α_i represents a vector of individual fixed effects, and δ_{yq} indicates a vector of year-quarter fixed effects.[16] Finally, $\mathbf{X}_{i,t}$ is a vector of individual-level time-varying controls, which includes monthly income, educational attainment, occupation, and homeownership status. The construction of all control variables is described in Appendix A.

The outcome variables we study using the above specification are balances along four broad trade lines: auto, mortgage, student debt, and credit cards. We also study how credit utilization ratios, credit limits, probabilities of default, and credit scores are influenced by the origination of MPL loans. For all our analyses, we double cluster our estimates at the individual and year-quarter level, unless specified otherwise.[17]

As described above, $Quarter_{-1}$ is the omitted category, and we refer to it as the *baseline period* in our analyses. Our empirical approach can be interpreted as an event study. The β coefficients in the above specification represent percentage differences from this baseline period, i.e., differences from the quarter prior to MPL loan origination.

B. Threats To Identification

B.1. Regional Economic Factors

Our baseline specification includes vectors of fixed effects that capture time-invariant, individual-specific trends and individual-invariant, time-specific trends. However, one possible issue is that our results could be driven by shocks at the geographic level that are exogenous to borrowers on MPL platforms. This could especially pose a problem

[16] Our results are unaffected if we replace year-quarter fixed effects with year-month fixed effects.

[17] Our results are also robust to double clustering at the individual and year-month levels.

for our results regarding credit expansion or credit contraction, since these practices are heavily dependent on the profitability estimates of bank branches at the state or county level. Moreover, negative region-specific economic shocks could explain default patterns unrelated to MPL borrowing activity. Thus, we re-estimate Equation (1) by replacing the vector of year-quarter fixed effects with a vector of (5-digit) ZIP code $\times$ year-quarter fixed effects, which allows us to capture time-varying trends within 5-digit ZIP codes.

B.2. Endogeneity Concerns Of Engaging On MPL Platforms

Our regression specification relies on identifying MPL borrowers as reported to the credit bureau by the MPL platform. However, this raises questions about individuals of certain specific characteristics self-selecting into borrowing from such online platforms. Thus, with our baseline specification, it is difficult to completely attribute our findings to the origination of the MPL loan, since our findings could be partially or fully driven by the above-mentioned selection bias. In order to mitigate these concerns, we attempt to create a matched sample of non-MPL borrowers that are similar on all dimensions to MPL borrowers with the only differentiating factor between the groups being the origination of MPL loans by MPL borrowers.

We utilize a modified k-nearest neighbors (k-NN) algorithm in order to construct our control sample of non-MPL borrowers. As a first step, for every MPL borrower, we identify all geographically proximate neighbors from the same 5-digit ZIP code during the month of MPL loan origination. Given that the average population of a 5-digit ZIP in the United States is approximately 7,500 people, this first step allows us to select non-borrowing neighbors from a relatively narrow geographical space. We ensure that individuals who fall in this neighbor sample belong to households other than the MPL borrower's household. Moreover, by identifying non-borrowing neighbors from the same 5-digit ZIP code in the month of MPL loan origination, we implicitly account for region-time-specific shocks. Our approach thus facilitates a cohort-level analysis, in which a cohort refers to each matched pair of an MPL borrower and her geographically proximate neighbors. Moreover, since cohorts are created in calendar time, the pre- and post-MPL loan origination time periods are the same for both MPL borrowers and their non-borrowing neighbors.

One shortcoming of this approach so far is that in our large set of identified neighbors, we also identify people who do not require additional credit. In this case, it is possible that a substantial segment of our identified neighbor population differs from MPL borrowers, who engage in MPL platforms because of additional credit requirements. Thus, within each cohort, we subset our large neighbor pool to include only those neighbors who have hard credit checks performed against them by banks in the three months before the month of MPL loan origination by the MPL borrower. In addition, we add filters to identify specifically those neighbors who do not receive additional credit through the extensive margin (new credit cards) or intensive margin (increased credit limits on existing credit cards). Hard credit checks or "hard pulls" are helpful in identifying individuals who "need" credit, since they are only performed by creditors following consumer-initiated actions. Moreover, hard pulls negatively impact consumer credit scores, and remain on consumers' credit reports for an extended period of time.[18] Thus, inquiries of this kind help identify individuals who have a "serious interest" in obtaining additional credit. The application of these filters within each cohort help identify non-MPL borrowing neighbors whose "need" for bank credit remains unfulfilled.[19]

In order to ease the computation associated with the k-NN algorithm, we subset the data to account only for neighbors whose credit card utilization ratios, credit card balances, and credit scores are within 10% of the MPL borrowing individual in their cohort in each of the three months before the month of MPL loan origination. Finally, we run the k-NN algorithm to identify the nearest single neighbor to every MPL borrower. The matching dimensions we use are credit score, credit card utilization ratio, the total number of open trade accounts, the number of credit card accounts, total credit card balance, monthly income, and the debt-to-income ratio. We choose these matching criteria because the descriptive statistics presented in Table I suggest that MPL borrowers differ most from the average U.S. population along these dimensions. In effect, we identify separate cohorts of MPL borrowers and their closest geographically and socioeconomically proximate neighbors. We refer to this matching approach as our *baseline* matching approach, and provide a detailed explanation of the matched-sample generation process in Appendix B.

As further robustness checks, we create additional matched samples of MPL borrowers and their non-borrowing neighbors using two variants of the "baseline" approach described above. The first variant relies on identifying MPL borrowers who are unsuccessful in acquiring bank credit in the three months before the month of MPL loan origination. Each of these borrowers is then matched with the nearest non-MPL bor-

[18] Hard credit checks can lower credit scores by 5–10 points. More information on credit checks, and their effect on credit scores can be found here: https://www.myfico.com/credit-education/questions/how-do-inquiries-impact-credit-scores/

[19] Our approach allows us to identify neighbors who require additional bank credit, but our approach does not allow us to further differentiate between people who were outright denied credit by the bank from people who, through a revealed preference argument, rejected credit that was provided at unfavorable terms. In this sense, our approach is similar to that in Jiménez et al. (2012, 2014).

rowing neighbor from the same 5-digit ZIP code, with neighbors limited to include only individuals who have not received additional bank credit. Thus, this approach relies on creating cohorts of MPL borrowers and their closest non-MPL borrowing neighbors in which both groups have been unsuccessful in obtaining bank credit. After rejection by a bank, MPL borrowers use MPL platforms for credit, whereas their neighbors do not.

In the second variant, we identify neighbors who reside in the same 9-digit ZIP code as the MPL borrower. According to descriptive statistics generated using the credit file, the average population of a 9-digit ZIP code in the United States is fewer than 10 people. Moreover, individuals of similar socioeconomic characteristics tend to co-locate in the United States. Thus, this process identifies a much more homogeneous set of MPL borrowers and matched neighbors. The remaining steps in the matching process are similar to the baseline approach. Detailed descriptions of all matching approaches are provided in Appendix B.

In order to study how MPL borrowers differ from non-MPL borrowing neighbors, we make use of the following fixed-effects cross-sectional regression specification:

$$\overline{ln\left(\frac{Y_{i,c,t}}{Y_{i,c,t-1}}\right)} = MPL\_Borrower_{i,c} + \gamma\bar{\mathbf{X}}_{i,c,t} + \alpha_c + \epsilon_{i,c,t}. \tag{2}$$

In the above regression specification, $MPL\_Borrower$ is an indicator variable that equals 1 for individuals borrowing on the MPL platform, and 0 otherwise. The subscripts i, t, and c identify individuals, year-months, and separate cohorts of matched MPL borrowers and their closest non-MPL borrowing neighbors. The specification includes a vector of cohort fixed effects; thus, this specification induces within-cohort variation by comparing outcomes for MPL borrowers relative to their neighbors. Standard errors are clustered at the 5-digit ZIP code level.

We run this specification separately for the quarters following MPL loan origination by MPL borrowers. The dependent variables of interest are average credit card balance growth, average credit utilization growth, average credit card limit growth, credit card defaults, and average credit score growth (these averages are computed separately for each quarter following MPL loan origination).

IV. Main Results

In this section, we present our main empirical results, which examine whether the origination of MPL loans induces the consolidation of expensive debt. In addition, we study the effect on credit utilization ratios, credit scores, and ex post delinquencies and defaults. As part of this process, we also gather insights into whether these borrower responses are complemented by credit activities from banking intermediaries.

A. Do Borrowers Consolidate Debt Using MPL Loans? If So, What Kind Of Debt?

In this section, we use Equation (1) to study whether MPL borrowers consolidate debt in the aftermath of MPL loan origination. And, if borrowers do consolidate debt, we analyze the type of debt that is consolidated. The broad categories of trade lines we consider are auto loans, mortgages, student debt, and credit card debt. The results of this analysis are presented in the form of event study plots in Figure I. The x-axis in Figure I displays time, in quarters, relative to the quarter of MPL loan origination. The y-axis expresses percentage differences relative to balance levels in the quarter immediately preceding MPL loan origination, $Quarter_{-1}$, which serves as the absorbed or baseline period for the event study analysis.

The plot for auto debt indicates that auto balances are not affected by the origination of MPL loans. Indeed, auto balances appear to remain constant over the 25-month window centered on the month in which the MPL loan is originated. Similarly, the plots indicate that mortgage and student debt levels are also not influenced by MPL loan originations.

On the other hand, credit card balances appear to follow a very different pattern. MPL borrowers accrue credit card debt in the months leading up to MPL loan origination. In our event study plot, we document an upward trend in credit card balances in the pre-origination period. However, in the quarter of MPL loan origination, we find that credit card balance levels are significantly lower relative to that in the quarter immediately before MPL loan origination. However, we document an increasing trend in credit card balances in subsequent quarters. Three quarters after origination, we note that credit card balances are insignificantly different relative to the baseline period.

We also display our results in tabular form in Table II. In columns (I), (II), and (III), we show that auto, mortgage, and student loan balances, respectively, are not affected in an economically significant manner by MPL loan origination. In column (IV), we present results for credit card balances. We find that MPL borrowers tend to accrue credit card debt in the months leading up to MPL loan origination. We find that in the quarter of MPL loan origination, credit card balances are more than 47% lower relative to the quarter before origination, which is consistent with the consolidation of credit card debt.[20] However, we also note that this consolidation phase appears to be short lived. In

[20]The estimate on $Quarter_0$ is -0.639, or -63.9%. However, the dependent variable is the logged monthly credit card balance. Thus, the percentage change equivalent is given by $100 \times [exp(-0.639) - 1] = -47.22\%$.

subsequent quarters, these borrowers begin re-accumulating additional credit card debt, so that three quarters after origination, credit card balance levels are not significantly different from pre-origination levels.

Taken together, our findings suggest that borrowers utilize MPL funds in a manner consistent with the vast majority of stated reasons on MPL platform loan applications. Given how marketplace lending platforms have no mechanism in place to enforce the appropriate use of borrowed funds, this finding suggests that the commonly stated aim of debt consolidation is rarely misreported on loan applications. Moreover, these borrowers only focus on consolidating their most expensive debt. The average interest rates on auto, mortgage, and student debt are significantly lower than the 15–20% rates charged on unsecured credit cards, which is the focus of MPL loan-induced consolidation activity.

However, our results also highlight the transience of this debt consolidation and debt reduction activity. MPL borrowers are quick to accumulate credit card debt following a short period of consolidation, which suggests that MPL platforms fail to change the fundamental underlying consumption behavior of such borrowers. Moreover, in terms of credit card debt, these borrowers are just as indebted three quarters after origination as they were in the quarter before origination. This finding is rather problematic, since it is important to note that MPL-induced credit card debt consolidation does not reduce the aggregate debt exposure of the borrowing individual: Expensive credit card debt is simply replaced with relatively less expensive MPL debt. Thus, these borrowers are already burdened with the monthly payments associated with amortized MPL loans when they begin consuming credit card debt again. This sort of "double dipping" activity leaves such borrowers significantly more indebted in the months following MPL loan origination relative to pre-origination levels.

B. How Are Credit Card Utilization Ratios Affected?

In this section, we study how the consolidation of credit card debt in the immediate aftermath of MPL loan origination, followed by a sustained period of debt accumulation, affects the credit card utilization ratios of these borrowers. The results of this analysis are presented in the form of an event study plot in Figure II. The associated tabular form results are presented in column (I) of Table III.

An analysis of the pre-trends reveals that the credit card utilization ratio of MPL borrowers increases in the quarters leading up to MPL loan origination. However, in the quarter of origination, these borrowers have utilization ratios that are 12% lower relative to the baseline period. As these borrowers begin accumulating credit card debt again in the quarters following consolidation, we note a corresponding steady rise in utilization ratios. Finally, we note that three quarters after origination, utilization ratios are, on average, approximately 4% lower relative to the baseline period.

This plot highlights two important and interesting findings. First, in the quarter of MPL loan origination, when credit consolidation activity is strongest, utilization ratios are only 12% lower relative to pre-consolidation levels. Table I documents that, on average, MPL borrowers have utilization ratios of 69%. A drop of 12% in this value still yields a utilization ratio of 60.7%. Thus, even in their "healthiest" financial situation, these borrowers have utilization ratios that are nearly double the national average. This further serves to highlight the difficult financial situation of people engaging in such online platforms.

Second, from Table II, we note that three quarters after origination, these borrowers are just as indebted in terms of credit card debt as they were before origination. However, our analysis here reveals that three quarters following origination, these borrowers have credit card utilization ratios that are significantly lower relative to pre-origination levels. Given that the utilization ratio is calculated as:

$$Utilization = \frac{Credit\ Balance}{Credit\ Limit},$$

these findings suggest that MPL borrowers experience an increase in their credit card limits. Holding credit card balances constant, as is the case three quarters after MPL loan origination, the only way that utilization ratios can decline is if credit card limits have been extended in the interim period. We examine this channel formally in the next section.

C. Do MPL Loans Alter The Level Of Credit Supply On Credit Cards?

We study whether credit card limits are affected by the consolidation activity fueled by MPL loan origination. The results of this analysis are plotted in Figure III, and presented in column (II) of Table III.

Our results indicate that in the pre-origination period, monthly credit card limit growth is steady and not significantly different from the growth in the quarter before MPL loan origination. However, our estimates on $Quarter_0$ and $Quarter_{+1}$ indicate that monthly credit limit growth is approximately 0.59% (significant at the 5% level) and 0.83% (significant at the 5% level) in the quarter of MPL loan origination and the quarter immediately after loan origination, respectively. This finding suggests that after origination, the increase in credit card limits outpaces the increase in credit card balances. Therefore, the utilization ratio of these borrowers remains lower approximately three quarters after origination, even though they have the same credit card debt as they had before MPL loan origination.

D. Does The Origination Of MPL Loans Affect Borrower Default Probabilities?

Our previous analysis highlights how the origination of MPL loans results in an increase in the *rate* of month-to-month credit card limit growth, which enables these borrowers to consume additional credit card debt while also maintaining lower credit utilization ratios. In this section, we examine whether this extension of credit is ex post justified by analyzing probabilities of default on credit cards using a linear probability model. The results of this analysis are plotted in Figure IV, and presented in column (III) of Table III.

Our results highlight an approximate U-shape in credit card default probabilities that bottoms out near the quarter of MPL loan origination. We find that default probabilities are declining in the quarters leading up to the baseline period. However, following origination, credit card default probabilities begin to increase again. Indeed, the estimates on $Quarter_{+1}$, $Quarter_{+2}$, and $Quarter_{+3}$ indicate that credit card default probabilities are 0.29 percentage points (pp), 0.84 pp, and 1.47 pp higher in the [+4,+6], [+7,+9], and [+10,+12] month windows (all significant at the 1% level), respectively, relative to the baseline period. Given average credit card default occurrences of 0.12% in the baseline period, this finding indicates that the probability of defaulting on credit cards is 13 times higher at the 1-year mark after MPL loan origination. In comparison, the credit bureau data suggests that MPL borrowers have an average credit card default rate of 0.45% four quarters prior to origination. Thus, relative to the one-year mark *preceding* origination, MPL borrowers exhibit credit card default rates that are over 3 times higher one year *following* origination.

These findings lead us to conclude that traditional banking intermediaries over-extrapolate the temporary downturn in credit card debt facilitated by MPL-induced debt consolidation. Our findings from the previous sections suggest that credit card limit growth is strongest when credit card debt (and associated utilization ratios) are lowest. Thus, credit extension decisions are made before observing the subsequent upturn in credit accumulation. As a result, these borrowers, faced with paying down borrowed MPL funds as well as the additionally extended credit, begin to default at higher rates in the quarters following MPL loan origination.

More broadly, we also study whether MPL loan origination is associated with higher default rates in other forms of debt besides credit cards. The results of our analysis are presented in Table IV. In column (I) of Table IV, we display the default rates on credit cards, as shown in column (III) of Table III. As before, we note that credit card default rates are 1.47 pp higher three quarters after MPL loan origination relative to pre-origination levels. On the other hand, our estimates in columns (II), (III), and (IV) suggest that default rates in auto loans, mortgage loans, and student loans, respectively, are not significantly higher (in an economic sense). In column (V), we report results for default rates on installment loans, and we note that, here too, the origination of MPL loans is not associated with an economically significant rise in default rates three quarters after origination. The findings reported in column (V) are interesting because MPL loans, given their amortized repayment schedule, are recorded as installment loans. Thus, taken together, our findings in columns (I) and (V) of Table IV suggest that, after MPL loan origination, default rates spike for credit cards, but not for the MPL loan itself.

E. Do MPL Loans Affect Credit Scores?

We document the effect of MPL-induced credit card debt consolidation activity on the credit scores of borrowing individuals. The results of this analysis are plotted in Figure V, and presented in column (IV) of Table III.

