Winners and Losers of Marketplace Lending: Evidence from Borrower Credit Dynamics

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Abstract

Does marketplace lending (MPL) benefit all its borrowers? Using comprehensive credit bureau data and MPL borrowers matched to non-MPL borrowers in the same ZIP code (or ZIP+4) with identical credit dynamics, we analyze credit profile evolution of borrowers on a major MPL platform, both prior to, and following, the loan origination. Consistent with the stated purpose for the loan, borrowers consolidate expensive credit card debt, leading to lower credit utilization ratios and higher credit scores in the two quarters after loan origination. But, during the same time period, they also receive additional credit from their existing bank relationships. Subsequently, MPL borrowers consume more credit, leaving them as indebted in credit card debt three quarters post-MPL loan origination as they were prior to borrowing on the MPL platform. Further, they experience a significant increase in credit card default occurrences in the months following MPL loan origination, with the effects more pronounced for subprime MPL borrowers. Our results highlight how MPL platforms substantially increase the probability of converting subprime (near-prime) borrowers into near-prime (prime) borrowers through credit card debt consolidation, and how the resulting "information cascade" to traditional banks could lead to some borrowers being worse off.

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I. Introduction

Contemporary banking theory identifies information processing and monitoring of borrowers as two important functions performed by banks in their role as financial intermediaries. Relative to individual lenders, banks enjoy economies of scale in reducing information asymmetries in the credit market in overcoming adverse selection, moral hazard, and costly state verification problems. These functions are important because significant information asymmetry, coupled with an absence of financial intermediation, can result in the breakdown of lending markets (Akerlof, 1970).

As of 2017, consumer lending accounts for a significant share of bank balance sheets in the U.S. totaling around \$3.6 trillion dollars. However, the credit market is rife with several inefficiencies[1] that have created potentially profitable entry opportunities for financial technology innovators such as marketplace lending (MPL) platforms that specialize in peer-to-peer (P2P) lending. These FinTech players, while still a small segment of the market, are experiencing a rapid growth in lending volumes.[2] They attempt to differentiate themselves by seeking to directly match borrowers and lenders through alternative screening and monitoring technology as compared to traditional banks. Moreover, these FinTech lenders engage in alternative interest rate pricing schemes through the use of alternative data and techniques, which can potentially improve the risk pricing of applicants.

In this paper, we analyze who benefits from borrowing on MPL platforms. Specifically, we aim to address the following questions. First, given that there are no mechanisms in place to monitor the actual usage of borrowed MPL funds, we analyze whether there is *misreporting* on loan applications regarding the stated aim of debt consolidation. 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) with identical credit dynamics, and analyze whether MPL borrowing impacts other credit profile characteristics, such as credit scores or credit availability of MPL borrowers. Finally, we compare and contrast the immediate versus long-term benefits or costs generated by MPL platforms on their borrowers, relative to non-MPL borrowing neighbors within the same cohort. In doing

[1]For example, imperfect pooling of borrowers of varying credit risk (Leland and Pyle, 1977); credit rationing (Stiglitz and Weiss, 1981), especially for applicants with poor hard information credentials, such as credit scores and utilization ratios. Finally, despite ultra-low short-term interest rates, the interest rates charged on credit cards and personal loans are high, even for high credit quality applicants (Stango and Zinman, 2009)

[2]From 2007:Q3 to 2017:Q3, Lending Club and Prosper, two dominant marketplace lending platforms in the consumer credit space, have disbursed approximately \$35 billion in online-originated, peer-financed loans. Goldman Sachs estimates that more than 31% of the \$843 billion unsecured personal lending market is prone to disruption by MPL.

so, we also identify the underlying mechanisms driving these benefits and costs.

As a starting step, we study the characteristics of individuals who borrow on peer-financed lending platforms. Using anonymized individual-level data, complete with rich dynamics at the year-month level and narrow geographic information, made available to us by a credit bureau, we identify approximately 1 million borrowers on MPL platforms in the month immediate prior to peer-financed loan origination, and compare them 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 American adult. MPL borrowers are found to 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 of 69% is over twice the national average of 30%. Additionally, MPL borrowers have average credit scores that are over 20 points below the national average, and a striking 80 points below the U.S. homeowners' average.

Consistent with this aspect of financial constraints, over 70% of loan applicants on MPL platforms in the United States list "expensive debt consolidation" as the primary reason for requesting funds. Thus, these applicants wish to pay off expensive debt, replacing it instead with monthly amortized payments of the requested MPL loan. However, MPL platforms have no mechanism in place to ensure that borrowed funds are used in manners consistent with the reasons stated on applications. Despite their non-verifiability, however, Michels (2012) documents that reasons stated on MPL loan applications affect both the probability of receiving funding, as well as rates charged on disbursed funds. Moreover, given the unsecured nature of peer-financed lending, investors face the entire risk of falsification on loan applications as well as borrower defaults. Thus, the prevalence of strategic misreporting on MPL loan applications is an important unsolved question, which our data's rich credit dynamics allow us to answer.

The results presented in this paper suggest that strategic misreporting on MPL loan applications is rare – borrowers use MPL funds for debt consolidation purposes. More importantly, these borrowers only consolidate their most expensive debt – credit cards. We do not observe significant incidences of inefficient consolidation in auto, mortgage, or student loans. We observe that credit card balances drop by approximately 64% 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. Finally, we document that average credit scores rise by nearly 3% in the quarter of MPL loan origination. Overall, in the immediate term, we document that MPL loans assist in significantly reducing debt burdens and associated financial constraints.

How long do these benefits last? Our evidence suggests that it depends on the actions of borrowers following MPL-induced debt consolidation. We find that in the quarter following peer-financed loan origination, borrowers revert to racking up credit card debt. Three quarters post-origination, MPL borrowers are as indebted in credit card debt as they were pre-origination. This is of interest for two reasons. Firstly, it shows that peer-to-peer consumer loans only provide temporary debt relief – i.e., they fail to change the fundamental credit behavior of deeply indebted, possibly financially unsophisticated, borrowers. Secondly, 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 start re-racking credit card debt post-consolidation, they are, in fact, more indebted (in an aggregate sense), since they are now faced with paying down both borrowed MPL funds and the newly accrued credit card debt.