Our findings indicate that the credit scores of these borrowers remain steady in the quarters leading up to the baseline period. In the quarter of MPL loan origination, credit scores are approximately 2.89%, or 19 points, higher relative to the baseline period (significant at the 1% level).[21] Our estimates for $Quarter_{+1}$ and $Quarter_{+2}$ also indicate that average credit scores in the [+4,+6] and [+7,+9] month windows are 1.5% and 0.5% higher relative to the baseline period. However, we also note that three quarters after origination, average credit scores are insignificantly different relative to the quarter before origination.

Thus, we note that the pattern of short-lived consolidation followed by long periods of debt accumulation is priced into credit scores, which spike when utilization ratios are temporarily deflated, and drop when utilization starts rising again, respectively. Three quarters after origination, these borrowers are as indebted as they were before origination and have higher default probabilities and higher default occurrences, which is reflected in credit scores that are not significantly different relative to the baseline period.

[21]Descriptive statistics presented in Table I show that the average credit score of MPL borrowers in the month immediately prior to loan origination is approximately 656. Thus, our coefficient estimate of 2.89% suggests that in the quarter of MPL loan origination, borrowers' credit scores increase by 19 points (*approx* 0.0289×656).

F. Robustness: Does Change In Employment Or Income Explain These Findings?

In this section, we study whether our results regarding increased credit limits on credit cards and spikes in credit card default rates in the post-MPL loan origination period can be explained through a change in the employment or income of the MPL borrower. It is important to note, however, that MPL loans differ from traditional loans only in means of origination, and thus, it is unlikely that they can impact the job profiles of individuals engaging in MPL platforms. Moreover, our findings also suggest that defaults on credit cards spike in the post-origination period; default rates on amortized MPL loans are economically negligible. Therefore, the job or income loss argument cannot explain both the higher rates of default on credit cards and the negligible rates of default on MPL loans.

In order to formally test this "job/income loss" hypothesis, we make use of Equation (1), and replace the dependent variable with a dependent variable that equals 1 if the individual's income in a given month differs from their income in the previous month, and 0 otherwise. The results of this analysis are presented in column (I) of Table V. We find that in the 12-month period before, and the 12-month period after the origination of MPL loans, the probability of income change remains stable. In fact, the estimate on $Quarter_0$ is -0.15% (significant at the 5% level), which suggests that the probability of monthly income changing is *lower* in the quarter of MPL loan origination relative to the quarter immediately preceding MPL loan origination. This effect is economically insignificant, however.

We also study Equation (1), with job change as the dependent variable. This variable accounts for changes in an individual's occupation, and takes the value of 1 when the job code in a given month differs from the job code in the previous month, and 0 otherwise. This variable also accounts for job loss, since unemployment is provided its own job code. The results of our analysis are presented in column (II) of Table V. Here again, we find that occurrences of job changes remain negligible in the months following MPL loan origination.

Taken together, our findings in this section suggest that MPL loan origination does not alter the job or income profiles of borrowers. Both monthly income and occupation remain stable in the year before and the year after MPL loan origination. Thus, our findings regarding increased credit card default rates cannot be attributed to loss of employment or loss of income on the part of borrowers.

G. Robustness: Do Region-Specific Economic Shocks Drive These Findings?

In this section, we document the robustness of our findings to region-specific factors. A key concern with our documented results is that our findings are driven by some regional economic characteristics that are exogenous to the decision of borrowing funds from an MPL platform. This is especially relevant for our results regarding credit limit extensions and borrower credit card defaults. Profitability estimates at the state or county level can affect bank decisions to expand or contract credit in different regions. Moreover, negative region-specific economic shocks could also explain borrower defaults that are independent of the decision to borrow on MPL platforms.

In order to account for these factors, we replace the year-quarter fixed effects in our base specification with (5-digit) ZIP code $\times$ year-quarter fixed effects in order to capture time-varying trends within 5-digit ZIP codes. Moreover, we double cluster our standard errors at the 5-digit ZIP and year-quarter levels. The results of this analysis are presented in Table VI. We note that our results regarding credit card balances, utilization ratios, credit limits, defaults, and credit scores are unaffected by this more stringent specification.

H. Accounting For Endogeneity Of Engaging On MPL Platforms

In this section, we compare the effects of MPL loan origination specific to MPL borrowers relative to a matched control sample of non-MPL borrowing neighbors residing in the same 5-digit ZIP code as the borrowing individual. The "baseline" matching approach used to create cohorts of MPL borrowers (treated) and their non-borrowing neighbors (control) is described in detail in Appendix B.

In Table VII, we present descriptive statistics highlighting the success of the "baseline" matching process. We note that in the three months leading up to MPL loan origination, MPL borrowers and their neighbors have similar amounts of credit card debt, identical credit card utilization ratios, and identical credit scores. Moreover, both groups show similar *trends* in the quarter leading up to the month of MPL loan origination for MPL borrowers. In addition, these similarities remain consistent within the subprime, near-prime, and prime segments. Finally, we note that both MPL borrowers and neighbors appear to have similar monthly incomes and debt-to-income ratios, with only minor differences in total credit balances.

The results of our fixed effects cross-sectional regression (Equation (2)) are presented in Table VIII. In Panel A, the dependent variable is the average monthly change in credit card balances. In column (I), we analyze average monthly credit card balance changes in the quarter of MPL loan origination (months [0,+3]). The coefficient on the

MPL borrower indicator is negative, suggesting that, relative to their neighbors, MPL borrowers display a 13.20% stronger declining trend in credit card balances in the quarter of MPL origination. In column (II), we analyze average monthly credit card balance changes in the quarter immediately following MPL loan origination (months [+4,+6]). Here, the indicator of interest is positive, and suggests that one quarter after origination, MPL borrowers accrue credit card debt at a rate that is 13.37% stronger relative to their neighbors. Positive and significant coefficients on the dummy of interest in columns (III)-(VI) suggest that the higher rate of debt accrual on credit cards by MPL borrowers persists for a relatively long time, but it also suggests that this rate declines over time. Six to seven quarters after MPL origination, we find no evidence suggesting that MPL borrowers accrue or pay down credit card debt at a greater rate relative to their nearest neighbors.

With our empirical specification, it is not possible to attribute our findings to MPL loan-induced consolidation activities by MPL borrowers. For example, the negative coefficient on the MPL borrower dummy in column (I) of Panel A could be driven by neighbors accruing credit card debt at a greater rate in the quarter of MPL loan origination, as opposed to our suggested interpretation of credit card debt consolidation on the part of MPL borrowers. Thus, we run Equation (1) separately for MPL borrowers and their neighbors, and present the associated event study plots for monthly credit card balances in Panel A of Figure VI. These plots suggest that MPL borrowers and their neighbors display similar trends and rates of credit card debt accumulation in the year leading up to MPL loan origination. However, once an MPL loan is originated, MPL borrowers display greater debt consolidation than their neighbors. The plot highlights that one quarter after origination, MPL borrowers revert to consuming on credit cards at a greater rate than their neighbors and this rate decreases over time. Taken together, our findings, as shown in Panel A of Table VIII and Panel A of Figure VI, indicate that MPL loans help MPL borrowers reduce debt in the immediate term. However, they also point out that this consolidation effect is relatively short lived.

In Panel B of Table VIII, we present results for average monthly changes in credit card utilization. Our findings suggest that MPL borrowers experience declining utilization ratios at a rate that is 3.15% stronger relative to neighbors in the quarter of MPL loan origination. In subsequent quarters, as MPL borrowers begin consuming on credit cards again, their utilization ratios grow at a faster rate relative to their neighbors. Our findings are also presented separately for MPL borrowers and neighbors in the form of event study plots in Panel B of Figure VI.

In Panel C of Table VIII, we analyze average monthly changes in credit card limits. In the quarter of MPL loan origination, our estimate suggests that MPL borrowers experience an increase in credit card limits that is 1.72% stronger relative to their neighbors. In fact, our estimates in columns (I)-(IV) suggest that MPL borrowers experience stronger credit limit growth rates than their neighbors for over one year following MPL loan origination. We find evidence suggesting that in subsequent quarters, the credit card limit growth rates of neighbors predominates. Panel C of Figure VI presents the associated event study plots for MPL borrowers and their neighbors.

We study credit card default rates using a linear probability model, and we present the associated findings in Panel D of Table VIII. Our findings suggest that, relative to a matched sample of neighbors, MPL borrowers initially default on credit cards at a lower rate. However, in the year following MPL loan origination, MPL borrowers default at significantly higher rates. Our findings suggest that two years after loan origination, MPL borrowers exhibit over a 2 pp higher propensity to default relative to their neighbors. The associated plots are displayed in Panel D of Figure VI.

Finally, in Panels E of Table VIII and Figure VI, we present our findings regarding credit scores. Our findings suggest that MPL borrowers experience stronger growth in credit scores in the quarter of MPL loan origination when credit card debt consolidation activity is strongest. Due to the subsequent rise in consumption, MPL borrowers experience stronger declines in credit scores relative to their neighbors.

In additional robustness tests, we report results for cohorts of borrowers and neighbors created using the two variants of the "baseline" matching approach. The results of these analyses are presented in Appendix Tables C.I and C.II, respectively. We document consistent estimates regardless of the matching approach used. We should discuss our results regarding the growth of credit card limits when we match MPL borrowers who were denied credit by banks to their nearest neighbors who were also denied credit by banks. Here, our findings suggest that the origination of MPL loans results in stronger credit limit growth for MPL borrowers relative to their neighbors. Thus, even MPL borrowers who were previously denied bank credit (or denied credit at favorable terms) experience increases in credit limits as a result of MPL loans.

V. Discussion: Who Wins Or Loses From Borrowing On MPL Platforms?

In this section, we discuss if there are systematics differences among the borrowers who benefit from borrowing from MPL platforms and those that don't benefit.

A. Winners And Losers Of Marketplace Lending

We analyze how our results vary across different cross-sections of our sample in order to understand the borrowers that may benefit and those that don't from borrowing from the MPL platform. The cross-sectional cuts we consider are (a) the credit status of the MPL borrower at the time of loan origination, (b) the interest rates charged on peer-funded MPL loans, and (c) the loan amounts extended through MPL platforms.

A.1. Role Of MPL Borrower Credit Quality

Thus far, our analysis has treated all MPL borrowers as if they were equal in terms of financial sophistication. In this subsection, we re-conduct the previous analysis in three separate credit segments: the *subprime* credit segment (i.e., credit score below 620 before loan origination), the *near-prime* segment (credit score greater than or equal to 620 and less than 680), and the *prime* segment (credit score greater than or equal to 680). The subprime, near-prime, and prime segments account for 23%, 50%, and 27% of all borrowers in our sample, respectively. The results of this analysis are presented in Table IX, and the event study plots are displayed in Figure VII.

In Panel A of Table IX, we present regression results for our analysis involving credit card balances. The analysis is run separately for the subprime, near-prime, and prime segments, and the results are displayed in columns (I), (II), and (III), respectively. Our estimates indicate that relative to their in-group baseline means, subprime (prime) borrowers consolidate the least (most) amount of credit card debt. Moreover, we find that starting from two quarters (three quarters) after MPL loan origination, average subprime (near-prime) credit card indebtedness is not significantly different relative to their in-group baseline mean. On the other hand, three quarters after origination, prime MPL borrowers appear to be 17.7% less indebted relative to their in-group baseline mean.

Our findings in Panel B suggest that all three segments have lower credit utilization ratios after MPL loan origination relative to the baseline period. Panel C shows how monthly credit card limit growth is affected by MPL loan origination. We find that subprime borrowers experience a 1.33% stronger increase in monthly credit card limit growth in the quarter of loan origination, and they experience a 1.44% stronger increase in the quarter immediately after origination. We also find that near-prime borrowers experience a 0.50% stronger increase in credit growth in the quarter of loan origination, but this estimate is only marginally significant. Finally, prime borrowers don't seem to experience a change in credit limit growth in the 25-month window centered on loan origination.

Panel D shows our analysis of credit card default rates. The results indicate that three quarters after origination, the subprime segment has a 5.07 pp higher default rate relative to the baseline period. The subprime MPL borrower segment has an average credit card default rate of 0.25% in the three months immediately preceding MPL loan origination. Thus, the coefficient estimate at the one-year mark suggests that credit card default rates are approximately 20 times higher for the subprime group one year following origination relative to the quarter immediately preceding origination. However, it is important to note from Figure VII (Panel E) that subprime borrowers display a declining trend in credit card default rates in the months leading up to MPL origination. In fact, four quarters prior to origination, the credit bureau data suggests that subprime borrowers have credit card default rates of approximately 1%. Thus, relative to the one-year mark *preceding* origination, our findings suggest that credit card default rates are approximately 5 times higher for the subprime group one year *following* origination.[22] The near-prime and prime segments experience economically and statistically insignificant changes in default rates, respectively.

Taken together, our above findings suggest that subprime borrowers consolidate a relatively smaller portion of their credit card debt using MPL funds, but they experience the strongest increase in monthly credit limit growth. Moreover, our estimates also suggest that the subprime segment is as indebted two quarters after origination as they were before origination. This "double dipping" into both MPL and credit card funds ironically increases the aggregate indebtedness of the subprime segment, thus making them more susceptible to default.

Finally, Panel E shows our analysis of the evolution of credit scores. We find that all three segments benefit from credit card debt consolidation, as reflected by higher credit scores in the quarters immediately following MPL loan origination. However, three quarters after origination, the subprime and near-prime segments have credit scores that are not significantly different from pre-origination levels in the baseline period. Moreover, the prime segment has credit scores that are actually 0.58% *lower* relative to the baseline period.

Taken together, our findings suggest that regardless of the borrower's credit quality at the time of loan origination, MPL loans are used to consolidate credit card debt. In doing so, these loans relax financial constraints for all borrowers through lower utilization ratios

[22] In addition, we also compare subprime MPL borrowers to their closest subprime non-MPL borrowing neighbors using the cohort-level framework described in Section III.B.2. We find that at the two-year mark post-origination, non-MPL subprime neighbors have average credit card default rates of 4.2% compared to subprime MPL borrowers, who exhibit average credit card default rates of 6.3%. This suggests that subprime MPL borrowers are approximately 1.5 times as likely to default on credit cards as subprime non-MPL neighbors.

and higher credit scores. Banks appear to react to this new information as well, since credit card limits increase significantly when debt is being consolidated. This growth in credit limits is strongest for the most constrained borrowers – the subprime segment. However, this segment is also quick to revert to consumption behavior; within six months of MPL loan origination, subprime borrowers are as indebted in credit card debt as they were before origination. Given the increased aggregate debt burden, credit card default rates rise dramatically for subprime borrowers in the post-origination period.[23]

A.2. Interest Rates On Loans

We next conduct cross-sectional tests based on interest rates charged on MPL platforms. These loans from MPL are typically installment loans with amortized monthly payments. From the credit bureau trades file, we know the total principal borrowed (P), the scheduled monthly payment (A), and the term of the loan (n) in months. Thus, we make use of the amortization formula,

$$A = P \times \frac{r \times (1+r)^n}{(1+r)^n - 1},$$

to back out the interest rate charged on the loan (r). Next, for each calendar year, we sort this interest rate into terciles, with the lowest (highest) tercile representing the portfolio of low (high) interest rate loans.

We conduct our analysis of credit card balances, utilization, limit growth, default rates, and credit scores separately for each of the three terciles. Appendix Table C.IV shows that the aforementioned negative aspects of MPL borrowing are concentrated in loans originated at high interest rates. Conversely, borrowers who receive these funds at low interest rates are better off.

A.3. Loan Amounts

For our next set of tests, we partition our sample of MPL borrowers into terciles on the basis of extended MPL loan amounts. These terciles are reconstituted for each calendar year, with the lowest (highest) tercile corresponding to the portfolio of loans with low (high) origination amounts. Appendix Table C.V shows that the negative (positive) aspects of MPL funds are concentrated in the portfolio of loans with low (medium- or high-) origination amounts.

[23] In additional results, presented in Appendix Table C.III, we document that, even for the subprime segment of MPL borrowers, defaults occur mostly on credit cards, and not the MPL loan itself.

B. Are There Improvements In Perceived Credit Quality Of MPL Borrowers?

Thus far, we have documented that the origination of MPL loans is associated with an immediate increase in limits on credit cards, and this increase is largest for the subprime and near-prime segments. We find no evidence of prime MPL borrowers experiencing abnormal limit growth following MPL loan origination. In this section, we attempt to identify whether MPL loans improve the perceived credit quality of borrowers, which could potentially explain the post-MPL loan origination increase in credit card limits.

In order to conduct our analysis, we utilize the baseline matching approach described earlier, and identify cohorts that were subprime in the month immediately before the month of MPL loan origination. On this set of subprime cohorts, we implement the following fixed effects cross-sectional regression:

$$Y_{i,c} = MPL\_Borrower_{i,c} + \gamma \overline{\mathbf{X}}_{i,c} + \alpha_c + \epsilon_{i,c}. \tag{3}$$

As before, $MPL\_Borrower$ is an indicator that equals 1 if the individual is an MPL borrower, and 0 otherwise. Y_i is the outcome variable, represented in the form of logged changes. For our analysis, we study changes in average outcomes in the three months following MPL loan origination to the three months immediately preceding MPL loan origination. $\mathrm{X}_{i,c}$ represents control variables, and α_c is a vector of cohort fixed effects. Standard errors are clustered at the 5-digit ZIP code level.

The results of our analysis are presented in Panel A of Table X. In column (I), the dependent variable is the average credit score growth, defined as the logged average credit score of the individual in months [+1,+3] less her logged average score in months [-3,-1], where month 0 refers to the month of MPL loan origination by the MPL borrower. The use of cohort-level fixed effects induces within-cohort comparisons between the MPL borrower and her neighbor. The estimate on the MPL borrower dummy indicates that, relative to their neighbors, MPL borrowers experience a 5.43% increase (significant at the 1% level) in average credit scores in the [+1,+3] window after MPL loan origination.[24]

Next, we study the impact of impact of increased credit scores on credit card limit growth in a 2SLS setting, where the change in credit scores is instrumented by a dummy variable indicating MPL borrower status. Thus, our regression results discussed in col-

[24]From descriptive statistics presented in Table VII, the average credit score of subprime MPL borrowers in the three months immediately preceding the month of MPL loan origination is approximately 600. Thus, in the [+1,+3] month window, previously subprime MPL borrowers experience average credit scores of approximately 633 ($\approx 1.0543 \times 600$). Note that this back-of-the-envelope calculation implicitly assumes that non-borrowing subprime neighbors do not experience any change in their credit score following MPL loan origination by the MPL borrower.

umn (I) above serve as the first stage of this instrumented regression. We use the same control variables and vector of fixed effects as in Equation 3. The results of this analysis are presented in column (II) of Panel A. The outcome variable is average credit card limit growth, defined as the logged average aggregate credit card limits for the individual in months [+1,+3] less her logged average aggregate credit card limits in months [-3,-1], where month 0 refers to the month of MPL loan origination. Here, our IV results suggest that MPL-loan induced 1% increases in credit scores results in 0.89% stronger credit limit growth (significant at 1% level) for the MPL borrower relative to her non-borrowing neighbor within the same subprime cohort. The F-statistic for the excluded instrument is well above 10, suggesting that it is a strong instrument. Finally, in column (III), we study the impact of credit score growth on credit limit growth in a fixed effects setting without the instrument, and note that within subprime cohorts, a 1% increase in credit scores results in 0.32% stronger credit limit growth.

In Panel B, we repeat the analysis for near-prime cohorts. In column (I) of Panel B, we note that near-prime MPL borrowers experience an average credit score increase of 4.25% relative to their near-prime neighbors within the same cohort.[25] In column (II), we study the impact of credit score changes on credit card limits in an instrumented setting, and note that within a near-prime cohort, an MPL-loan induced 1% increase in credit scores results in 0.11% stronger credit limit growth (significant at 1% level) for the MPL borrower relative to her non-borrowing neighbor. The non-instrumented counterpart, presented in column (III), suggests that within near-prime cohorts, a 1% increase in credit scores is associated with a 0.05% stronger growth in credit card limits.

Column (I) in both panels suggest large increases in credit scores for MPL borrowers in the quarter immediately following MPL loan origination. Thus, we study whether MPL loans results in MPL borrowers crossing industry-standard credit score thresholds in the aftermath of origination.[26] We empirically test this statement for the subprime cohort by making use of Equation (3), and replace the dependent variable with a dummy that takes the value of 1 if the individual's credit score crosses the 620 threshold in months [+1,+3], and 0 otherwise. The results of this analysis are presented in column (IV) of Panel A. The coefficient estimate suggests that subprime MPL borrowers are nearly 35%

[25]From descriptive statistics presented in Table VII, the average credit score of near-prime MPL borrowers in the three months immediately preceding the month of MPL loan origination is approximately 649. Thus, our estimate suggests that near-prime MPL borrowers enjoy an average credit score of 677 ($\approx 1.0425 \times 649$) in the three months immediately following MPL loan origination. Again, we assume that non-borrowing near-prime neighbors do not experience any change in their credit scores in the post-MPL loan origination period.

[26]See Keys et al. (2010), Rajan, Seru, and Vig (2015), and Agarwal et al. (2018) for the importance of credit scores in bank lending decisions.

more likely (significant at the 1% level) to cross the subprime/near-prime threshold in the quarter following MPL loan origination than a matched sample of geographically proximate subprime neighbors. Similar analysis conducted for near-prime segments suggests that near-prime MPL borrowers are nearly 33% more likely (significant at the 1% level) to cross the near-prime/prime credit score threshold of 680 in the quarter after MPL loan origination than their near-prime neighbors.

The results in this section suggest that MPL platforms may not be generating any new soft information about borrowers on their platforms that are unavailable to their banks. Moreover, our findings also do not necessarily indicate that MPL platforms are better than banks at screening, as argued in Balyuk (2018). While MPL loans assist in reducing financial constraints on borrowers through lower credit card balances, lower utilization, and higher credit scores, they also trigger actions from traditional bank creditors. It appears that banks possibly overweight the short-lived credit score increase induced through loans from MPL, even though the associated consolidation activity is both short-lived and at odds with their (very recent) historical consumption patterns. Taken together, our results in Tables IX and X suggest that this extension of limits is inefficient ex post, especially for subprime MPL borrowers. Our results strongly suggest that bank credit extension decisions are strongly influenced by credit scores, consistent with the arguments posed in Rajan, Seru, and Vig (2015) and Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018).

VI. Conclusion

In this paper, we document some of the benefits and drawbacks of the emergence of MPLs for consumer loans. Incidences of misreporting appear to be rare, despite the fact that MPLs have no mechanism in place to ensure loans made on such platforms are used for credit card debt consolidation, which is frequently stated by applicants as the purpose of the loan. However, it appears that these loans fail to change the fundamental behavior of the relatively undisciplined and financially troubled MPL borrowers. More importantly, the temporary financial relief bought on by such loans is incorrectly interpreted by some traditional lenders, who subsequently extend additional credit to these borrowers. These borrowers, in turn, consume the newly extended credit and are thus more indebted after origination, in aggregate. Due to this increased overall indebtedness, MPL borrowers have higher probabilities of default in the months after MPL loan inception. Finally, cross-sectional analysis reveals that subprime borrowers, who account for nearly 1 in 4 people borrowing on such platforms, are most negatively affected.

Our results suggest that MPLs can be attractive sources of funding for deeply indebted people who seek to alleviate financial constraints. Indeed, our results indicate that MPL funds help reduce credit card debt by approximately 47%, on average, in the quarter of loan origination. While the absolute level of debt payment is lower for the subprime segment, subprime borrowers still enjoy a credit score increase of approximately 3.5% relative to their pre-origination levels. MPL borrowers also enjoy lower utilization ratios post-MPL origination. Thus, at least in the short run, MPL borrowers benefit through lower interest payments, improvement in credit scores, and increases in credit limit.

In the longer horizon following debt consolidation, the benefits to MPL borrowers depend on their subsequent credit utilization. The borrowers who benefit from MPLs are those who have the financial discipline to avoid drawing down on their subsequently higher credit limits. However, borrowers who lack this financial discipline, or who are too financially stressed to avoid drawing down on their higher credit limits, end up in a worse financial condition after obtaining an MPL loans. These MPL borrowers, many of them subprime, default at a significantly higher rate, even when compared to their non-MPL borrowing neighbors with similar ex ante credit dynamics. Thus, there are winners and losers among MPL borrowers.

In line with the arguments posed in Rajan, Seru, and Vig (2015) and Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018), our results suggest that bank credit extension decisions are strongly influenced by credit scores. To the extent that credit card debt consolidation through MPL loans influence credit scores and thereby bank credit extension decisions, our results have broader implications for credit extension decisions by traditional banks.

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Figure I: Is there Debt Consolidation Using MPL Funds as Stated on MPL Applications?

In this figure, we present event study plots that capture the consolidation of debt along various broad trade lines in the months surrounding the origination of marketplace lending (MPL) platform trades. We focus on one-time MPL borrowers. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage difference in balances relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The plots below display event study estimates, and associated 95% confidence intervals presented in bar form. All specifications include individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A.

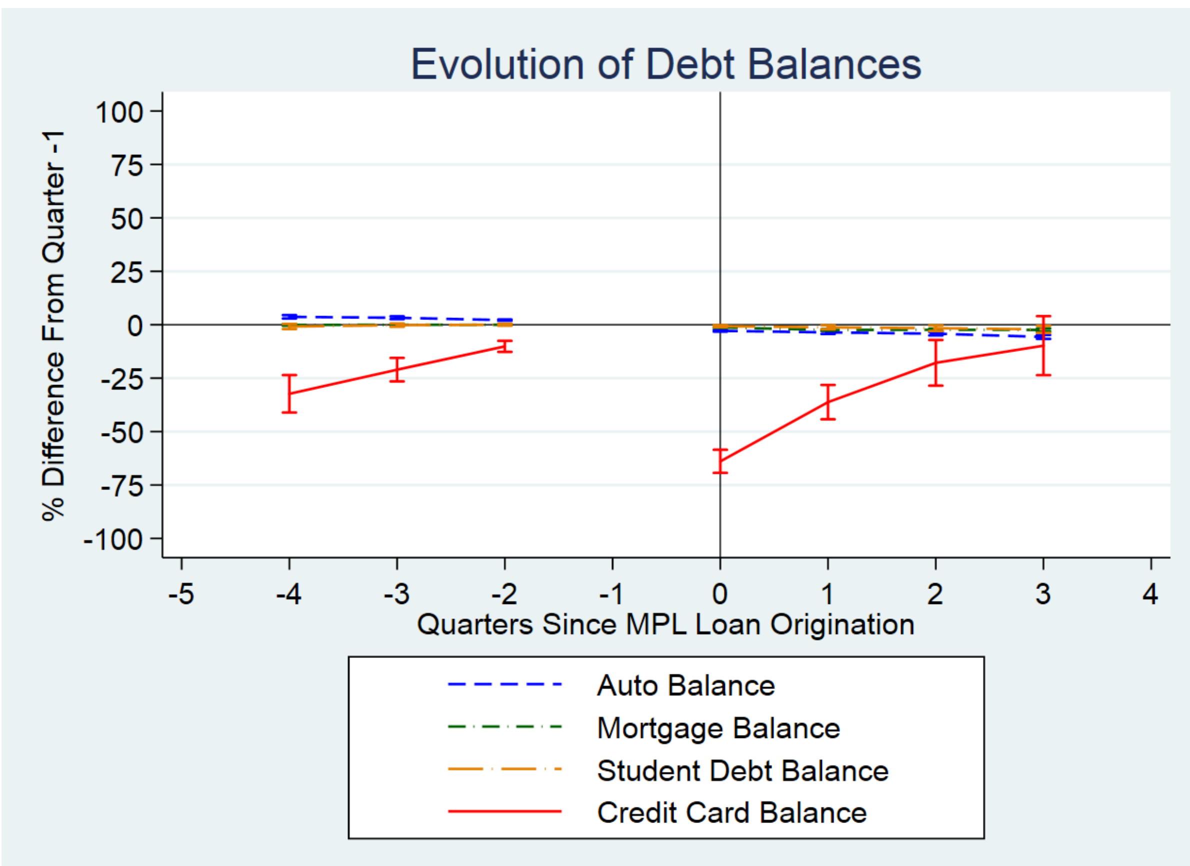


Figure II: Do MPL Loans Affect Credit Card Utilization Ratios?

We present an event study plot that captures the evolution of credit card utilization ratios in the months surrounding the origination of marketplace lending (MPL) platform trades. We focus on one-time MPL borrowers. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the month in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage difference in utilization relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The black line graph below represents event study estimates, while the shaded area represents the associated 95% confidence interval. The specification includes individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A.

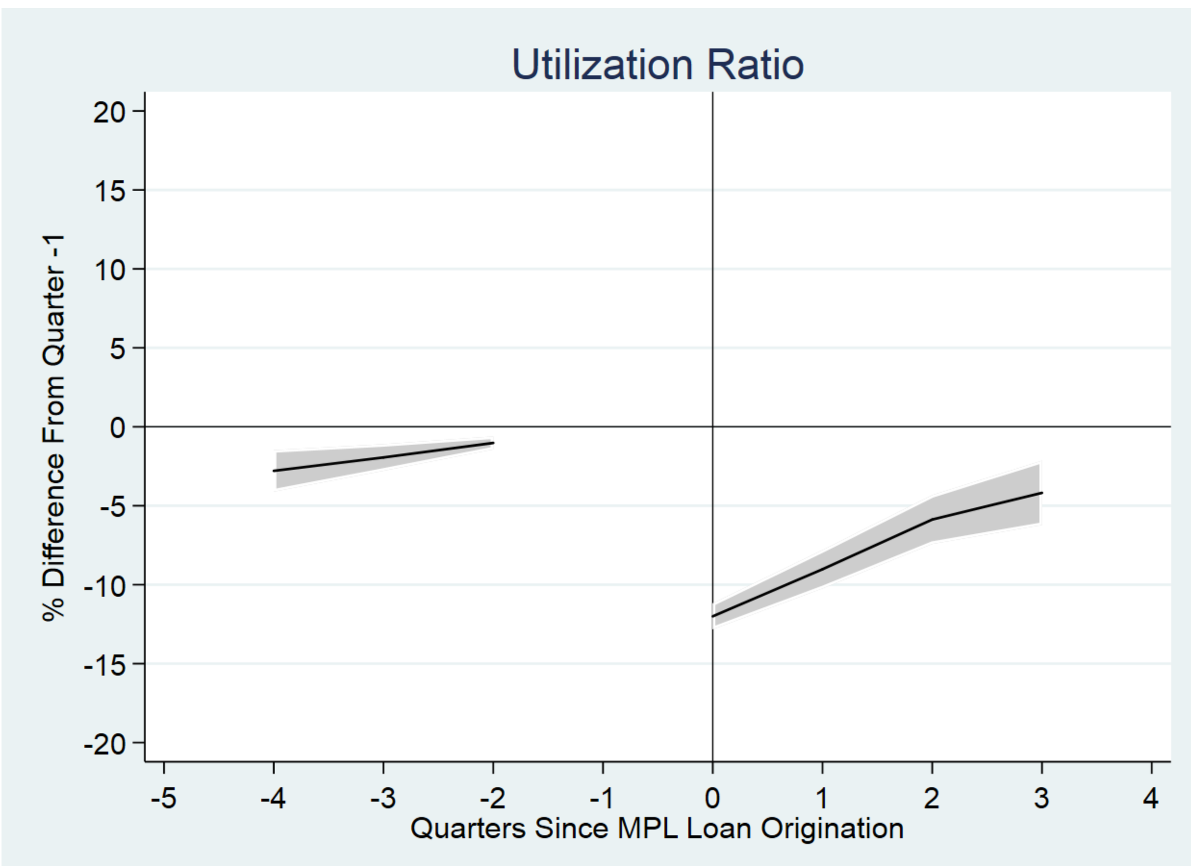


Figure III: Are Credit Card Limits Altered Because of MPL Loans?

We present an event study plot that captures the monthly growth in credit card limits in the months surrounding the origination of marketplace lending (MPL) platform trades. We focus on one-time MPL borrowers. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage difference in credit card limit growth relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The black line graph below represents event study estimates, while the shaded area represents the associated 95% confidence interval. The specification includes individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A.

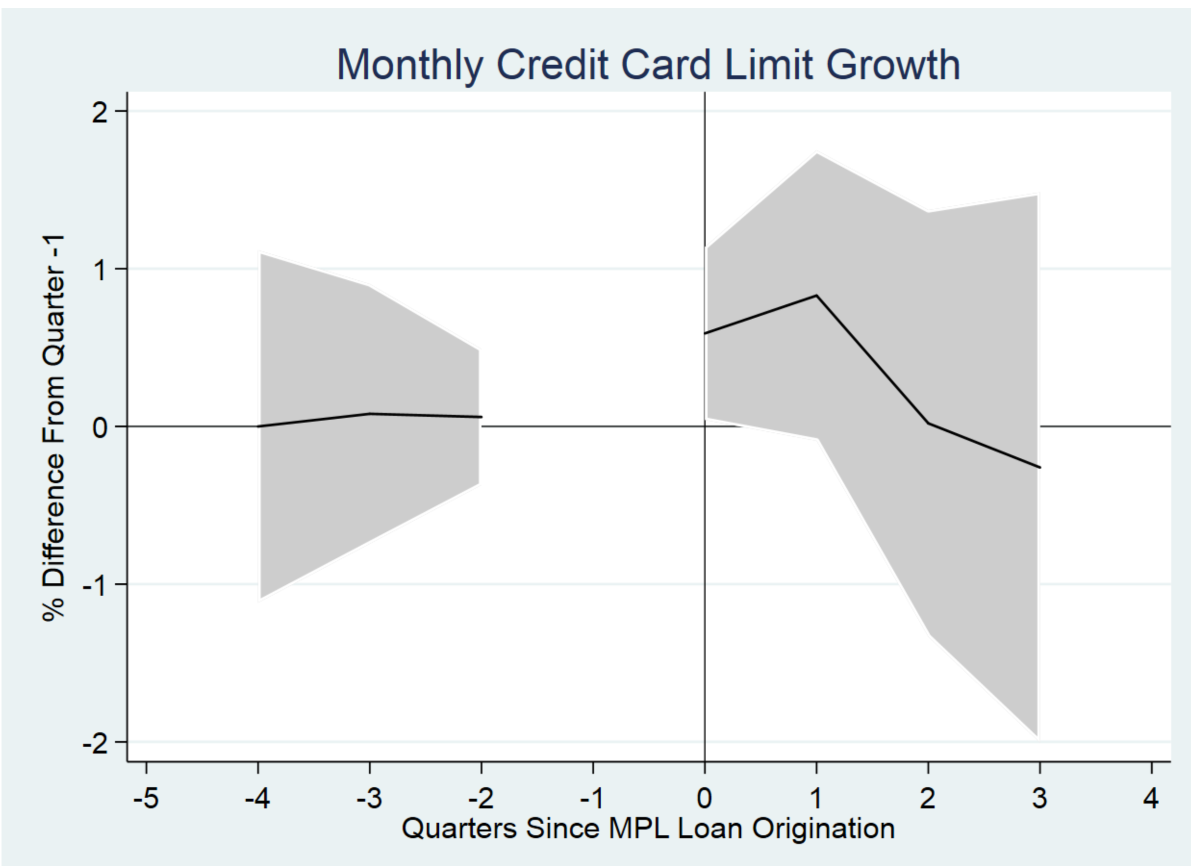


Figure IV: Do MPL Loans Affect Credit Card Default Rates?