More strikingly, increased credit card consumption post-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. This post-origination extension of limits allows MPL borrowers to consume on credit cards at pre-origination levels, while still maintaining utilization ratios below pre-origination levels.

Consistent with the idea of increased indebtedness being positively correlated with probability of default, we find that credit card default probabilities are 10–13 times higher a year post-origination relative to pre-origination levels. 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, which induces defaults in an already financially undisciplined group of borrowers. However, this kind of activity is shown to be sub-optimal, as evidenced by increased credit card defaults in the subsequent quarters. 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 extremely rare. It appears that upon entering financial distress post-origination, these borrowers focus on repaying peer-financed loans at the expense of loans made by traditional banks.

A potential concern with our approach is that our results are possibly driven by certain omitted variables that are specific to the MPL borrower, and independent of the origination of the MPL loan. However, our findings show that MPL borrower credit scores are stable in the year leading up to peer-financed loan origination, and only start fluctuating beginning the quarter of origination. This indicates that any possible unaccounted factors capable of explaining our findings are not related to information on the credit files of these borrowers. Some non-credit file factors that can explain changes in credit card consolidation behavior include fluctuating monthly income or changes in occupation. However, we confirm that both measures are stable in the period of time surrounding the origination of the MPL loan. Moreover, we control for both these factors in our empirical specifications to reduce concerns of omitted variables driving our results.

We verify that our observed results are not simply a manifestation of economic conditions local to the MPL borrower, and completely exogenous to the origination of the peer-financed loan itself, by including (5-digit) ZIP code $\times$ year-quarter fixed effects to capture any regional time-varying trends. Time-varying trends are important for our results regarding credit limit extensions, since these practices are heavily reliant on bank profitability estimates at the local regional level. Moreover, it's also possible that our findings regarding increased credit card default rates are entirely driven by negative regional economic shocks. Our results are robust to this more stringent specification.

Finally, we also account for the possibility that borrowers on MPL platforms are fundamentally different from the average population by making use of 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 identify MPL borrowers and their non-borrowing neighbors residing in the same (5-digit) ZIP code in the month immediately prior to MPL loan origination. The average 5-digit ZIP code population in the United States is approximately 7,500 people.[3] We are thus able to identify such "neighbors" at a narrow geographic level. Cohorts are created on various factors, such as credit need, credit scores, credit card balances and utilization ratios, the total number of open trade accounts and credit cards, homeownership status, monthly income, and the debt-to-income ratio. In effect, we attempt to create a matched sample of MPL borrowers and neighbors that are similar on all criteria in the months leading up to MPL loan origination. Thus, within each cohort, the only factor differentiating an MPL borrower from their neighbor is the origination of the MPL loan itself. In additional robustness tests, we conduct the kNN algorithm at the 9-digit ZIP code (ZIP+4) level.[4] This approach limits our analysis to a smaller number of cohorts. Regardless of the matching approach used, we note that

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

[4] 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. Thus, running the algorithm at the ZIP+4 level helps in identifying non-MPL borrowing neighbors at a much narrower geographic level relative to our baseline kNN analysis conducted at the 5-digit ZIP level. Moreover, given that individuals of similar socio-economic characteristics tend to co-locate in the United States, our analysis at the 9-digit ZIP level implicitly accounts for a wide range of relevant socio-economic characteristics.

despite having identical trends in credit profile characteristics in the year leading up to MPL loan origination, the origination of said loan drastically alters the credit profile patterns of the MPL borrower relative to his closest non-borrowing neighbor within the same cohort.

We also perform cross-sectional tests, and study the credit behavior of subprime, 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. Moreover, we find that the increase in traditional credit limits is concentrated in borrowers who were subprime and near-prime prior to 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 the MPL loan itself.

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. Using our cohorts of MPL borrowers and neighbors described above, we document that relative to subprime neighbors, subprime MPL borrowers experience a 5.55% increase in credit scores in the quarter of MPL loan origination. This translates into a 34% higher probability of subprime MPL borrowers crossing the subprime/near-prime credit score threshold of 620 relative to non-MPL borrowers. Consequently, subprime MPL borrowers experience significantly stronger credit limit growth relative to their non-borrowing subprime neighbors. We repeat the analysis for cohorts of near-prime MPL borrowers matched to their nearest near-prime non-MPL borrowing neighbors, and find that near-prime borrowers are 30% more likely to cross the near-prime/prime credit score threshold of 680 relative to their closest neighbors. Subsequently, they 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 MPL loan-induced debt consolidation activity. This reliance on credit scores can explain the strong increases in credit limits enjoyed by even the subprime segment of MPL borrowers relative to their geographically, and socioeconomically proximate non-MPL borrowing subprime neighbors. While we cannot altogether rule out 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 do document that such spillovers (if they happen) are ex post inefficient for a segment of the MPL borrower base since they induce overborrowing and increased probabilities of default. Given our highly significant results pertaining to the MPL loan-induced crossing of the subprime/near-prime and the near-prime/prime credit score thresholds, we believe 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.

Our paper relates to several strands of literature. First, it adds to the extant MPL literature in 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 in order to overcome adverse selection. Moreover, Iyer, Khwaja, Luttmer, and Shue (2015) document that peer lenders are more accurate at predicting the borrowers' likelihood of defaulting on loans than credit scores. A second strand focuses on borrower-specific determinants of probability of funding success and 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).[5] In contrast, our paper focuses on the utilization of peer-financed funds, and the net 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 that lose bank branches and areas that have highly concentrated banking markets, arguing in favor of credit expansion through financial technology to credit worthy borrowers not served by banks. On the opposite side, Wolfe and Yoo (2017) document that small, rural commercial banks lose lending volumes to peer-to-peer lenders, which suggests non-trivial credit substitution. In the mortgage space, Buchak, Matvos, Piskorski, and Seru (2017) document that shadow banks gained a larger market share among less creditworthy borrowers, and filled the gap left behind by credit contraction by traditional banks in areas where traditional lenders face more capital and regulatory constraints. Within this subset of shadow banks, FinTech lenders account for approximately 25% of shadow bank originations, serving more creditworthy borrowers.

[5]In the mortgage setting, Bartlett, Morse, Stanton, and Wallace (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.