We present an event study plot that captures the evolution of credit card default rates in the months surrounding the origination of marketplace lending (MPL) platform trades. We focus on one-time MPL borrowers. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage point difference in credit card default rates relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The black line graph below represents event study estimates, while the shaded area represents the associated 95% confidence interval. The specification includes individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A.

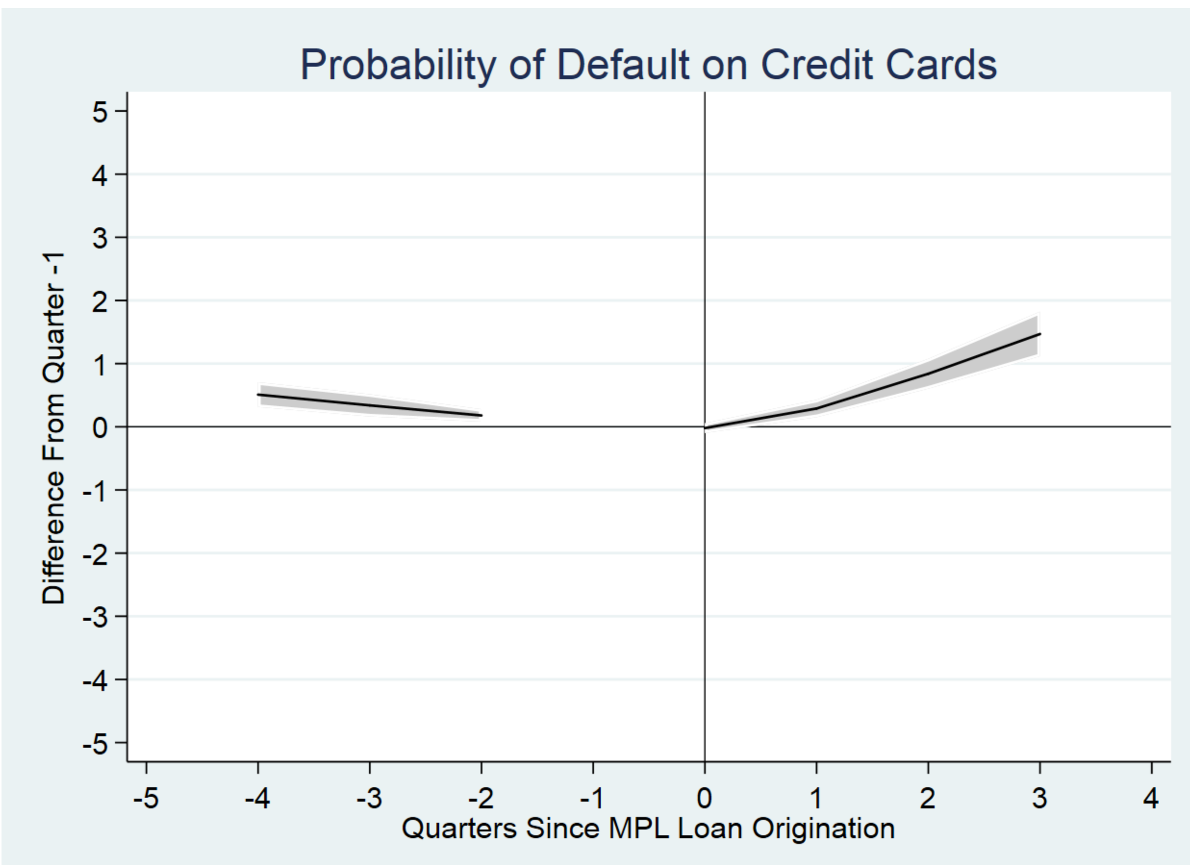


Figure V: Effect of MPL Loans on Borrowers' Credit Scores

We present an event study plot that captures the evolution of credit scores in the months surrounding the origination of marketplace lending (MPL) platform trades. We focus on one-time MPL borrowers. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage difference in credit scores relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The black line graph below represents event study estimates, while the shaded area represents the associated 95% confidence interval. The specification includes individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A.

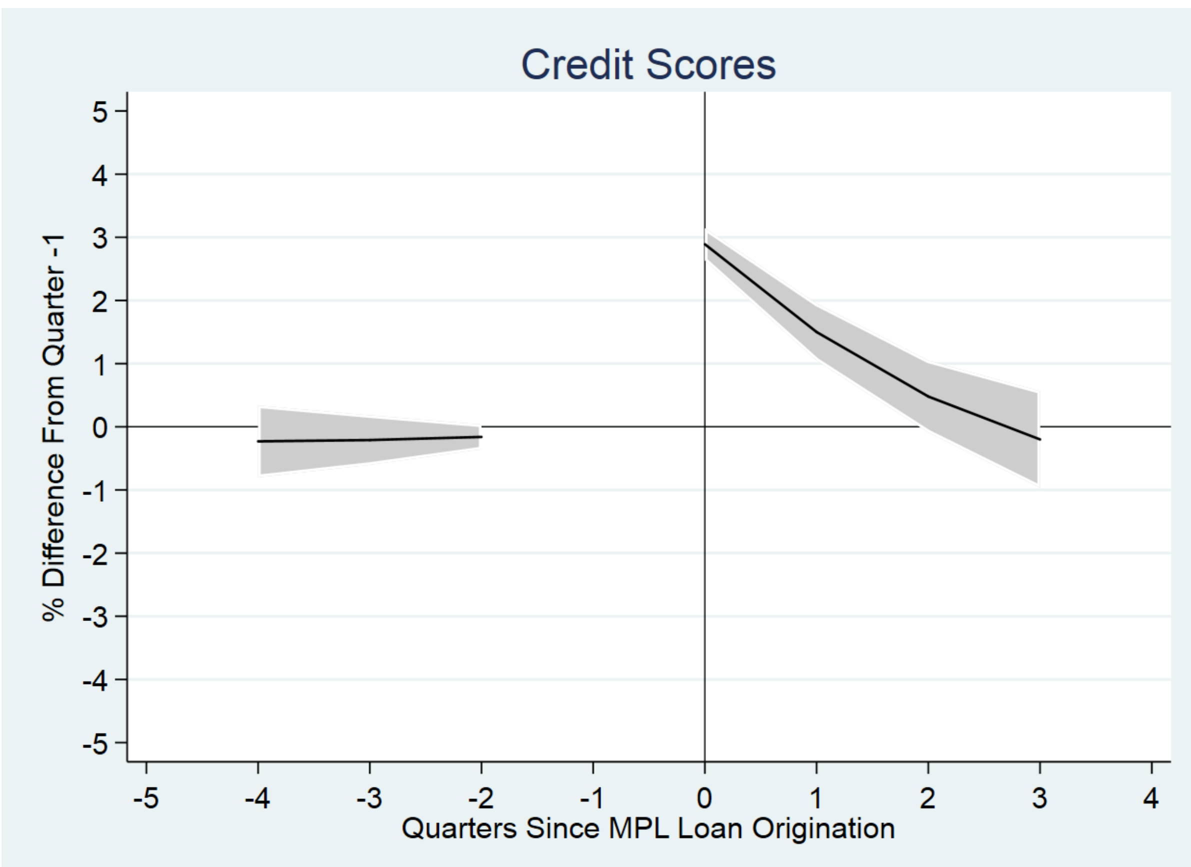
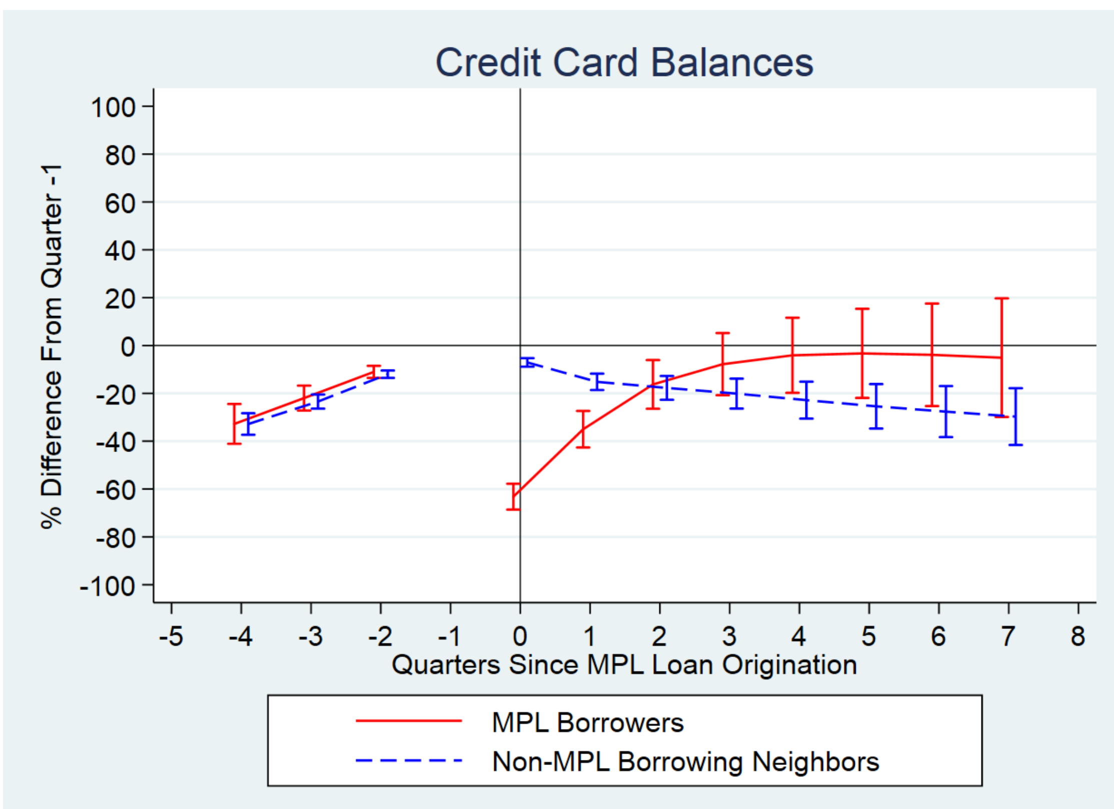
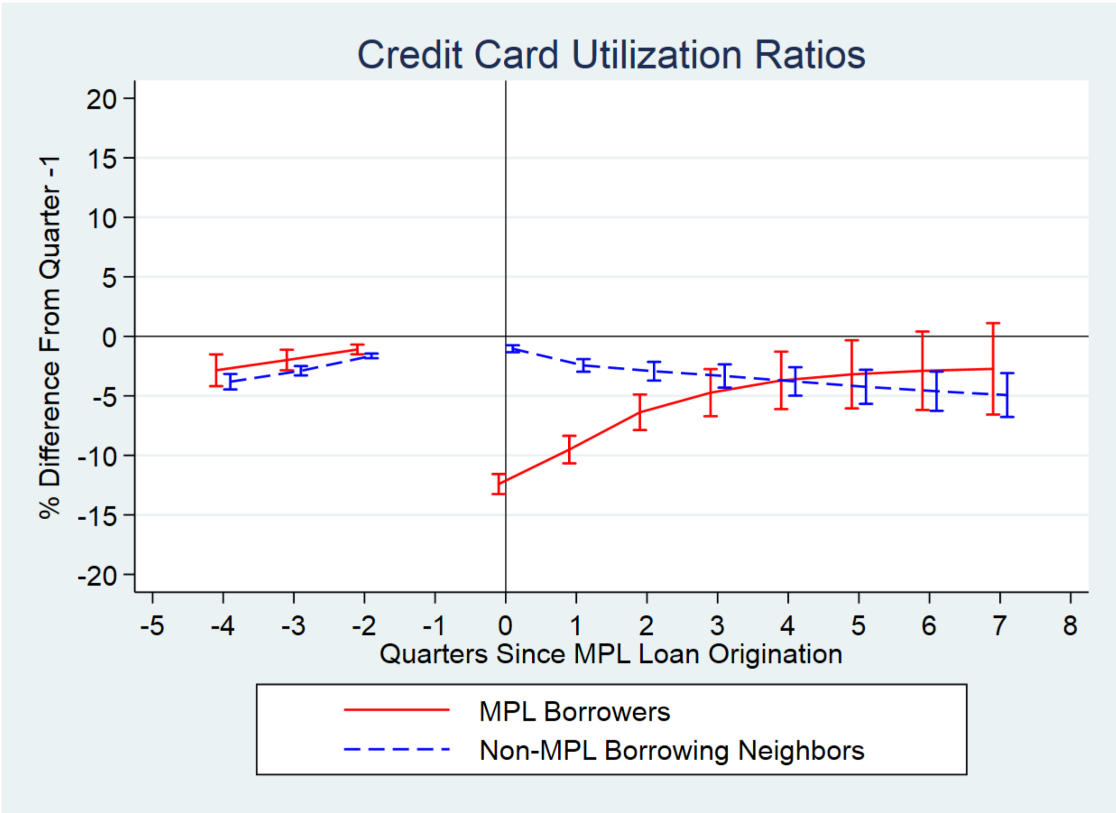


Figure VI: MPL Borrower v. Closest Non-MPL Borrowing Neighbor

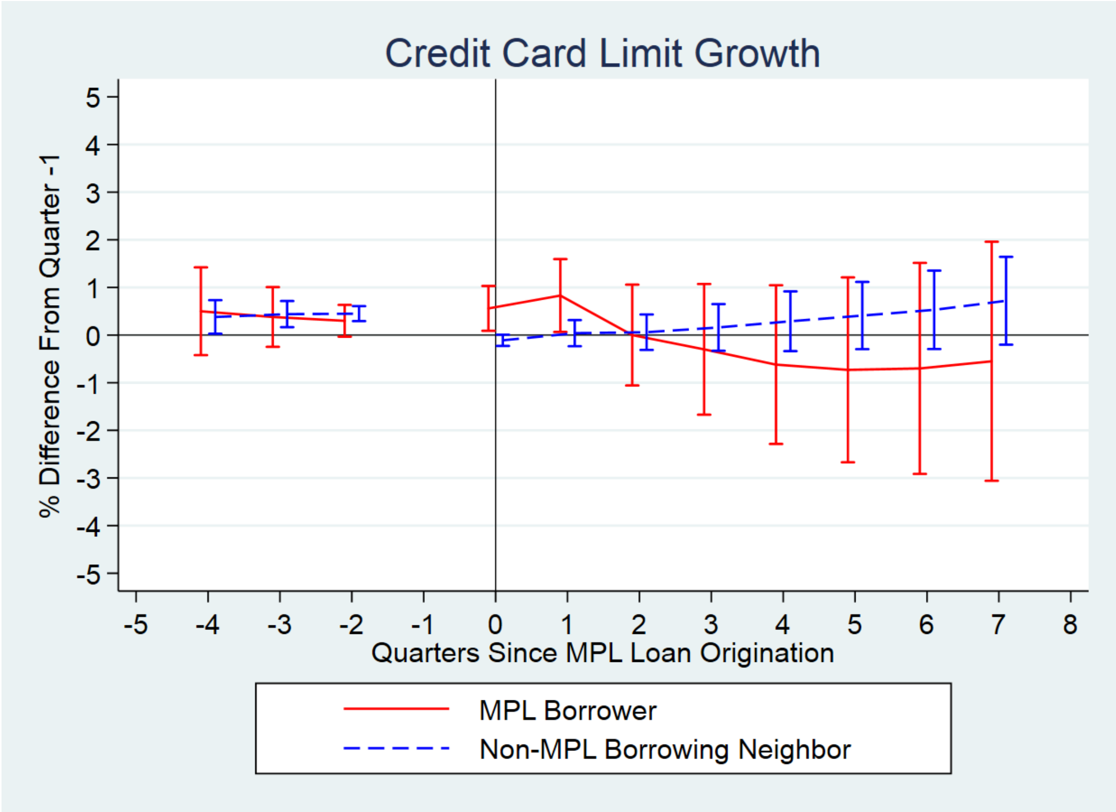
In this set of figures, we present event study plots documenting the differential trends in credit profile characteristics of marketplace lending (MPL) platform borrowers and their geographically- and socioeconomically-proximate non-MPL borrowing neighbors in the months surrounding the origination of MPL loans by MPL borrowers. Every matched pair of MPL borrower and their nearest non-borrowing neighbor is referred to as a cohort. The analysis is conducted separately for MPL borrowers and non-borrowers. Panels A, B, C, D, and E show the analysis of credit card balances, credit card utilization, credit card limit growth, credit card default occurrences, and credit scores, respectively. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The plots below represent event study estimates, and the associated 95% confidence intervals are presented in bar form. The separate specifications for MPL borrowers and non-borrowers include individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A. The algorithm underlying the matched sample of MPL borrowers and their neighbors, referred to as the "baseline" algorithm, is described in detail in Appendix B.