Two papers that are closely related to ours are Demyanyk, Loutskina, and Kolliner (2017) and Balyuk (2018). Contrary to our findings, 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, rich credit bureau data allows us to track MPL borrowers in the months surrounding peer-financed loan origination. Given how most MPL-induced credit profile changes occur in the months immediately following MPL loan origination, the high granularity of the data allows us to implement stringent specifications that track dynamics more accurately. Moreover, while our results concur with Demyanyk et al. (2017) in regards to ex post credit card defaults, our cross-sectional results help us identify the subprime MPL borrower segment as being most susceptible to this problem.

Similar to one of our results, Balyuk (2018) also finds that credit limits on existing credit cards increase post-MPL loan origination. She argues that MPL platforms improve the information environment in credit markets, and as a result, banks extend credit limits to MPL borrowers. While our results do not necessarily rule out this possibility, we do show that such limit extensions are ex post inefficient for almost one quarter of the MPL borrower base. Contrary to Balyuk (2018), our results suggest that MPL loan-induced credit limit extensions lead to overborrowing for subprime borrowers, which leads to higher incidences of credit card defaults. 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 et al. (2015). Moreover, due to data constraints, the analysis in Balyuk (2018) is limited to individuals who apply multiple times on MPL platforms; 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 allows us to track over time.

The rest of the paper is organized as follows. In Section II and III, we provide institutional details on marketplace lending, and discuss our data sources, respectively. In Section IV, we discuss our empirical methodology, and describe identification challenges. In Sections V and VI, we present our main findings and robustness tests, respectively. We also provide a discussion of our results. In Section VII, we perform cross-sectional cuts. We study whether peer-financed loans alter the perceived creditworthiness of borrowers in Section VIII. Finally, we conclude in Section IX.

II. Institutional Background

A. Broad Overview

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 the informational and diversification advantages they enjoy over individual lenders. Thus, with limited competition from other players, banks have developed significant bargaining power vis-a-vis borrowers. 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 end up subsidizing 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. Such information includes FICO credit scores, past delinquencies, revolving credit balance, utilization ratios, monthly income, and the debt-to-income ratio of the loan applicant. This credit information can help reduce frictions between individual lenders and borrowers, allowing the latter to receive loans for personal use or for small- and medium-sized enterprises. Moreover, MPLs function completely online, and thus do not incur the fixed investment costs of setting up and maintaining brick-and-mortar branches that banks face. Phillippon (2015) shows that the cost of traditional financial intermediaries in the United States has remained between 1.5–2% of intermediated assets over the last thirty 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.[6] Finally, MPL platforms are

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

advantageously positioned to potentially reduce systematic risk since they only match borrowers to investors, and do not hold any loan related debt on their balance sheet.

B. Peer-to-Peer Loan Application Process

The MPL lending process begins with a loan application. Prospective borrowers are required to have a bank account to be eligible for such a loan. Thus, these loans are not available to the unbanked population. The borrower submits the requested loan amount, his 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 credit report, the lending platform comes up with an interest rate quote, which becomes the pre-set interest rate at which the loan is provided if originated.

MPL lenders provide unsecured loans for successful loan applications. As mentioned earlier, prospective borrowers are required to provide the intended purpose for the borrowed funds. Reasons provided in the loan applications range from debt consolidation and 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 enforce that borrowed funds are used for the purpose stated in the loan application. Thus, it is unclear if borrowers actually use funds for their stated purpose or simply game the system to increase the probability of loan origination.[7]

III. Data and Descriptive Statistics

In this section, we discuss the sources used to construct our data, and 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 national population, and to a 33% random sample of homeowners in the United States.

[7]Michels (2012) finds that providing a reason on the loan application significantly increases the probability of the loan being funded. Thus, MPL lenders assign importance to this information instead of treating it as noise owing to its non-verifiable status.

A. Data Sources

A.1. 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. The reported lines of credit span many domains such as mortgage, auto, student loans, credit cards, personal/business loans, and utilities, among many others. Each credit line is associated with a bureau-generated individual key to identify the borrower and a bureau-supplied creditor key that identifies the name of the creditor. Using the creditor key, we identify all individuals who have opened a peer-financed MPL trade over the time period 2011 to 2016. The MPL platform we consider for our analysis is one of the largest in the United States.

In order to ensure the validity of the records, we only consider 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 be associated with non-missing closing dates. For our analysis. we only focus on one-time MPL platform borrowers over the period 2011–2016. Thus, we exclude individuals who have borrowed multiple times from the MPL, which reduces concerns of strategic borrower behavior, and ensures no contamination in our analysis of post-loan origination credit behavior. Following our data cleaning process, we are left with approximately 1 million individuals who opened a single peer-financed MPL credit line over the period 2011–2016.

A.2. Attributes File

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

We use the data on MPL borrowers gathered from the trades file and merge it with the attributes file on the basis of the individual identifier. For every MPL borrower, we merge in the inquiries, balance, 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 peer-financed 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.

A.3. 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), and their use can result in significant fees to the CRAs. Thus, we use the Vantage 3.0 score, which is highly positively correlated with all three FICO scores, as a proxy.[8] 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 peer-financed loan is originated. We exclude individuals with invalid Vantage 3.0 scores (below 300 or above 850) at any point from our analyses.

A.4. Demographics File

The demographics file contains information on individual monthly income, occupation, education level, homeownership status, location, and various other socio-economic measures. The data in this file is matched to MPL borrowers from the merged Trades-Attributes-Scores file on the basis of the individual key. Unlike the Attributes and Scores files, Demographics information is available at the individual level every 6 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.

The variables gathered from the Demographics file serve as control variables in our empirical analysis. Demographics data is 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.

A.5. Performance File

The performance file keeps detailed records of the financial health of all individuals along broad trade lines, and is 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 then aggregated

[8] 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`

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

B. Descriptive Statistics

In this section, we compare the profile characteristics of all MPL borrowers at the time of peer-financed 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. This activity helps us identify if there are significant differences between the credit, income, and default risk profiles of borrowers on MPL platforms and the average consumer in the United States. The results are presented in Table I.

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

IV. Empirical Methodology and Threats to Identification

In this section, we describe the basic empirical approach we undertake to examine peer-financed loan-induced changes in the credit profiles of MPL borrowers. Moreover, we discuss some threats to our identification, and the methods we employ to overcome challenges of endogeneity with respect to the self-selection process of borrowing on marketplace lending platforms.