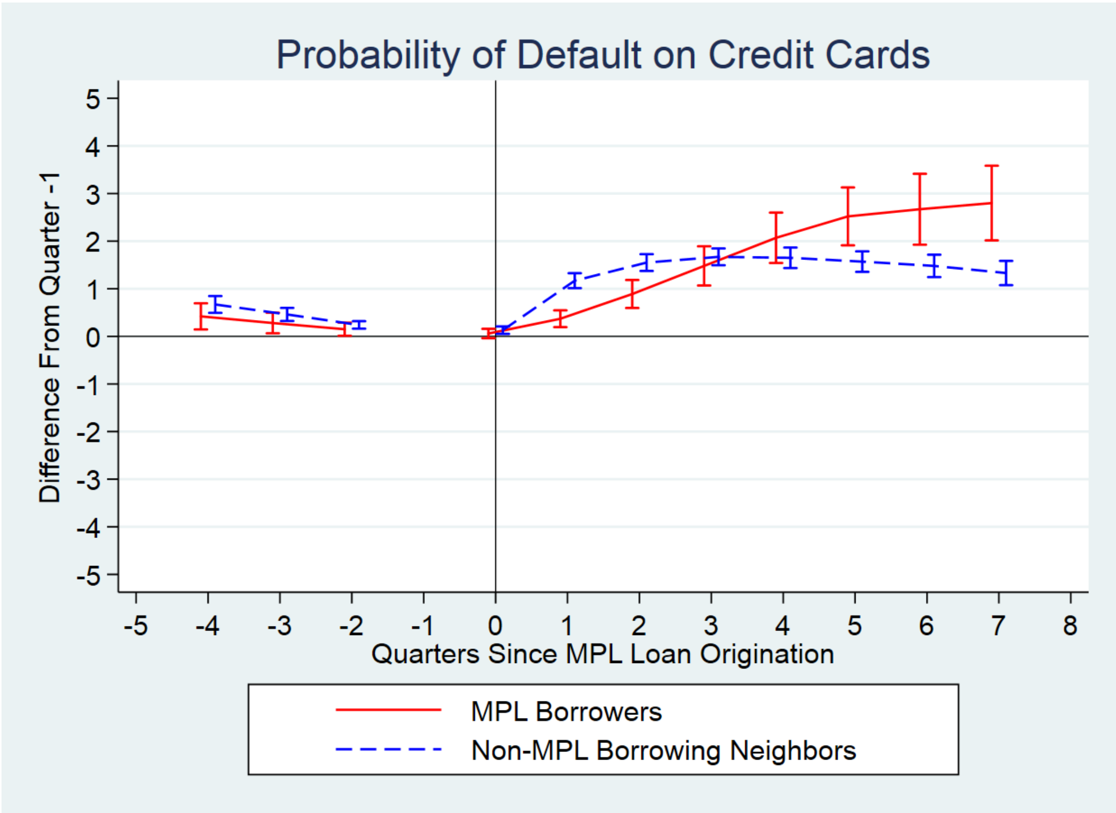
(a) *Credit Card Balances*



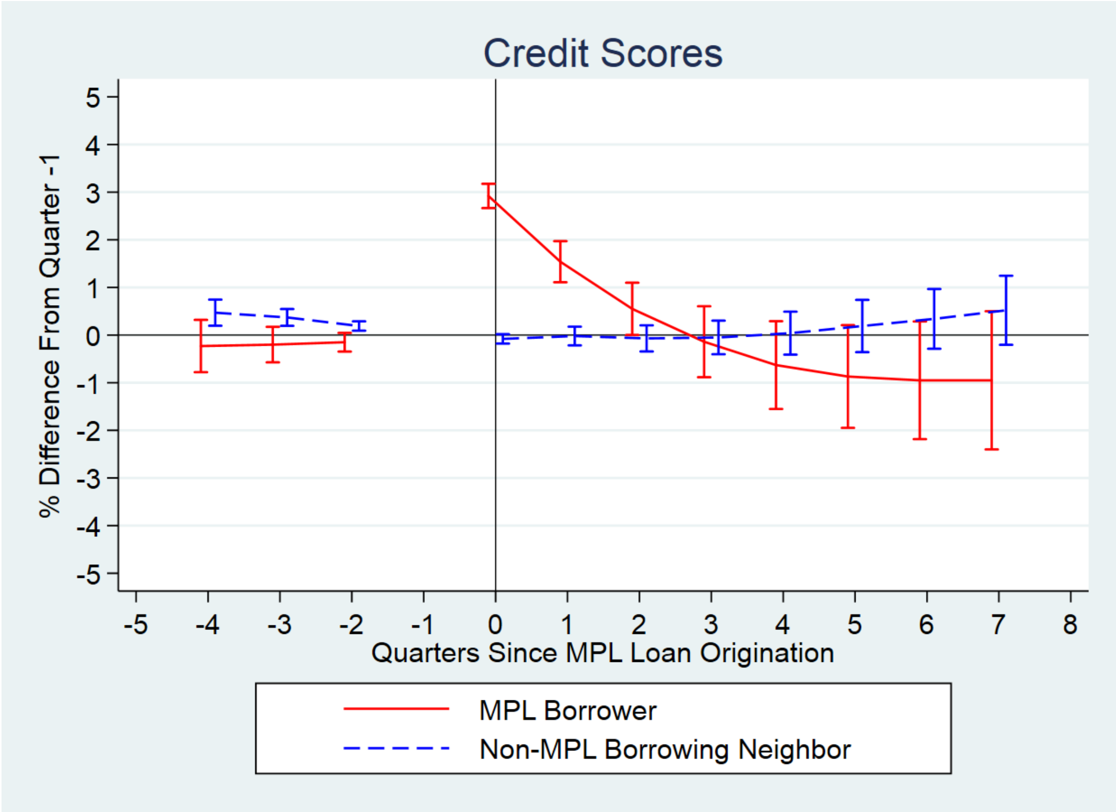
(b) *Credit Card Utilization*



(c) *Credit Card Limits*



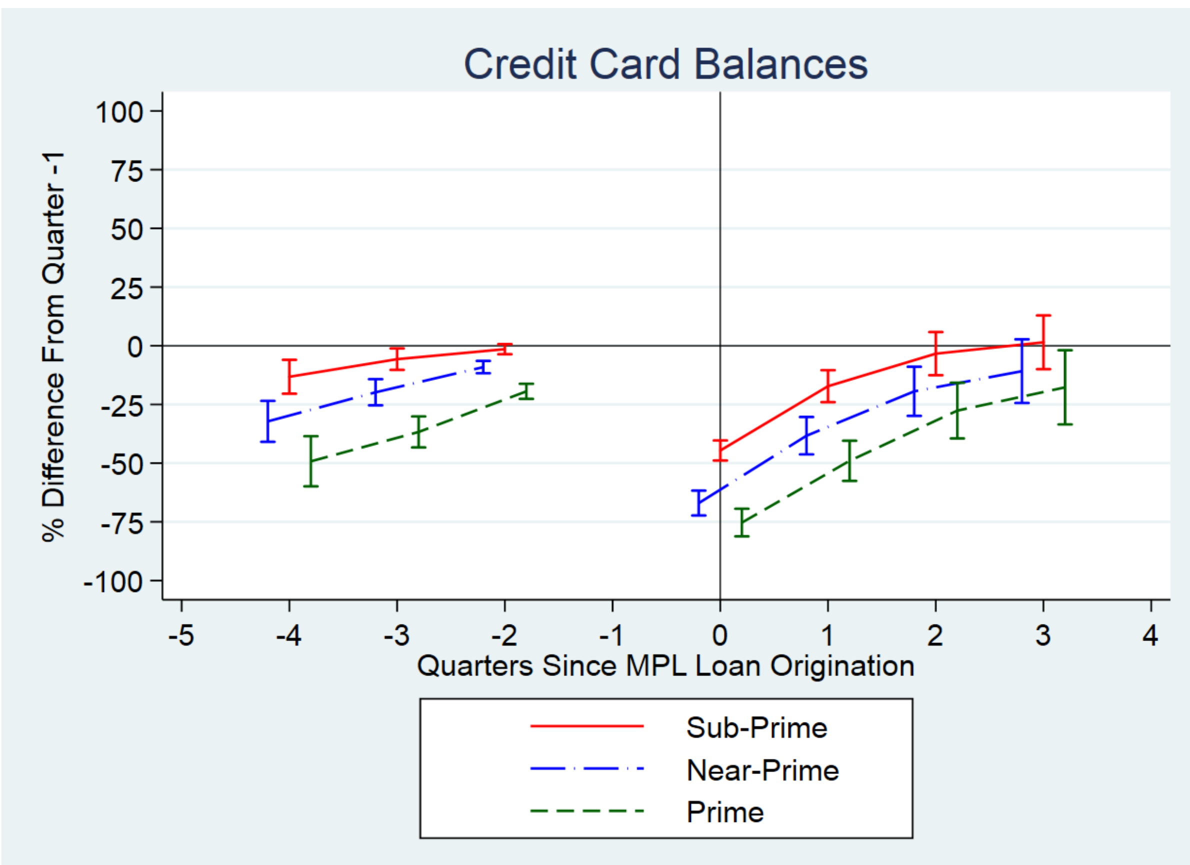
(d) $\mathbb{P}$*(Credit Card Defaults)*



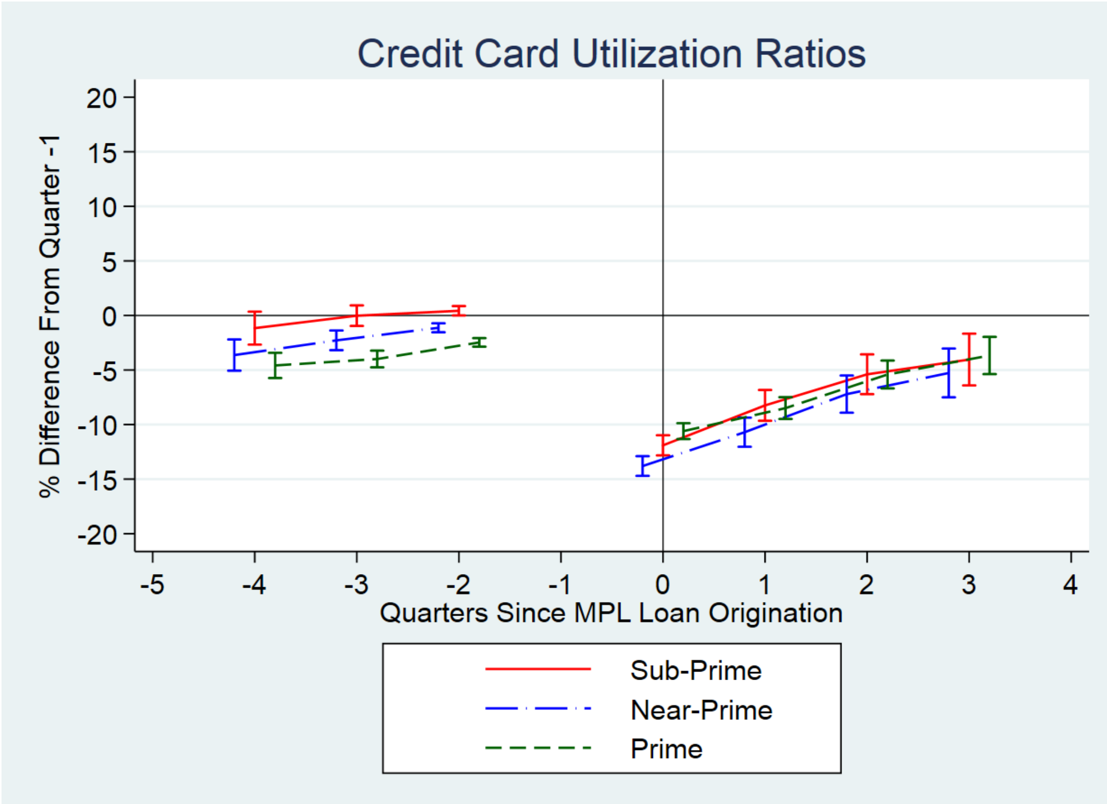
(e) *Credit Scores*

Figure VII: Impact of Ex Ante Credit Quality of MPL Borrowers

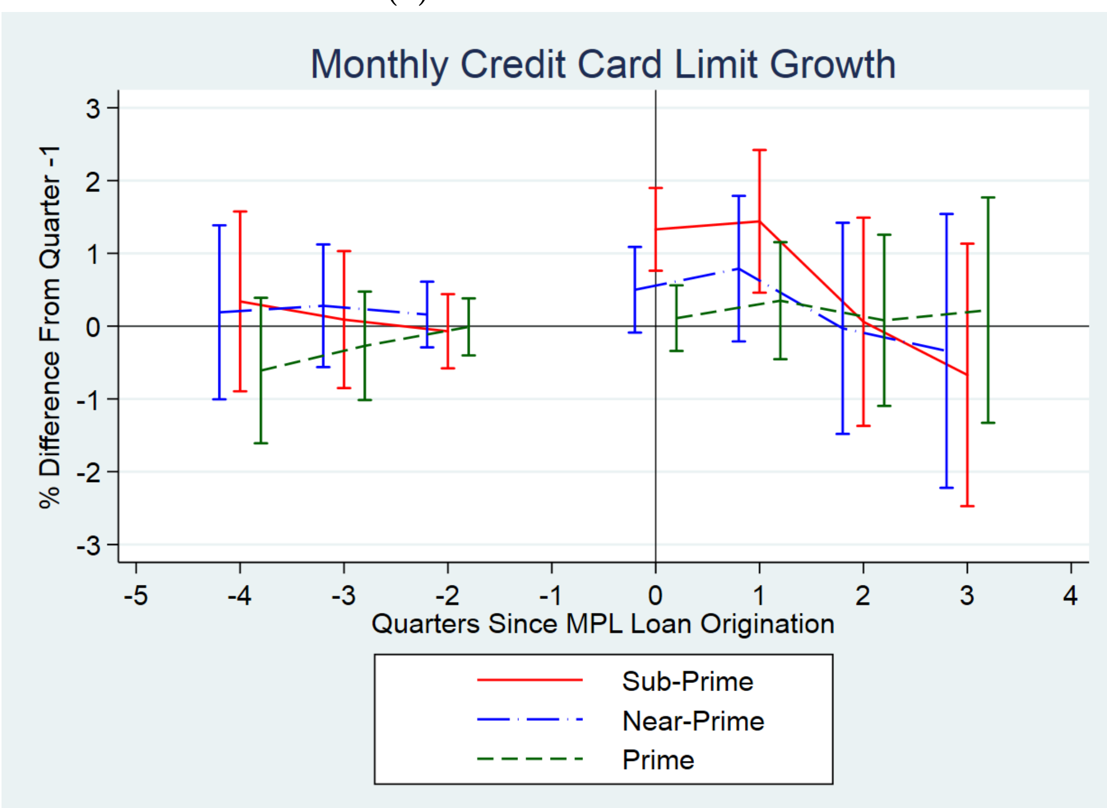
In this set of figures, we present event study plots that highlight differences in the evolution of credit profiles of marketplace lending (MPL) platform borrowers, differentiated by the credit quality of the borrower. We focus on one-time MPL borrowers. An MPL borrower is classified as *subprime*, *near-prime*, or *prime* if their credit score is below 620, between 620 and 680, and greater than equal to 680, respectively, in the month immediately before MPL loan origination. Panels A, B, C, D, and E show our analysis of credit card balances, credit card utilization, credit card limit growth, credit card default occurrences, and credit scores, respectively. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays the percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. The plots below represent event study estimates, and the associated 95% confidence intervals are presented in bar form. The separate specifications for subprime, near-prime, and prime MPL borrowers include individual and year-quarter fixed effects, with robust standard errors double clustered at the individual and year-quarter levels. All control variables included in the analysis are defined in Appendix A.