A. Base Specification

We examine how the origination of peer-financed loans change 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 the monthly frequency and 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:

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

In our analysis, we have observations at the individual level at a monthly frequency. 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.[9] 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 card. In addition, 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.[10]

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 vector of 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 and individual-invariant, time-specific trends. However, a possible

[9]Our results are unaffected if we replace the vector of year-quarter fixed effects with year-month fixed effects.

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

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 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. Regional Economic and Individual Factors

Our regression specification relies on identifying MPL borrowers as reported to the credit bureau by the MPL platform. However, this raises questions of individuals of certain specific characteristics self-selecting into borrowing from such online peer-based platforms. Thus, with our baseline specification, it is difficult to completely attribute our findings to the origination of the peer-financed 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 peer-financed 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 peer-financed 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.[11] We ensure that individuals falling 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 in the month of MPL loan origination, we implicitly account for region-time-specific shocks. Our approach thus facilitates a cohort-level analysis, where a cohort refers to each matched pair of an MPL borrower and their 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.

A shortcoming of the approach so far is that in our large set of identified neighbors, we also identify people that do not require additional credit. In this case, it is possible

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

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 only include those neighbors who have hard credit checks performed against them by banks in the three months prior to 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.[12] Thus, inquiries of this kind help in identifying individuals with a "serious interest" in obtaining additional credit. The application of these filters within each cohort help in identifying non-MPL borrowing neighbors whose "need" for bank credit remains unfulfilled.[13]

In order to ease the computation associated with the k-NN algorithm, we subset the data to only account 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 prior to the month of peer-financed 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

[12]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/

[13]It is important to note that while our approach allows us to identify neigbhors who require additional bank credit, it 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) and Jiménez et al. (2014).

described above. The first variant, which we refer to as the "bank-unsatisfied" matching approach, relies on identifying MPL borrowers who are unsuccessful in acquiring bank credit in the three months prior to the month of MPL loan origination. Each such borrower is then matched with their nearest non-MPL borrowing neighbor from the same 5-digit ZIP, where the neighbor pool is limited to only include 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, where both groups have been unsuccessful in obtaining bank credit; post-bank rejection, MPL borrowers look to MPL platforms to satisfy their credit needs, whereas their neighbors do not. An detailed explanation of the "bank-unsatisfied" matching process is provided in Appendix B.

In the second variant, we identify neighbors residing 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 in the United States is under 10 people. Moreover, individuals of similar socio-economic characteristics tend to co-locate in the United States. The remaining steps in the matching process are similar to the "baseline" approach. We refer to this second variant as the "narrow neighborhood" matching approach, and provide a detailed explanation of the matching process 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:

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

In the above regression specification, $MPL\_Borrower$ is an indicator variable that is 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.

The specification is run 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 default occurrences, and average credit score growth. The averages of all dependent variables of interest are computed separately for each quarter following MPL loan origination.

V. 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 also 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. Debt Balances

In this section, we use Equation (1) to study whether MPL borrowers consolidate debt in the aftermath of peer-financed loan origination, and if so, analyze the type of debt that is consolidated. The broad categories of trade lines we consider are auto, mortgage, student debt, and credit card debt. The results of this analysis are presented in Table II.

In column (I), we study auto debt balances in the period of time surrounding the origination of the MPL loan. Our estimates indicate a steady decline in auto balances in the 2-year window under consideration. This finding, consistent with consistent debt repayment behavior, appears to be unaffected by the origination of the MPL loan. Our analysis of mortgage balances (column (II)) and student debt balances (column (III)) also yields similar findings.

In column (IV), we present results for credit card balances. We find that MPL borrowers tend to rack up credit card debt in the months leading up to peer-financed loan origination. Indeed, the estimates on $Quarter_{-4}$, $Quarter_{-3}$, and $Quarter_{-2}$, which measure percentage differences in credit card debt relative to the immediate quarter pre-origination, are all negative and declining in absolute magnitude as the MPL borrower approaches loan origination in event time. In the quarter of MPL loan origination, we find that credit card balances are 63.9% lower relative to the quarter prior to origination, consistent with the consolidation of credit card debt. However, we also note that this consolidation phase appears to be short-lived. In subsequent quarters, these borrowers begin re-accumulating additional credit card debt, such that 3 quarters post-origination, credit card balance levels are insignificantly different from pre-origination levels.

We also present our findings in the form of event study plots in Figure 1. The plots indicate that auto, mortgage, and student debt balance levels are unaffected by the origination of MPL loans. However, credit card balances follow a very different pattern – MPL borrowers rack up credit card debt in the months leading up to MPL loan origination, part of which is consolidated in the quarter of origination, before these borrowers revert to re-accumulating debt.

Taken together, our findings suggest that borrowers utilize peer-financed 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 strategic reason reporting on loan applications is not a significant concern on these platforms. Moreover, these borrowers only focus on consolidating the 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 short-livedness 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 as indebted 3 quarters post-origination as they were in the quarter prior to 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 peer-financed loan origination relative to pre-origination levels.

B. Credit Card Utilization Ratios

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 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 peer-financed 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 3 quarters post-origination, utilization ratios are, on average, 4.2% lower relative to the baseline period. These estimates are also presented in the form of an event study plot in Figure 2.

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, peer-funded platforms.

Second, from Table II, we note that 3 quarters post-origination, these borrowers are as indebted in terms of credit card debt as they were prior to origination. However, our analysis here reveals that 3 quarters following origination, these borrowers have credit card utilization ratios that are significantly lower relative to pre-origination levels. Given how the utilization ratio is calculated as follows:

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

these findings suggest that MPL borrowers experience an increase in their credit card limits. Holding credit card balances constant, as is the case 3 quarters post-MPL loan origination, the only way 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. Extension of Commercial Credit?

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

Our results indicate that monthly credit card limit growth is steady, and insignificantly different from the growth in the quarter prior to peer-financed loan origination. However, our estimates on $Quarter_0$ and $Quarter_{+1}$ indicate that monthly credit limit growth is 0.59% (significant at the 5% level) and 0.83% (significant at the 10% level) in the quarter of, and the immediate quarter following, MPL loan origination, respectively. This finding suggests that post-origination, the increase in credit card limits outpaces the increase in credit card balances. Thus, even though approximately 3 quarters post-origination, while these borrowers are as indebted in terms of credit card debt as they were prior to MPL loan origination, their utilization ratio remains lower in the post-origination period.

In Figure 3, we present event study plots that capture changes in credit limit growth in the months surrounding MPL loan origination. In Panel A, we present univariate results that document the evolution of credit card limits in the 25-month window centered on the month of loan origination. We note that both prior to and following loan origination, these borrowers experience a month-over-month increase in their credit card limits, on average. However, the *rate* of monthly limit growth appears to be much larger in the post-origination period. In Panel B, we present multivariate results which document that monthly credit limit growth rates remain steady in the year prior to MPL loan origination. However, in the months following origination, we document that the monthly growth rate of credit card limits is significantly higher than that in the baseline period. These findings are consistent with our univariate results in Panel A.

D. Delinquencies and Defaults

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 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 start increasing again. Indeed, the estimates on $Quarter_{+1}$, $Quarter_{+2}$, and $Quarter_{+3}$ indicate that credit card default probabilities are 0.29 percentage points, 0.84 percentage points, and 1.47 percentage points higher in the [+4,+6], [+7,+9], and [+10,+12] month windows (all significant at the 1% level) relative to the baseline period, respectively. 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 folds higher at the one-year mark post-MPL loan origination. Our event study plot (Figure 4) yields consistent inferences in graphical form.

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 prior to observing the subsequent upturn in credit accumulation. As a result, these borrowers, who are faced with paying down borrowed MPL funds and the additionally extended credit, start defaulting at greater rates in the quarters following MPL loan origination.

E. Effect on Credit Scores

We document the effect of MPL-induced credit card debt consolidation activity on the credit scores of borrowing individuals. For our analysis, we proxy credit scores using the Vantage 3.0. The results of this analysis are 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 2.9% higher relative to the baseline period (significant at the 1% level). 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 3 quarters post-origination, average credit scores are insignificantly different relative to the quarter prior to origination. Figure 5 presents our estimates in graphical form.

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 post-origination, these borrowers are as indebted as they were pre-origination and have higher default probabilities and default occurrences, which is reflected in credit scores insignificantly different relative to the baseline period.

VI. Robustness Checks

A. Accounting for Changing Job Characteristics

Does the origination of MPL loans affect the job profiles of borrowers? If so, our findings regarding increased occurrences of credit card defaults can be explained by reduced wages or job loss on the part of MPL borrowers in the post-origination period. However, given how MPL loans differ from traditional loans only in means of origination, it appears 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. Thus, 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 IV. We find that in the 12-month period prior to, and the 12-month period following the origination of MPL loans, the probability of income change remains stable.

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. Given how unemployment is provided its own job code, this variable also accounts for job loss. The results of our analysis is presented in column (II) of Table IV. 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 and income profiles of borrowers. Both monthly income and occupation remain stable in the year prior to, and the year following, MPL loan origination. Thus, our findings regarding increased credit card default rates cannot be attributed to loss of job or loss of income on the part of borrowers.

B. Controlling for Region-Specific Factors

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 triple cluster our standard errors at the individual, 5-digit ZIP, and year-quarter levels. The results of this analysis are presented in Table V. We note that our results regarding credit card balances, utilization ratios, credit limits, defaults, and credit scores are unaffected by this more stringent specification.

C. Controlling for Region- and Individual-Specific Factors

In this section, we compare the effects of peer-financed 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 VI, we present descriptive statistics highlighting the success of the "baseline" matching process. We note that in the three months leading up to peer-financed loan origination, MPL borrowers and their neighbors have similar amounts of credit card debt, credit card utilization ratios, and credit scores. Moreover, both groups show similar *trends* in the quarter leading up to the month of peer-financed 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 VII. In Panel A, the dependent variable is average monthly changes 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, and suggests that, relative to their neighbors, MPL borrowers display a declining trend in credit card balances in the quarter of MPL origination that is 13.20% stronger. 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 post-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 that this rate declines over time. 6–7 quartes post-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 peer-financed 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 6. The 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 a peer-financed loan is originated, MPL borrowers display greater debt consolidation than their neighbors. One quarter post-origination, the plot highlights that MPL borrowers revert to consuming on credit cards at a greater rate than neighbors, and that this rate decreases over time. Taken together, our findings from Panel A of Table VII and Panel A of Figure 6 show that peer-financed loans help MPL borrowers reduce debt in the immediate term, but also point out that this consolidation effect is relatively short-lived.

In Panel B of Table VII, 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 6.

In Panel C of Table VII, 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 neighbors. In fact, our estimates in columns (I)-(IV) suggest that MPL borrowers experience stronger credit limit growth rates than neighbors for over a year following MPL loan origination. In subsequent quarters, we find evidence which suggests that limit growth rates of neighbors dominates. The associated event study plots for MPL borrowers and neighbors are presented in Panel C of Figure 6.

We study credit card default rates using a linear probability model, and present the associated findings in Panel D of VII. 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 peer-financed loan origination, MPL borrowers default at significantly higher rates. Our findings suggest that two years post-loan origination, MPL borrowers exhibit over a 2 percentage point higher propensity to default relative to their neighbors. The associated plots are displayed in Panel D of Figure 6.

Finally, in Panels E of Table VII and Figure 6, 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 neighbors.

In additional robustness tests, we report results for cohorts of borrowers and neighbors created using the "bank-unsatisfied" and "narrow-neighborhood" matching approaches. 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 – baseline, bank-unsatisfied, or narrow-neighborhood. Our results for credit card limit growth using the "bank-unsatisfied" matching approach deserve a special mention. Here, our findings suggest that the origination of peer-financed 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 peer-financed loans.

VII. Cross-Sectional Heterogeneity

In this section, we analyze how our results vary across different cross-sections of our sample. The cross-sectional cuts we consider are MPL borrower credit status at the time of loan origination, interest rates charged on peer-funded MPL loans, and loan amounts extended through MPL platforms.