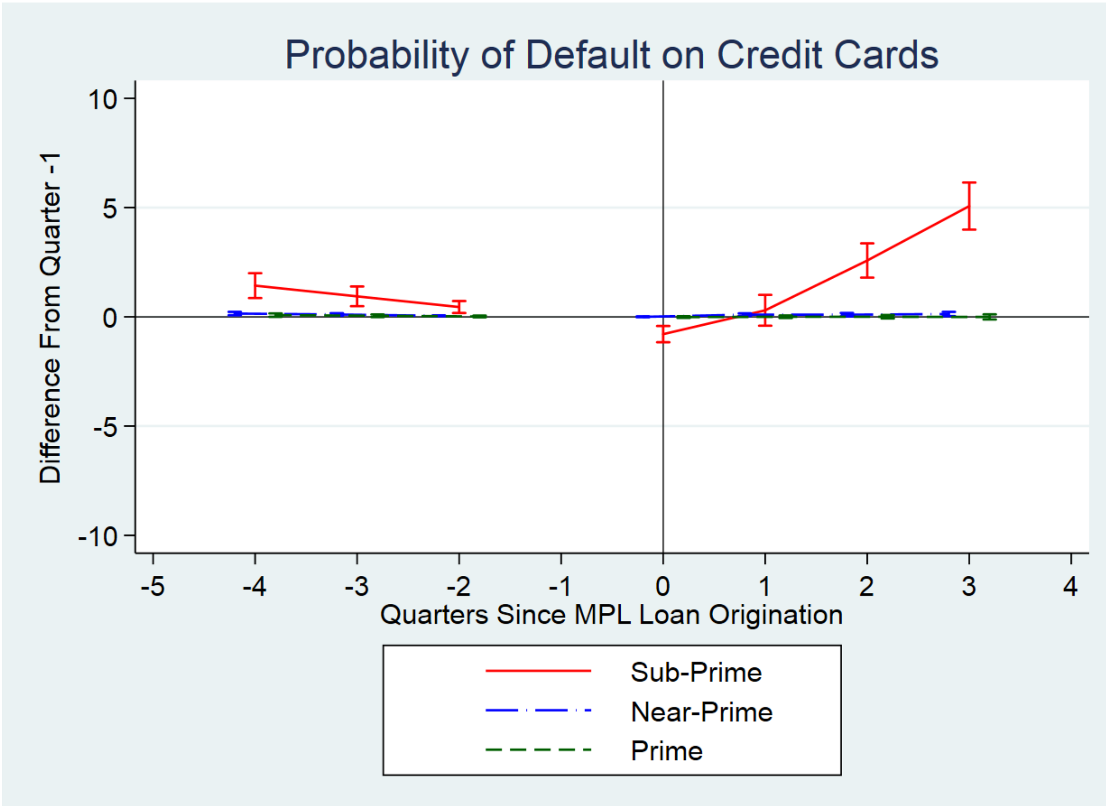
(a) *Raw Credit Card Balance*



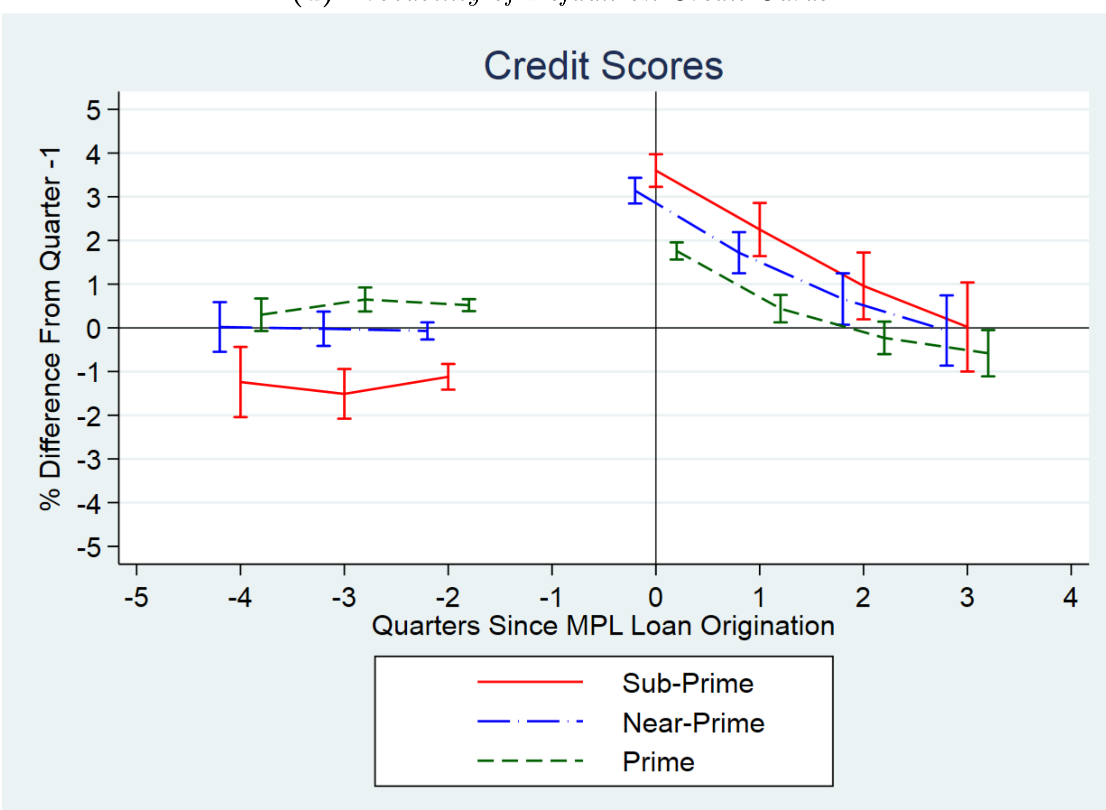
(b) *Credit Card Utilization*



(c) *Credit Card Limit Growth*



(d) *Probability of Default on Credit Cards*



(e) *Credit Scores*

Table I: Comparing MPL Borrowers to the Average American Resident

In this table, we present descriptive statistics comparing the credit and income characteristics of individuals who borrow funds from marketplace lending (MPL) platforms, relative to the average U.S. population. The descriptive statistics for MPL borrowers are presented in column (I). In columns (II) and (III), we present univariate statistics for a 5% random sample of the U.S. population, and for a 33% random sample of U.S. homeowners. Panel A and Panel B contain statistics on credit characteristics and income characteristics, respectively.

	MPL Platform Borrowers	National Average	Homeowners Average
	(I)	(II)	(III)
Panel A: Credit Characteristics			
# Open Trades	10.49	4.68	7.58
# Auto Trades	1.02	0.66	0.84
# Mortgage Trades	0.86	0.79	1.07
# Student Loan Trades	2.23	1.66	1.49
# Credit Card Trades	3.84	1.97	2.74
Credit Score	656.44	675.47	733.84
Total Balance	$232,463	$208,195	$310,142
Auto Balance	$20,659	$17,038	$20,648
Mortgage Balance	$189,597	$186,237	$274,244
Student Loan Balance	$24,425	$19,122	$20,210
Credit Card Balance	$9,821	$4,197	$5,994
Credit Card Utilization	69.42%	30.89%	28.55%
Panel B: Income Characteristics			
Monthly Income	$3,602	$3,437	$5,232
Debt-to-Income	41.03%	27.82%	45.39%

Table II: What Kind of Debt is Consolidated Using MPL Funds?

In this table, we report regression results that document the fluctuation of debt balances along broad trade lines in the months surrounding the origination of MPL loans. We subset our analysis to one-time MPL borrowers. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. The estimates represent percentage differences in balances relative to levels in $Quarter_{-1}$, which serves as the absorbed period for our event study. Columns (I), (II), (III), and (IV) report event study estimates for auto, mortgage, student debt, and credit card balances, respectively. All specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Auto Balance	Mortgage Balance	Student Debt Balance	Credit Card Balance
	(I)	(II)	(III)	(IV)
Pre-MPL Loan Origination Trends				
$Quarter_{-4}$	3.72***	-0.03	-0.82	-32.30***
	(0.41)	(0.21)	(0.62)	(4.47)
$Quarter_{-3}$	3.29***	-0.004	-0.17	-21.00***
	(0.33)	(0.14)	(0.40)	(2.80)
$Quarter_{-2}$	2.18***	0.01	0.04	-10.10***
	(0.16)	(0.08)	(0.24)	(1.32)
Post-MPL Loan Origination Trends				
$Quarter_0$	-2.83***	-1.21***	-0.65***	-63.90***
	(0.20)	(0.11)	(0.24)	(2.76)
$Quarter_{+1}$	-3.55***	-2.42***	-1.19**	-36.20***
	(0.38)	(0.18)	(0.49)	(4.10)
$Quarter_{+2}$	-4.16***	-2.36***	-1.60**	-17.80***
	(0.42)	(0.27)	(0.68)	(5.45)
$Quarter_{+3}$	-5.68***	-2.40***	-2.13**	-9.77
	(0.47)	(0.33)	(0.85)	(7.04)
Observations	5,753,781	3,529,229	3,218,142	10,499,164
Adjusted R^2	0.82	0.96	0.98	0.59
Controls	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

Table III: Effect of MPL Loans on Other Credit Profile Characteristics

This table reports results documenting the evolution of credit profile characteristics in the months surrounding the origination of MPL loans. We subset our analysis to one-time MPL borrowers. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Columns (I), (II), (III), and (IV) report event study estimates for credit card utilization, monthly credit card limit growth, credit card default rates, and credit scores, respectively. All specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Card Utilization	Credit Card Limit Growth	Credit Card Default Rates	Credit Score
	(I)	(II)	(III)	(IV)
Pre-MPL Loan Origination Trends				
$Quarter_{-4}$	-2.79***	0.00	0.51***	-0.23
	(0.67)	(0.57)	(0.10)	(0.29)
$Quarter_{-3}$	-1.94***	0.08	0.34***	-0.21
	(0.43)	(0.42)	(0.09)	(0.20)
$Quarter_{-2}$	-1.02***	0.06	0.18***	-0.16
	(0.21)	(0.22)	(0.05)	(0.10)
Post-MPL Loan Origination Trends				
$Quarter_0$	-12.00***	0.59**	-0.02	2.89***
	(0.42)	(0.28)	(0.04)	(0.13)
$Quarter_{+1}$	-9.02***	0.83*	0.29***	1.50***
	(0.62)	(0.47)	(0.07)	(0.23)
$Quarter_{+2}$	-5.87***	0.02	0.84***	0.48*
	(0.79)	(0.69)	(0.12)	(0.29)
$Quarter_{+3}$	-4.18***	-0.26	1.47***	-0.20
	(1.04)	(0.89)	(0.18)	(0.39)
Observations	11,146,916	9,986,676	10,128,710	11,147,416
Adjusted R^2	0.60	0.01	0.15	0.67
Controls	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

Table IV: Do Defaults Occur on All Forms of Debt After MPL Loan Origination?

This table reports results analyzing whether the origination of MPL loans is associated with increased default rates in loans across broad lines of trade. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Columns (I), (II), (III), (IV), and (V) report event study estimates for default rates in credit cards, auto loans, mortgage loans, student loans, and installment loans, respectively. The installment loans studied in column (V) also include the originated MPL loan itself. All specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Cards	Auto Loans	Mortgage Loans	Student Loans	Installment Loans (+ MPL Loan)
	(I)	(II)	(III)	(IV)	(V)
Pre-MPL Loan Origination Trends					
$Quarter_{-4}$	0.51***	0.17***	0.28***	0.57***	0.55***
	(0.10)	(0.02)	(0.03)	(0.04)	(0.04)
$Quarter_{-3}$	0.34***	0.13***	0.27***	0.48***	0.38***
	(0.09)	(0.01)	(0.02)	(0.03)	(0.03)
$Quarter_{-2}$	0.18***	0.07***	0.16***	0.27***	0.21***
	(0.05)	(0.01)	(0.01)	(0.02)	(0.02)
Post-MPL Loan Origination Trends					
$Quarter_0$	-0.02	-0.02***	-0.04***	0.09***	0.04***
	(0.04)	(0.01)	(0.01)	(0.02)	(0.01)
$Quarter_{+1}$	0.29***	0.01	0.01	0.22***	0.15***
	(0.07)	(0.01)	(0.02)	(0.03)	(0.03)
$Quarter_{+2}$	0.84***	0.07***	0.07**	0.31***	0.28***
	(0.12)	(0.02)	(0.03)	(0.04)	(0.04)
$Quarter_{+3}$	1.47***	0.13***	0.12***	0.32***	0.35***
	(0.18)	(0.03)	(0.04)	(0.04)	(0.05)
Observations	10,128,710	5,753,759	3,529,140	3,218,398	8,815,419
Adjusted R^2	0.15	0.30	0.39	0.19	0.18
Controls	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

Table V: Can Fluctuating Employment or Income Profiles Explain Credit Profile Patterns of MPL Borrowers?

In this table, we report regression results that document fluctuations in income and job profiles in the months surrounding the origination of MPL loans. We subset our analysis to one-time MPL borrowers. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In column (I), the dependent variable is an indicator that equals 1 if the individual's monthly income in a given month differs from their income in the previous month, and 0 otherwise. In column (II), the dependent variable is an indicator that equals 1 if the MPL borrower's job code in a given month differs from their job code in the previous month, and 0 otherwise. Both specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbb{P}$(Income Change)	$\mathbb{P}$(Job Change)
	(I)	(II)
Pre-MPL Loan Origination Trends		
$Quarter_{-4}$	-0.02	1.63*
	(0.14)	(0.86)
$Quarter_{-3}$	0.17	0.28
	(0.11)	(0.32)
$Quarter_{-2}$	0.06	0.16
	(0.06)	(0.16)
Post-MPL Loan Origination Trends		
$Quarter_0$	-0.15**	-0.52**
	(0.07)	(0.20)
$Quarter_{+1}$	-0.15	-0.55
	(0.12)	(0.39)
$Quarter_{+2}$	-0.20	-0.62
	(0.16)	(0.54)
$Quarter_{+3}$	-0.27	-0.70
	(0.21)	(0.69)
Observations	16,174,176	16,174,176
Adjusted R^2	0.01	0.01
Controls	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q

Table VI: Robustness – Controlling for Region-Specific Economic Shocks

This table reports results documenting the robustness of MPL-induced credit profile changes to regional factors. We subset our analysis to one-time MPL borrowers. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Columns (I), (II), (III), (IV) and (V) report event study estimates for credit card balances, credit card utilization, credit card limit growth, credit card default rates, and credit scores, respectively. All specifications include individual (I) and ZIP code × year-quarter ($Z \times Y\text{-}Q$) fixed effects. Robust standard errors, double clustered at the individual and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Card Balances	Credit Card Utilization	Credit Card Limit Growth	Credit Card Default Rates	Credit Score
	(I)	(II)	(III)	(IV)	(V)
Pre-MPL Loan Origination Trends					
$Quarter_{-4}$	-31.20***	-2.64***	-0.03	0.50***	-0.27
	(4.49)	(0.68)	(0.58)	(0.09)	(0.30)
$Quarter_{-3}$	-20.30***	-1.82***	0.05	0.34***	-0.24
	(2.84)	(0.44)	(0.42)	(0.08)	(0.21)
$Quarter_{-2}$	-9.60***	-0.94***	0.03	0.17***	-0.18*
	(1.35)	(0.21)	(0.22)	(0.05)	(0.11)
Post-MPL Loan Origination Trends					
$Quarter_0$	-63.00***	-11.90***	0.60**	-0.02	2.85***
	(2.76)	(0.43)	(0.28)	(0.03)	(0.14)
$Quarter_{+1}$	-35.50***	-8.93***	0.82*	0.29***	1.48***
	(4.16)	(0.63)	(0.48)	(0.07)	(0.23)
$Quarter_{+2}$	-17.40***	-5.83***	0.04	0.85***	0.48
	(5.57)	(0.81)	(0.70)	(0.11)	(0.29)
$Quarter_{+3}$	-9.24	-4.14***	-0.24	1.47***	-0.21
	(7.12)	(1.05)	(0.90)	(0.18)	(0.40)
Observations	10,499,164	11,146,916	9,986,676	10,128,710	11,147,416
Adjusted R^2	0.61	0.62	0.005	0.20	0.70
Controls	✓	✓	✓	✓	✓
Fixed Effects	I, $Z \times Y\text{-}Q$	I, $Z \times Y\text{-}Q$	I, $Z \times Y\text{-}Q$	I, $Z \times Y\text{-}Q$	I, $Z \times Y\text{-}Q$

Table VII: Descriptives – Matching MPL Borrowers to Nearest Non-MPL Borrowing Neighbors Within Same 5-Digit ZIP Code

In this table, we present descriptive statistics comparing the credit and income profiles of borrowers on marketplace lending (MPL) platforms relative to their closest non-MPL borrowing neighbors in the quarter leading up to MPL loan origination. For every MPL borrower, we identify the closest geographically and socioeconomically proximate non-MPL borrowing neighbor in calendar time. We proxy geography through ZIP codes, and match socioeconomic characteristics by using a modified k-nearest neighbors (kNN) algorithm. The matching process used to generate the sample is the "baseline" matching algorithm, which is described in detail in Appendix B. For each matching variable, the subscript indicator next to its name represents the time in months relative to the month of MPL loan origination. We subset our analysis to one-time MPL borrowers.

	Overall		By Credit Status					
			Subprime		Near-Prime		Prime	
	Borrower	Neighbor	Borrower	Neighbor	Borrower	Neighbor	Borrower	Neighbor
Credit Profile Characteristics								
Credit Score$_{(-3)}$	654.20	655.43	602.63	599.52	648.57	649.47	706.84	711.92
Credit Score$_{(-2)}$	654.54	655.10	601.29	597.80	648.75	649.12	708.73	712.75
Credit Score$_{(-1)}$	654.96	655.36	596.67	595.71	649.42	649.49	712.64	714.58
Credit Card Util.$_{(-3)}$	69.81%	70.01%	85.05%	85.68%	73.80%	74.27%	49.90%	49.57%
Credit Card Util.$_{(-2)}$	70.39%	70.57%	85.99%	86.66%	74.56%	74.97%	49.88%	49.53%
Credit Card Util.$_{(-1)}$	70.71%	70.77%	86.90%	87.30%	75.10%	75.34%	49.34%	49.13%
Log(Total Balance)$_{(-3)}$	12.23	12.23	12.27	12.23	12.26	12.26	12.14	12.19
Log(Total Balance)$_{(-2)}$	12.23	12.24	12.28	12.23	12.26	12.27	12.14	12.19
Log(Total Balance)$_{(-1)}$	12.23	12.24	12.28	12.23	12.26	12.27	12.14	12.19
Log(Mortgage Balance)$_{(-3)}$	11.93	11.95	11.96	11.92	11.96	11.97	11.86	11.93
Log(Mortgage Balance)$_{(-2)}$	11.93	11.95	11.96	11.93	11.96	11.97	11.86	11.93
Log(Mortgage Balance)$_{(-1)}$	11.93	11.95	11.97	11.93	11.96	11.97	11.86	11.93
Log(Credit Card Balance)$_{(-3)}$	8.64	8.64	8.84	8.50	8.74	8.78	8.31	8.49
Log(Credit Card Balance)$_{(-2)}$	8.68	8.67	8.88	8.53	8.79	8.82	8.35	8.52
Log(Credit Card Balance)$_{(-1)}$	8.72	8.69	8.91	8.55	8.83	8.84	8.38	8.53

			Subprime		Near-Prime		Prime	
	Borrower	Neighbor	Borrower	Neighbor	Borrower	Neighbor	Borrower	Neighbor
# Trades$_{(-3)}$	10.76	9.75	10.62	9.40	8.80	8.09	7.29	6.55
# Trades$_{(-2)}$	10.82	9.79	10.71	9.49	8.87	8.15	7.32	6.56
# Trades$_{(-1)}$	10.90	9.83	10.80	9.56	8.95	8.20	7.34	6.57
# Credit Card Trades$_{(-3)}$	3.90	3.25	4.55	3.57	3.76	3.27	3.65	3.04
# Credit Card Trades$_{(-2)}$	3.94	3.27	4.59	3.60	3.81	3.29	3.69	3.05
# Credit Card Trades$_{(-1)}$	3.98	3.29	4.64	3.63	3.84	3.31	3.72	3.06
Income Characteristics								
Log(Monthly Income)$_{(-3)}$	8.14	8.23	8.07	8.09	8.13	8.23	8.21	8.35
Log(Monthly Income)$_{(-2)}$	8.14	8.23	8.07	8.09	8.14	8.23	8.21	8.35
Log(Monthly Income)$_{(-1)}$	8.14	8.24	8.07	8.09	8.14	8.24	8.21	8.35
Debt-to-Income$_{(-3)}$	41.04%	47.14%	46.08%	53.22%	41.81%	47.69%	35.57%	41.34%
Debt-to-Income$_{(-2)}$	41.07%	47.43%	45.77%	53.33%	41.99%	48.04%	35.59%	41.67%
Debt-to-Income$_{(-1)}$	41.23%	47.44%	46.07%	53.47%	42.19%	48.03%	35.59%	41.63%
Observations	702,628	690,863	156,033	137,522	357,975	325,030	194,958	238,388

Table VIII: Robustness – Comparing MPL Borrowers to Nearest Non-MPL Borrowing Neighbors Within Same 5-Digit ZIP Code

In this table, we present results documenting the differential trends in credit profile characteristics of marketplace lending (MPL) platform borrowers relative to their geographically and socioeconomically proximate non-MPL borrowing neighbors in the months following MPL loan origination. Every matched pair of an MPL borrower and their closest non-borrowing neighbor is referred to as a cohort. The independent variable of interest, *MPL Borrower*, is an indicator that equals 1 for MPL platform borrowers, and 0 for non-borrowers. The dependent variables in the analysis are monthly credit card balance changes, monthly credit card utilization changes, monthly credit card limit changes, credit card default occurrences, and monthly credit score changes, which are presented separately in Panels A, B, C, D, and E, respectively. Within each panel, columns (I)–(VIII) identify the time period since MPL loan origination by the MPL borrower under consideration. For example, in column (I) of Panel A, we present results comparing monthly credit card balance changes in the quarter of MPL loan origination ($Quarter_0$) for MPL borrowers relative to their non-borrowing neighbors. The estimates presented in all other columns of all other panels are to be interpreted analogously. All specifications include cohort fixed effects (C), with robust standard errors (presented in parentheses) clustered at the ZIP code level. All variables included in the analysis are defined in Appendix A. The matching process used to generate the sample is the "baseline" matching algorithm, which is described in detail in Appendix B. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Δ(Monthly Credit Card Balance)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-13.20***	13.37***	6.21***	3.36***	1.56***	0.72***	0.13	-0.13
	(0.10)	(0.12)	(0.12)	(0.13)	(0.15)	(0.17)	(0.19)	(0.23)
Observations	1392677	1307373	1246310	1191416	1095271	941331	787385	619054

Panel B: Δ(Monthly Credit Card Utilization Ratio)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-3.15***	1.96***	1.07***	0.64***	0.42***	0.26***	0.17***	0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	1392676	1307372	1246309	1191416	1095269	941330	787384	619064

Panel C: Δ(Monthly Credit Card Limits)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	1.72***	1.86***	0.97***	0.45***	-0.13***	-0.40***	-0.53***	-0.55***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Observations	1392676	1307372	1246309	1191416	1095269	941330	787384	619054

Panel D: $\mathbb{P}$(Credit Card Default)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-1.28***	-1.78***	-1.29***	-0.22***	0.90***	1.69***	1.96***	2.09***
	(0.02)	(0.04)	(0.05)	(0.06)	(0.07)	(0.08)	(0.09)	(0.10)
Observations	1367121	1287167	1229065	1176579	1082768	932274	780902	614671

Panel E: Δ(Monthly Credit Score)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	0.92***	-0.30***	-0.21***	-0.18***	-0.13***	-0.09***	-0.06*	-0.10***
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Observations	1393957	1315948	1260796	1213513	1124408	974727	821928	650885

Table IX: Does Ex Ante MPL Borrower Credit Quality Matter?

This table reports results documenting the evolution of credit profile characteristics in the months surrounding the origination of MPL loans, separately for the subprime, near-prime, and prime segments of MPL borrowers. An MPL borrower is deemed subprime, near-prime, or prime if their credit score is below 620, between 620 and 680, or greater than or equal to 680, respectively, in the month immediately before the month of MPL loan origination. We subset our analysis to one-time MPL borrowers. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A, B, C, D, and E focus on balances, utilization, credit limit growth, default rates (all in the credit card domain), and credit scores, respectively. In each panel, columns (I), (II), and (III) focus on subprime, near-prime, and prime MPL borrowers. All specifications include individual and year-quarter fixed effects. Robust standard errors, double clustered at the individual (I) and year-quarter (Y-Q) levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Credit Card Balances			**Panel B**: Credit Card Utilization		
	Sub-Prime	Near-Prime	Prime	Sub-Prime	Near-Prime	Prime
	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-13.20***	-32.20***	-49.20***	-1.16	-3.63***	-4.58***
	(3.68)	(4.45)	(5.45)	(0.77)	(0.73)	(0.59)
$Quarter_{-3}$	-5.70**	-19.80***	-36.70***	-0.02	-2.28***	-3.99***
	(2.33)	(2.84)	(3.37)	(0.48)	(0.46)	(0.39)
$Quarter_{-2}$	-1.45	-9.09***	-19.40***	0.43**	-1.13***	-2.47***
	(1.10)	(1.34)	(1.64)	(0.22)	(0.21)	(0.20)
Post-MPL Loan Origination Trends						
$Quarter_0$	-44.60***	-67.00***	-75.30***	-11.90***	-13.80***	-10.60***
	(2.18)	(2.70)	(3.00)	(0.47)	(0.46)	(0.37)
$Quarter_{+1}$	-17.20***	-38.30***	-49.00***	-8.24***	-10.70***	-8.49***
	(3.47)	(4.06)	(4.36)	(0.72)	(0.68)	(0.51)
$Quarter_{+2}$	-3.35	-19.40***	-27.60***	-5.39***	-7.21***	-5.41***
	(4.69)	(5.34)	(6.05)	(0.93)	(0.87)	(0.65)
$Quarter_{+3}$	1.48	-10.80	-17.70**	-4.04***	-5.27***	-3.67***
	(5.84)	(6.92)	(8.06)	(1.21)	(1.14)	(0.87)
Observations	2,467,653	5,222,937	2,808,574	2,457,795	5,203,935	2,797,433
Adjusted R^2	0.68	0.59	0.54	0.50	0.53	0.58
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

	Panel C: Credit Card Limit Growth			**Panel D**: Credit Card Default Rate			**Panel E**: Credit Scores		
	Sub-Prime	Near-Prime	Prime	Sub-Prime	Near-Prime	Prime	Sub-Prime	Near-Prime	Prime
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends									
$Quarter_{-4}$	0.34	0.19	-0.61	1.43***	0.15***	0.08*	-1.24***	0.02	0.30
	(0.63)	(0.61)	(0.51)	(0.29)	(0.04)	(0.04)	(0.41)	(0.29)	(0.19)
$Quarter_{-3}$	0.09	0.28	-0.27	0.94***	0.11***	0.05*	-1.51***	-0.02	0.65***
	(0.48)	(0.43)	(0.38)	(0.23)	(0.03)	(0.03)	(0.29)	(0.20)	(0.14)
$Quarter_{-2}$	-0.07	0.16	-0.01	0.45***	0.05***	0.02	-1.12***	-0.07	0.52***
	(0.26)	(0.23)	(0.20)	(0.14)	(0.01)	(0.02)	(0.15)	(0.10)	(0.07)
Post-MPL Loan Origination Trends									
$Quarter_{0}$	1.33***	0.50*	0.11	-0.79***	0.002	-0.01	3.60***	3.14***	1.76***
	(0.29)	(0.30)	(0.23)	(0.19)	(0.01)	(0.02)	(0.19)	(0.15)	(0.10)
$Quarter_{+1}$	1.44***	0.79	0.35	0.30	0.10***	0.004	2.25***	1.72***	0.44***
	(0.50)	(0.51)	(0.41)	(0.36)	(0.03)	(0.03)	(0.31)	(0.24)	(0.16)
$Quarter_{+2}$	0.06	-0.03	0.08	2.58***	0.10**	0.004	0.96**	0.66**	-0.23
	(0.73)	(0.74)	(0.60)	(0.40)	(0.04)	(0.04)	(0.39)	(0.30)	(0.19)
$Quarter_{+3}$	-0.67	-0.34	0.22	5.07***	0.13**	-0.004	0.02	-0.06	-0.58**
	(0.92)	(0.96)	(0.79)	(0.55)	(0.05)	(0.06)	(0.52)	(0.41)	(0.27)
Observations	2,346,117	4,968,410	2,672,149	2,318,161	4,230,312	3,580,237	2,595,499	5,547,189	3,004,728
Adjusted R^2	0.01	0.01	0.00	0.25	0.20	0.16	0.47	0.43	0.53
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

Table X: Do MPL Loans Alter the Perceived Credit Quality of Borrowers?

In this table, we present results documenting the effects of MPL-induced credit card debt consolidation activities on the perceived credit quality of MPL borrowers. Our analysis relies on comparing outcomes for MPL borrowers relative to their geographically and socio-economically proximate non-MPL borrowing neighbors. Every matched pair of an MPL borrower and their non-borrowing neighbor is referred to as a cohort. In Panel A (Panel B), we compare MPL borrowers to non-MPL borrowing neighbors who are subprime (near-prime) in the month immediately before the origination of the MPL loan by MPL borrowers. In column (I) of both panels, the dependent variable is the individual's logged average credit score in months [+1,+3] less their logged average credit score in months [-3,-1]. The window [x,y] captures months relative to the month of MPL loan origination. In columns (II) and (III) of both panels, the dependent variable is the individual's logged average credit card limit in months [+1,+3] less their logged average limits in months [-3,-1]. In Panel A (Panel B), the dependent variable in column (IV) is an indicator variable, which is 1 if the individual's credit score crosses the 620 (680) threshold in months [+1,+3], and 0 otherwise. All specification include cohort fixed effects (C). Robust standard errors, clustered at the (5-digit) ZIP code level, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. The algorithm underlying the matching of MPL borrowers and non-MPL borrowing neighbors, referred to as the baseline matching criteria, is described in detail in Appendix B. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Subprime Cohorts				**Panel B**: Near-Prime Cohorts			
	1st Stage	IV	OLS		1st Stage	IV	OLS	
	Δ(Credit Score)	Δ(CC Limits)	Δ(CC Limits)	$\mathbb{I}(Score_{post} >= 620)$	Δ(Credit Score)	Δ(CC Limits)	Δ(CC Limits)	$\mathbb{I}(Score_{post} >= 680)$
	(I)	(II)	(III)	(IV)	(I)	(II)	(III)	(IV)
MPL Borrower	5.43***			34.80***	4.25***			32.70***
	(0.09)			(0.27)	(0.04)			(0.31)
Δ(Credit Score)		0.89***	0.32***			0.11***	0.05***	
		(0.05)	(0.03)			(0.01)	(0.02)	
Observations	228051	228051	228051	228051	523674	523674	523674	523674
Adjusted R^2	0.16	0.01	0.03	0.17	0.13	0.01	0.03	0.17
Fixed Effects	C	C	C	C	C	C	C	C
Controls	✓	✓	✓	✓	✓	✓	✓	✓
F-Stat (Excl Instr.)		7140				11600		

Appendix A - Variable Definitions

- *Standardized Income* – Monthly income standardized using the average and standard deviation of monthly income for every year-month included in the analysis.
- *Homeowner* – Indicator variable that equals 1 if the individual is identified as a homeowner by the credit bureau, and 0 otherwise.
- *College Educated* – Indicator variable that equals 1 if the individual has a college degree as identified by the credit bureau, and 0 otherwise.
- *Financially Sophisticated Job* – Indicator variable that equals 1 if the individual is identified to work in a field that requires financial sophistication, and 0 otherwise.

Appendix B - k-Nearest Neighbors Matching Process

In this section, we explain in detail the algorithmic process we use to create a matched sample of marketplace lending (MPL) platform borrowers and non-MPL borrowers. Broadly, this algorithm relies on matching each MPL borrower to the closest non-MPL borrowing neighbor on the basis of geographic and socio-economic proximity, and it is a minor variant of the k-nearest neighbors (kNN) algorithm. We perform this process in calendar time, which allows us to create cohorts of MPL borrowers and non-MPL borrowing neighbors. The steps listed below highlight our approach and provide the necessary details and discussion.

Matching MPL Borrowers to Nearest Non-MPL Borrowing Neighbors Within Same 5-Digit ZIP

- Step 01: For each MPL borrower, we identify all neighbors living in the same 5-digit ZIP code as the MPL borrower in the month of MPL loan origination. The neighbors are identified such that they belong to a household distinct from the household of the MPL borrower. Within this set, we identify the subset of neighbors who have never opened a MPL trade over the period 2010–2017.

  Our baseline analysis is conducted at the 5-digit ZIP code level, since the average 5-digit ZIP code population in the United States is approximately 7,500 people.[27] This disaggregated geographic level allows for the optimal trade-off between identifying geographically proximate non-MPL borrowers, while still allowing for a sizeable matched sample of borrowers to neighbors.

- Step 02: From the subset of neighbors identified at the end of the preceding step, we further subset our non-MPL borrowing neighbors sample to include only those neighbors who have had a non-utilities, bank hard credit check performed against them in the quarter before the MPL borrower originates his MPL loan. A "hard" credit check or inquiry is performed when an individual applies for a loan, and the prospective lender requests the applicant's credit report and score from a credit bureau. A single hard credit inquiry can typically drop the applicant's credit score by 5 to 10 points, which can result in higher interest rates for subsequent loans. Thus, hard inquiries can serve as a proxy for "serious interest" in obtaining credit from a lender.

  For the purpose of our analysis, we consider non-MPL borrowing neighbors who have applied for loans at traditional banking institutions. Moreover, we consider only neighbors who fail to obtain traditional bank credit. In effect, we can identify non-MPL borrowing neighbors who have a "need" for credit that remains unfulfilled by the traditional banking institution. This process helps us create a more appropriate control group of non-MPL borrowers, who might differ from individuals who have no need for additional credit from banks.

[27] https://www.zip-codes.com/zip-code-statistics.asp

- Step 03: From the subset of neighbors identified in the above step, we make use of our cohort-level, calendar-time approach to next identify neighbors who have displayed credit profile trends that are similar to ones shown by the MPL borrower in their cohort in the quarter leading up to MPL loan origination. We require that certain credit profile characteristics display identical trends for both the non-borrowing neighbor and the MPL borrower. These characteristics are credit card balances, credit card utilization ratios, and credit scores.

- Step 04: As a final step, we identify the nearest (top 1) neighbor in month preceding MPL loan origination using the k-nearest neighbor algorithm. The dimenions included in the kNN algorithm include credit score, credit card utilization ratio, number of open trade accounts, credit card balance, mortgage balance, total balance, personal monthly income, and the debt-to-income ratio.

  In effect, we create a matched sample of MPL borrowers and non-MPL borrowers who reside in the same geographical space, and display similar credit profile trends in the calendar months leading up to the MPL borrower originating an MPL loan. The only differentiating characteristic between MPL borrowers and non-MPL borrowers is the origination of the MPL loan.

In addition to the baseline matching approach discussed above, we demonstrate the robustness of our results to two additional matching techniques:

Matching Bank Credit-Denied MPL Borrowers to Nearest Non-MPL Borrowing Bank Credit-Denied Neighbors Within Same 5-Digit ZIP

- Identical to the baseline matching approach, except that MPL borrowers and their neighbors are both subsetted such that both groups contain only individuals who have applied for, and have been denied, credit from traditional banks in the quarter preceding the origination of the MPL loan by the MPL borrower. In effect, we are identifying the set of individuals who have unsuccessfully applied for bank credit. The differentiating factor between MPL borrowers and their non-MPL borrowing neighbors is that the former originate MPL loans.

Matching MPL Borrowers to Nearest Non-MPL Borrowing Neighbors Within Same 9-Digit ZIP

- Identical to the baseline approach, with the exception being that we consider neighbors from the same 9-digit ZIP code as the MPL borrower. Given that the average population of a 9-digit ZIP in the United States is fewer than 10 people, and given that individuals of similar socioeconomic characteristics tend to co-locate in the United States, we can identify a very close match of non-MPL borrowing neighbors using this approach. Moreover, our findings are re-affirmed in this significantly smaller matched sample.

Appendix C - Additional Tables

In this section, we present additional results that supplement the main findings of the paper, but were left out of the main text of the paper due to length considerations.

A brief summary of the additional tests is presented below:

- In Appendix Table C.I, we present results that document the robustness of our findings to the matching algorithm that relies on pairing bank credit-denied MPL borrowers with socio-economically similar non-MPL borrowing, bank credit-denied neighbors. The implementation of the algorithm is described in Appendix B.
- In Appendix Table C.II, we show that our results presented in Table VIII hold even when creating a matched sample of MPL borrowers and socio-economically similar non-MPL borrowing neighbors selected from the MPL borrowers' 9-digit ZIP codes. The baseline analysis in Table VIII creates the matched sample at the 5-digit ZIP code level.
- In Appendix Table C.III, we show that, for the subprime segment of the MPL borrower base, defaults in the post-MPL loan origination period are concentrated in credit cards, and not in other forms of debt, including the originated MPL loan itself.
- In Appendix Table C.IV, we present results documenting MPL loan-induced credit profile changes along cross-sectional cuts based on the interest rates charged on such loans. The analysis is conducted separately for different terciles of charged interest rates.
- In Appendix Table C.V, we present results documenting MPL loan-induced credit profile changes along cross-sectional cuts based on MPL loan amounts. The analysis is conducted separately for different terciles of borrowed MPL amounts.