A. Role of MPL Borrower Credit Quality

Thus far, our analysis has treated all MPL borrowers as if they are of equal financial sophistication. In this subsection, we proxy financial sophistication through the Vantage 3.0 score in the month prior to MPL loan origination, and re-conduct the previous analysis in three separate credit segments: the *subprime* credit segment (Vantage score below 620 prior to loan origination), the *near-prime* segment (Vantage score greater than or equal to 620 and less than 680), and the *prime* segment (Vantage 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 VIII, and the event study plots are displayed in Figure 7.

In Panel A of Table VIII, 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) post-MPL loan origination, average subprime (near-prime) credit card indebtedness is insignificantly different relative to their in-group, baseline mean. On the other hand, three quarters post-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 post-MPL loan origination relative to the baseline period. In Panel C, we study how monthly credit card limit growth is affected by MPL loan origination. We find that subprime borrowers experience a 1.33% and 1.44% stronger increase in monthly credit card limit growth in the quarter of, and the quarter immediately following, loan origination, respectively. We also find that near-prime borrowers experience a 0.50% stronger increase in credit growth in the quarter of loan origination, but note that the estimate is only marginally significant. Finally, prime borrowers appear to experience no change in credit limit growth in the 25-month window centered on loan origination.

In Panel D, we study credit card default rates, and conclude that three quarters post-origination, the subprime segment has a 5.07% higher default rate relative to the baseline period. The near-prime and prime segments experience economically and statistically insignificant changes in default rates, respectively. Taken together, our findings suggest that subprime borrowers consolidate a relatively smaller chunk of their credit card debt using peer-financed funds, but experience the strongest increase in monthly credit limit growth. Moreover, our estimates also suggest that the subprime segment is as indebted two quarters post-origination as they were prior to origination. This "double dipping" into both peer-financed and credit card funds ironically increases the aggregate indebtedness of the subprime segment, thus making them more susceptible to default.

Finally, in Panel E, we study the evolution of credit scores, as proxied by the Vantage 3.0. We find that while 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 post-origination, the subprime and near-prime segments have credit scores that are insignificantly different from pre-origination levels in the baseline period. Moreover, the prime segment has credit scores that are actually 0.58% *lower* relative ot 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, they relax financial constraints, through lower utilization ratios and higher credit scores, for all borrowers. 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 6 months of MPL loan origination, subprime borrowers are as indebted in credit card debt as they were pre-origination. Given the increased aggregate debt burden, we note that credit card default rates rise dramatically for subprime borrowers in the post-origination period.

B. Interest Rates on Loans

We also conduct cross-sectional tests based on interest rates charged on MPL platforms. These kinds of loans are 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. We find that the negative aspects of MPL funds, as documented in the above analyses, are concentrated in loans originated at high interest rates. Conversely, borrowers who receive these funds at low interest rates are shown to be better off. The results of this analysis are presented in Appendix Table C.III.

C. Loan Amounts

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

VIII. Improvement 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 that 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.

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

$$Y_i = MPL\_Borrower_i + \gamma\overline{\mathbf{X}}_i + \alpha_c + \epsilon_i \tag{3}$$

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, 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 IX. In column (I), the dependent variable is average credit score growth, defined as the average credit score of the individual in months [+1,+3] divided by their 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 induce within-cohort comparisons between the MPL borrower and their neighbor. The estimate on the MPL borrower dummy indicates that relative to neighbors, MPL borrowers experience a 5.55% (significant at the 1% level) increase in average credit scores in the [+1,+3] window post-MPL loan origination. From descriptive statistics presented in Table VI, we note that 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] window, previously subprime MPL borrowers experience average credit scores of approximately 633 (= 1.055*600).

The large increase in credit scores induced by MPL loans effectively pushes the subprime segment of MPL borrowers into the near-prime category in the 3 months following the month of MPL loan origination. We empirically test this statement by making use of Equation (3), with the dependent variable being 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 (II) of Panel A. The coefficient estimate suggests that subprime MPL borrowers are over 34% more likely to cross the subprime/near-prime threshold in months [+1,+3] than a matched sample of geographically proximate subprime neighbors.

Given how MPL loans generate large increases in credit scores and increase the probability of crossing an industry-standard benchmark in bank lending decisions, we next study credit limit growth for subprime MPL borrowers relative to their subprime neighbors.[14] For this analysis, we re-run Equation (3) with average credit card limit growth as the dependent variable. This variable is created as the individual's average credit limit in months [+1,+3] divided by their average credit limit in months [-3,-1]. The results are

[14]See Keys, Mukherjee, Seru, and Vig (2010) and Rajan, Seru, and Vig (2015) for a discussion on the importance of credit scores in bank lending decisions.

reported in column (III) of Panel A. Our estimate suggests relative to subprime neighbors, subprime MPL borrowers experience an increase in credit limits of 4.87% in the immediate aftermath of MPL loan origination.

We repeat the analysis described above for cohorts of near-prime MPL borrowers and their near-prime neighbors. The results of this analysis are presented in Panel B. Our estimate in column (I) indicates that near-prime MPL borrowers experience an average credit score increase of 4.35% relative to their near-prime neighbors.[15] In fact, results presented in column (II) of Panel B indicate that near-prime MPL borrowers are 30% more likely than their neighbors to cross the near-prime/prime credit score threshold of 680. Finally, results presented in column (III) indicate that near-prime MPL borrowers enjoy average credit limit increases of 4.12% relative to their neighbors in the immediate aftermath of peer-financed loan origination.

The results presented in this section present suggestive evidence that MPL platforms do not generate 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). Rather, our results strongly suggest that bank credit extension decisions are strongly influenced by credit scores. 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 peer-financed loans, even though the associated consolidation activity is short-lived, and at odds with their (very recent) historical consumption patterns. Taken together, our results in Tables VIII and IX suggest that this extension of limits is ex post inefficient, especially for subprime MPL borrowers. In this sense, our results are most consistent with the arguments posed in Rajan, Seru, and Vig (2015).

IX. Conclusion

This paper documents both the benefits and drawbacks of the emergence of marketplace lending platforms for consumer loans. We find that despite having no mechanism in place to ensure loans made on such platforms are used in a manner consistent with the vast majority of stated reasons on loan applications (credit card debt consolidation), incidences of misreporting appear to be rare. However, it appears that these loans fail to

[15] According to descriptive statistics presented in Table VI, the average credit score 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 (= 1.0435*649) in the three months immediately following MPL loan origination.

change the fundamental behavior of the relatively undisciplined and financially troubled borrowers among those that apply for MPL loans. More importantly, the temporary financial relief bought on by such loans is incorrectly interpreted by some traditional lenders who extend new credit to these borrowers, who consume it and are thus more indebted on aggregate post-origination. The increased overall indebtedness results in MPL borrowers having higher probabilities of default in the months following 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.

A. Implications for individuals looking to borrow on marketplace lending platforms

The results of our analyses in this study suggest that marketplace lending platforms can be attractive sources of funding for deeply indebted people looking to alleviate financial constraints. Indeed, our results indicate that peer-financed funds help in reducing credit card debt by approximately 60% in the quarter of loan origination, on average. While the absolute level of debt payment is lower for the sub-prime segment this group still enjoys higher credit scores as a result of this consolidation activity. In fact, despite their muted consolidation activity relative to the near-prime and prime segments, the sub-prime segment enjoys a credit score increase of approximately 3.5% relative to pre-origination levels. More importantly, all three segments enjoy lower utilization ratios in post-origination period. Thus, at least in the immediate term, MPL loans unequivocally improve the financial situations of borrowers, regardless of credit status.

In the longer horizon, the benefits of MPL loans depend exclusively on the actions of borrowers following consolidation. It is important to note that MPL loans are a form of cheaper debt. Thus, consolidation using MPL loans does not change the aggregated indebtedness of the individual; rather, it changes the composition of the individual's debt. Thus, consuming on credit cards when payments of the MPL loan remain to be made will strictly increase the indebtedness of the MPL borrower. It is important, therefore, that MPL borrowers carefully consider their credit card consumption activities in the months following MPL loan origination. Of important consequence here is the fact that MPL loans can strictly improve the borrower's financial condition in the immediate term. How long these benefits last depends on the actions of the borrowing individual in the post-origination period.

B. Implications for banking intermediaries

A key channel documented in this article is that banks increase credit limits on credit cards issued to MPL borrowers. This limit increase occurs immediately following a short-lived debt consolidation phase at odds with the individual's past behavior. Moreover, this extension of additional credit is revealed to be inefficient ex post for the subprime segment of the population, who increase consumption and subsequently default at greater rates.

Thus, given the increasing market share of peer-financed loans in the unsecured consumer credit space, from the bank's perspective, it would be prudent to make credit limit increase decisions on a longer, sustained history of consumer activity.

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Table I: Profile Comparison

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 American 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
Vantage 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: Evolution of Debt Balances

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 and year-quarter 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.

	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	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

Table III: Evolution of 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 (proxied through Vantage 3.0), respectively. All specifications include individual and year-quarter 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.

	Credit Card Utilization	Credit Card Limit Growth	Credit Card Default Rates	Credit Score (Vantage 3.0)
	(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	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

Table IV: Evolution of Job Profile Characteristics

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 and year-quarter 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.

	$\mathbb{P}$(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)
$Quarter_{-4}$	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	$I, Y\text{-}Q$	$I, Y\text{-}Q$

Table V: Robustness Check I: Controlling for Regional Factors

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 (proxied through Vantage 3.0), respectively. All specifications include individual and ZIP code × year-quarter 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.

	Credit Card Balances	Credit Card Utilization	Credit Card Limit Growth	Credit Card Default Rates	Credit Score (Vantage 3.0)
	(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 VI: Descriptives – Matching MPL Borrowers to Nearest Non-MPL Borrowing Neighbors (Baseline)

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 socio-economically proximate non-MPL borrowing neighbor in calendar time. We proxy geography through ZIP codes, and match socio-economic 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 VII: Robustness Check II: MPL Borrowers v. Neighbors

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 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, 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.

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 Vantage 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 VIII: Heterogeneous Effects – Impact of Credit Quality of MPL Borrowers on Profile Characteristics

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 prior to 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 and year-quarter levels, are presented in parentheses. All control variables included in the analysis are defined in Appendix A.

	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	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

	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 IX: Marketplace Loan Induced Changes in Borrowers' Perceived Credit Quality

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 prior to the origination of the MPL loan by MPL borrowers. In column (I) of both panels, the dependent variable is the individual's average credit score in months [+1,+3] relative to their average credit score in months [-3,-1]. The window [x,y] captures months relative to the month of MPL loan origination. In Panel A (Panel B), the dependent variable in column (II) 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. In column (III) of both panels, the dependent variable is the individual's average credit card limit in months [+1,+3] relative to their average limits in months [-3,-1]. All specification include cohort fixed effects. 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.

	Panel A: Subprime Comparison			**Panel B**: Near-Prime Comparison		
	$\frac{\overline{Score}_{post}}{\overline{Score}_{pre}}$	$\mathbb{P}(Score_{post} >= 620)$	$\frac{\overline{Limits}_{post}}{\overline{Limits}_{pre}}$	$\frac{\overline{Score}_{post}}{\overline{Score}_{pre}}$	$\mathrm{P}(Score_{post} >= 680)$	$\frac{\overline{Limits}_{post}}{\overline{Limits}_{pre}}$
	(I)	(II)	(III)	(I)	(II)	(III)
MPL Borrower	5.55***	34.41***	4.87***	4.35***	30.53***	4.12***
	(0.10)	(0.50)	(0.29)	(0.20)	(1.57)	(0.45)
Observations	201244	201244	200620	454100	454100	453121
Adjusted R^2	0.13	0.20	0.03	0.06	0.14	0.08
Controls	✓	✓	✓	✓	✓	✓

Figure 1: Evolution of Debt Balances

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 prior (months [-3,-1]) to 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.