Table C.I: Robustness – Comparing Bank Credit-Denied MPL Borrowers to Closest Non-MPL Borrowing Bank Credit-Denied Neighbors Within Same 5-Digit ZIP Code

In this table, we present results documenting the differential trends in credit profile characteristics of marketplace lending (MPL) platform borrowers relative to their geographically and socio-economically proximate non-MPL borrowing neighbors in the months following MPL loan origination. Every matched pair of an MPL borrower and her closest non-borrowing neighbor is referred to as a cohort. The independent variable of interest, *MPL Borrower*, is an indicator that equals 1 for MPL platform borrowers, and 0 for non-borrowers. The dependent variables in the analysis are monthly credit card balance changes, monthly credit card utilization changes, monthly credit card limit changes, credit card default occurrences, and monthly credit score changes, which are presented separately in Panels A, B, C, D, and E, respectively. Within each panel, columns (I)–(VIII) identify the time period since MPL loan origination by the MPL borrower under consideration. For example, in column (I) of Panel A, we present results comparing monthly credit card balance changes in the quarter of MPL loan origination ($Quarter_0$) for MPL borrowers relative to their non-borrowing neighbors. The estimates presented in all other columns of all other panels are to be interpreted analogously. All specifications include cohort fixed effects (C), with robust standard errors (presented in parentheses) clustered at the ZIP code level. All variables included in the analysis are defined in Appendix A. The matching process used to generate the sample is described in detail in Appendix B. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Δ(Monthly Credit Card Balance)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-12.65***	12.96***	6.35***	3.37***	1.58***	0.52	0.28	0.44
	(0.28)	(0.35)	(0.36)	(0.37)	(0.43)	(0.49)	(0.56)	(0.64)
Observations	185317	173351	164607	157090	144912	124323	103586	84482

Panel B: Δ(Monthly Credit Card Utilization Ratio)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-2.95***	1.86***	1.04***	0.63***	0.40***	0.25***	0.18***	0.14**
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
Observations	185317	173351	164606	157089	144912	124323	104126	84482

Panel C: Δ(Monthly Credit Card Limits)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	1.49***	2.02***	1.05***	0.42***	-0.03	-0.23**	-0.43***	-0.26*
	(0.06)	(0.08)	(0.08)	(0.09)	(0.10)	(0.11)	(0.13)	(0.14)
Observations	185317	173351	164606	157089	144912	124323	104126	84482

Panel D: $\mathbb{P}$(Credit Card Default)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-1.31***	-1.72***	-1.05***	-0.11	1.03***	1.64***	2.03***	1.69***
	(0.07)	(0.10)	(0.13)	(0.16)	(0.18)	(0.21)	(0.25)	(0.28)
Observations	181363	170149	161803	154663	142795	122781	102996	83653

Panel E: Δ(Monthly Credit Score)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	0.66***	-0.50***	-0.37***	-0.29***	-0.23***	-0.16***	-0.10***	-0.10***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Observations	185473	174405	166407	159856	148565	128504	108337	88413

Table C.II: Robustness – Comparing MPL Borrowers to Nearest Non-MPL Borrowing Neighbors Within Same 9-Digit ZIP Code

In this table, we present results documenting the differential trends in credit profile characteristics of marketplace lending (MPL) platform borrowers relative to their geographically and socio-economically proximate non-MPL borrowing neighbors in the months following MPL loan origination. Every matched pair of an MPL borrower and her closest non-borrowing neighbor is referred to as a cohort. The independent variable of interest, *MPL Borrower*, is an indicator that equals 1 for MPL platform borrowers, and 0 for non-borrowers. The dependent variables in the analysis are monthly credit card balance changes, monthly credit card utilization changes, monthly credit card limit changes, credit card default occurrences, and monthly credit score changes, which are presented separately in Panels A, B, C, D, and E, respectively. Within each panel, columns (I)–(VIII) identify the time period since MPL loan origination by the MPL borrower under consideration. For example, in column (I) of Panel A, we present results comparing monthly credit card balance changes in the quarter of MPL loan origination ($Quarter_0$) for MPL borrowers relative to their non-borrowing neighbors. The estimates presented in all other columns of all other panels are to be interpreted analogously. All specifications include cohort fixed effects (C), with robust standard errors (presented in parentheses) clustered at the ZIP code level. All variables included in the analysis are defined in Appendix A. The matching process used to generate the sample is described in detail in Appendix B. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Δ(Monthly Credit Card Balance)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-13.47***	12.09***	5.16***	2.39***	2.14**	0.90	-0.33	-0.63
	(0.56)	(0.74)	(0.71)	(0.80)	(0.91)	(1.04)	(1.29)	(1.62)
Observations	44632	41767	39754	36519	31338	26110	20458	16149

Panel B: Δ(Monthly Credit Card Utilization Ratio)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-3.01***	1.77***	0.97***	0.48***	0.38***	0.21**	0.18	0.08
	(0.06)	(0.07)	(0.07)	(0.08)	(0.09)	(0.10)	(0.11)	(0.14)
Observations	44632	41767	39754	36519	31338	26110	20458	16149

Panel C: Δ(Monthly Credit Card Limits)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	1.25***	1.38***	0.65***	0.24	-0.06	-0.46*	-0.56**	-0.67**
	(0.11)	(0.15)	(0.16)	(0.18)	(0.20)	(0.24)	(0.26)	(0.32)
Observations	44632	41767	39754	36519	31338	26110	20458	16149

Panel D: $\mathbb{P}$(Credit Card Default)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	-0.97***	-1.46***	-1.07***	-0.46	0.09	1.05**	1.35***	1.28**
	(0.13)	(0.20)	(0.25)	(0.30)	(0.36)	(0.45)	(0.50)	(0.56)
Observations	43725	41013	39086	36006	30914	25796	20264	16293

Panel E: Δ(Monthly Credit Score)

	$Quarter_0$	$Quarter_{+1}$	$Quarter_{+2}$	$Quarter_{+3}$	$Quarter_{+4}$	$Quarter_{+5}$	$Quarter_{+6}$	$Quarter_{+7}$
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
MPL Borrower	0.75***	-0.39***	-0.07	-0.08	0.05	0.03	-0.12	0.12
	(0.04)	(0.06)	(0.11)	(0.10)	(0.11)	(0.16)	(0.18)	(0.19)
Observations	44667	42010	40161	37151	32132	26970	21297	16942

Table C.III: Do Defaults Occur on All Forms of Debt After MPL Loan Origination for Subprime Borrowers?

This table reports results analyzing whether the origination of MPL loans is associated with increased default rates in loans across broad lines of trade for MPL borrowers who were subprime at the time of MPL loan origination. The independent variables represent time in quarters relative to the quarter of MPL loan origination, $Quarter_0$. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Columns (I), (II), (III), (IV), and (V) report event study estimates for default rates in credit cards, auto loans, mortgage loans, student loans, and installment loans, respectively. The installment loans studied in column (V) also include the originated MPL loan itself. All specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Credit Cards	Auto Loans	Mortgage Loans	Student Loans	Installment Loans (+ MPL Loan)
	(I)	(II)	(III)	(IV)	(V)
Pre-MPL Loan Origination Trends					
$Quarter_{-4}$	1.43***	0.21***	0.42***	0.81***	0.86***
	(0.29)	(0.04)	(0.10)	(0.12)	(0.09)
$Quarter_{-3}$	0.94***	0.17***	0.51***	0.77***	0.63***
	(0.23)	(0.03)	(0.06)	(0.09)	(0.06)
$Quarter_{-2}$	0.45***	0.14***	0.30***	0.50***	0.39***
	(0.14)	(0.02)	(0.04)	(0.06)	(0.04)
Post-MPL Loan Origination Trends					
$Quarter_0$	-0.79***	-0.08***	-0.08**	0.05	-0.01
	(0.19)	(0.02)	(0.03)	(0.06)	(0.03)
$Quarter_{+1}$	0.30	-0.03	-0.00	0.20**	0.17***
	(0.36)	(0.03)	(0.06)	(0.10)	(0.06)
$Quarter_{+2}$	2.58***	0.09**	0.05	0.30**	0.36***
	(0.40)	(0.04)	(0.10)	(0.14)	(0.09)
$Quarter_{+3}$	5.07***	0.19***	0.14	0.43***	0.55***
	(0.55)	(0.05)	(0.11)	(0.16)	(0.12)
Observations	2,318,161	1,510,989	807,781	727,415	1,898,407
Adjusted R^2	0.25	0.33	0.42	0.22	0.20
Controls	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

Table C.IV: Do Interest Rates Charged on MPL Loans Matter?

This table reports results documenting the evolution of credit profile characteristics in the months surrounding the origination of MPL loans. We subset our analysis to one-time MPL Borrowers. The independent variables represent quarters relative to MPL loan origination, where $Quarter_0$ refers to the quarter in which the MPL loan is originated. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A, B, C, D, and E focus on balances, utilization, credit limit growth, default rates (all in the credit card domain), and credit scores, respectively. In each panel, columns (I), (II), and (III) focus on low-interest rate, medium-interest rate, and high-interest rate borrowers. All specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter level, are presented in parentheses. All control variables in the analysis are defined in Appendix A.

	Panel A: Credit Card Balances			**Panel B**: Credit Card Utilization		
	Low Rate	Medium Rate	High Rate	Low Rate	Medium Rate	High Rate
	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-32.80***	-33.10***	-28.70***	-3.25***	-3.66***	-2.65***
	(4.09)	(4.58)	(4.62)	(0.49)	(0.72)	(0.93)
$Quarter_{-3}$	-21.00***	-21.60***	-18.70***	-2.02***	-2.44***	-1.91***
	(2.72)	(3.00)	(3.08)	(0.34)	(0.47)	(0.61)
$Quarter_{-2}$	-9.78***	-10.40***	-9.37***	-0.91***	-1.25***	-1.09***
	(1.36)	(1.52)	(1.57)	(0.19)	(0.24)	(0.28)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	-81.00***	-65.30***	-42.40***	-13.70***	-13.30***	-10.30***
	(2.82)	(2.92)	(2.58)	(0.40)	(0.50)	(0.45)
$Quarter_{+1}$	-56.60***	-34.60***	-14.60***	-11.60***	-10.00***	-6.60***
	(4.25)	(4.45)	(4.08)	(0.57)	(0.72)	(0.76)
$Quarter_{+2}$	-33.50***	-15.40***	-2.49	-8.16***	-6.33***	-4.07***
	(5.28)	(5.65)	(5.49)	(0.68)	(0.90)	(1.01)
$Quarter_{+3}$	-21.20***	-7.00	0.41	-6.03***	-4.26***	-3.09**
	(7.10)	(6.84)	(6.75)	(0.91)	(1.11)	(1.28)
Observations	3,395,020	3,249,139	3,045,146	3,388,435	3,235,939	3,027,700
Adjusted R^2	0.59	0.60	0.60	0.65	0.56	0.48
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

	Panel C: Δ(Credit Card Limits)			**Panel D**: $\mathbb{P}$(Credit Card Defaults)			**Panel E**: Credit Scores		
	Low Rate	Medium Rate	High Rate	Low Rate	Medium Rate	High Rate	Low Rate	Medium Rate	High Rate
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends									
$Quarter_{-4}$	-0.12	-0.20	0.27	0.17***	0.40***	0.95***	-0.14	0.13	-0.74*
	(0.41)	(0.64)	(0.80)	(0.05)	(0.09)	(0.17)	(0.20)	(0.29)	(0.40)
$Quarter_{-3}$	-0.06	-0.08	0.33	0.12***	0.25***	0.65***	-0.20	0.06	-0.54*
	(0.30)	(0.47)	(0.58)	(0.04)	(0.09)	(0.16)	(0.14)	(0.21)	(0.28)
$Quarter_{-2}$	-0.01	-0.03	0.17	0.07***	0.15***	0.32***	-0.19**	-0.01	-0.31**
	(0.15)	(0.25)	(0.31)	(0.02)	(0.05)	(0.10)	(0.08)	(0.11)	(0.14)
Post-MPL Loan Origination Trends									
$Quarter_{0}$	0.53**	0.55*	0.75**	0.01	-0.01	-0.12*	3.30***	3.11***	2.21***
	(0.22)	(0.29)	(0.37)	(0.02)	(0.04)	(0.07)	(0.12)	(0.15)	(0.15)
$Quarter_{+1}$	0.80**	0.86*	0.87	0.13***	0.22***	0.38**	2.09***	1.61***	0.73**
	(0.35)	(0.50)	(0.66)	(0.03)	(0.08)	(0.16)	(0.19)	(0.26)	(0.28)
$Quarter_{+2}$	0.33	0.10	-0.29	0.26***	0.64***	1.56***	1.38***	0.53*	-0.56
	(0.51)	(0.73)	(0.95)	(0.06)	(0.11)	(0.20)	(0.22)	(0.32)	(0.38)
$Quarter_{+3}$	0.31	-0.24	-0.89	0.45***	1.23***	2.83***	0.95***	-0.22	-1.47***
	(0.64)	(0.95)	(1.25)	(0.08)	(0.16)	(0.31)	(0.31)	(0.40)	(0.50)
Observations	3,238,108	3,089,236	2,888,599	3,252,021	3,123,578	2,967,918	3,513,640	3,449,778	3,319,095
Adjusted R^2	0.003	0.01	0.01	0.18	0.20	0.21	0.68	0.59	0.58
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

Table C.V: Does the Amount of MPL Credit Disbursed Influence Credit Profile Characteristics?

This table reports results documenting the evolution of credit profile characteristics in the months surrounding the origination of MPL loans. We subset our analysis to one-time MPL borrowers. The independent variables represent quarters relative to MPL loan origination, where $Quarter_0$ refers to the quarter in which the MPL loan is originated. All other quarter indicators are defined in a similar manner. The estimates represent percentage differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A, B, C, D, and E focus on balances, utilization, credit limit growth, default rates (all in the credit card domain), and credit scores, respectively. In each panel, columns (I), (II), and (III) focus on low-MPL amount, medium-MPL amount, and high-MPL amount loan borrowers. All specifications include individual (I) and year-quarter (Y-Q) fixed effects. Robust standard errors, double clustered at the individual and year-quarter level, are presented in parentheses. All control variables in the analysis are defined in Appendix A.

	Panel A: Credit Card Balances			**Panel B**: Credit Card Utilization		
	Low Amount	Medium Amount	High Amount	Low Amount	Medium Amount	High Amount
	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-26.70***	-33.00***	-35.50***	-1.50*	-3.30***	-4.74***
	(4.86)	(5.00)	(3.64)	(0.86)	(0.75)	(0.53)
$Quarter_{-3}$	-17.10***	-21.50***	-23.10***	-0.95*	-2.26***	-3.13***
	(3.15)	(3.29)	(2.43)	(0.54)	(0.50)	(0.36)
$Quarter_{-2}$	-8.29***	-10.30***	-11.10***	-0.50*	-1.15***	-1.57***
	(1.58)	(1.62)	(1.17)	(0.27)	(0.24)	(0.19)
Post-MPL Loan Origination Trends						
$Quarter_0$	-36.30***	-72.10***	-79.70***	-7.82***	-13.90***	-15.20***
	(3.08)	(3.10)	(2.76)	(0.50)	(0.46)	(0.48)
$Quarter_{+1}$	-14.90***	-39.70***	-51.00***	-5.48***	-10.30***	-12.30***
	(4.45)	(4.56)	(3.72)	(0.75)	(0.69)	(0.60)
$Quarter_{+2}$	-5.34	-19.80***	-26.90***	-3.90***	-6.67***	-8.03***
	(5.91)	(5.99)	(4.67)	(0.97)	(0.86)	(0.73)
$Quarter_{+3}$	-2.47	-11.20	-15.30**	-3.28***	-4.76***	-5.53***
	(7.36)	(7.54)	(6.08)	(1.23)	(1.13)	(0.93)
Observations	3,030,999	3,041,245	3,579,830	2,891,741	2,903,206	3,420,996
Adjusted R^2	0.61	0.60	0.60	0.01	0.002	0.004
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

	Panel C: Δ(Credit Card Limits)			**Panel D**: $\mathbb{P}$(Credit Card Defaults)			**Panel E**: Credit Scores		
	Low-Amount	Medium-Amount	High-Amount	Low-Amount	Medium-Amount	High-Amount	Low-Amount	Medium-Amount	High-Amount
	(I)	(II)	(III)	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends									
$Quarter_{-4}$	-0.25	0.12	0.09	0.72***	0.44***	0.27***	-1.28***	-0.21	0.74***
	(0.81)	(0.64)	(0.40)	(0.14)	(0.11)	(0.07)	(0.35)	(0.31)	(0.22)
$Quarter_{-3}$	-0.03	0.16	0.08	0.44***	0.30***	0.20***	-0.90***	-0.19	0.42***
	(0.58)	(0.46)	(0.30)	(0.13)	(0.09)	(0.06)	(0.25)	(0.22)	(0.16)
$Quarter_{-2}$	0.06	0.08	0.01	0.22***	0.17***	0.11**	-0.51***	-0.15	0.15*
	(0.30)	(0.25)	(0.16)	(0.07)	(0.05)	(0.04)	(0.12)	(0.11)	(0.09)
Post-MPL Loan Origination Trends									
$Quarter_{0}$	0.90**	0.66**	0.31	-0.11*	-0.03	0.02	1.37***	3.11***	4.06***
	(0.36)	(0.32)	(0.20)	(0.06)	(0.04)	(0.04)	(0.14)	(0.15)	(0.15)
$Quarter_{+1}$	0.79	1.05*	0.73**	0.33***	0.14	0.22***	0.15	1.61***	2.63***
	(0.66)	(0.54)	(0.32)	(0.12)	(0.09)	(0.05)	(0.26)	(0.24)	(0.22)
$Quarter_{+2}$	0.02	0.13	0.04	1.28***	0.66***	0.49***	-0.67**	0.50*	1.52***
	(0.94)	(0.78)	(0.48)	(0.17)	(0.12)	(0.09)	(0.33)	(0.30)	(0.26)
$Quarter_{+3}$	-0.39	-0.18	-0.14	2.21***	1.30***	0.90***	-1.25***	-0.26	0.82**
	(1.23)	(0.98)	(0.63)	(0.24)	(0.19)	(0.14)	(0.45)	(0.40)	(0.33)
Observations	3,048,835	3,051,204	3,589,266	2,983,120	2,931,748	3,428,649	3,336,950	3,220,792	3,724,771
Adjusted R^2	0.59	0.54	0.58	0.21	0.20	0.19	0.69	0.68	0.65
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$