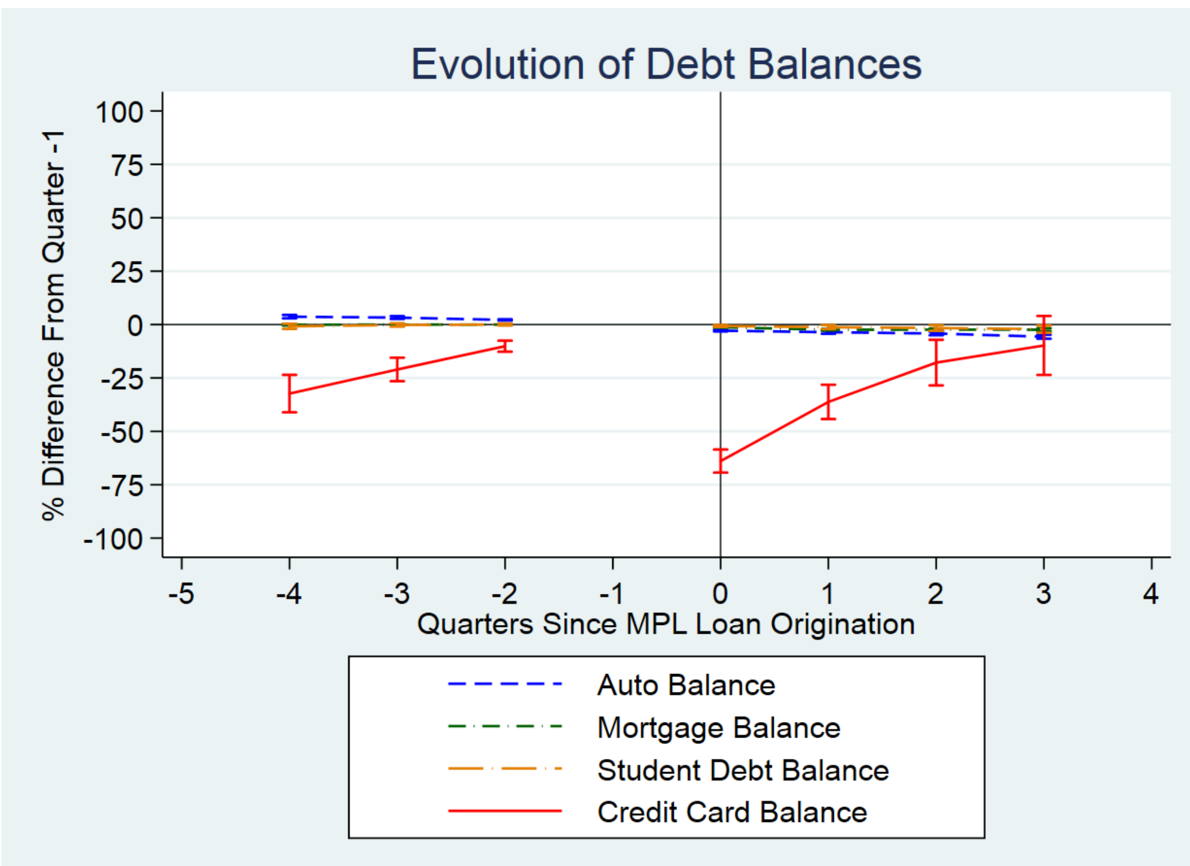


Figure 2: Evolution of Credit Card Utilization Ratios

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 prior (months [-3,-1]) to 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.

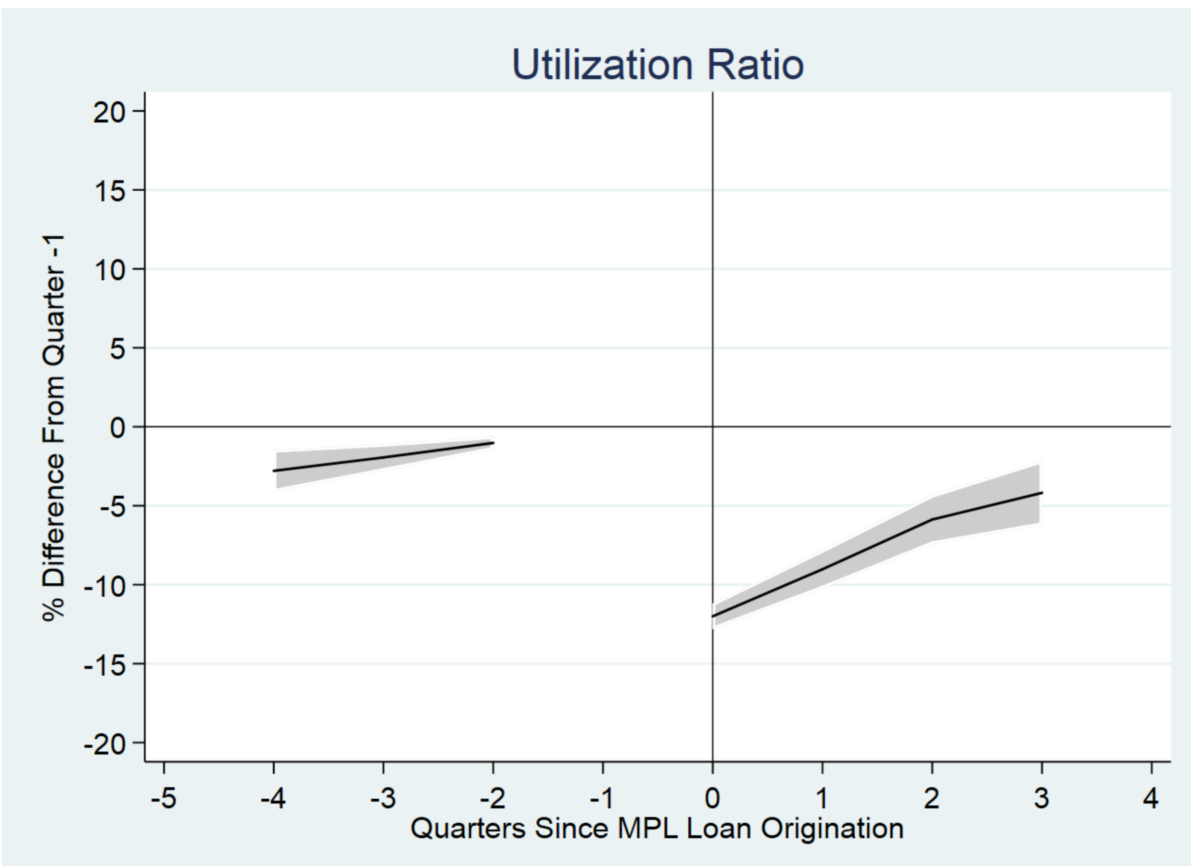


Figure 3: Credit Card Credit Limit Extension?

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 prior (months [-3,-1]) to 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.

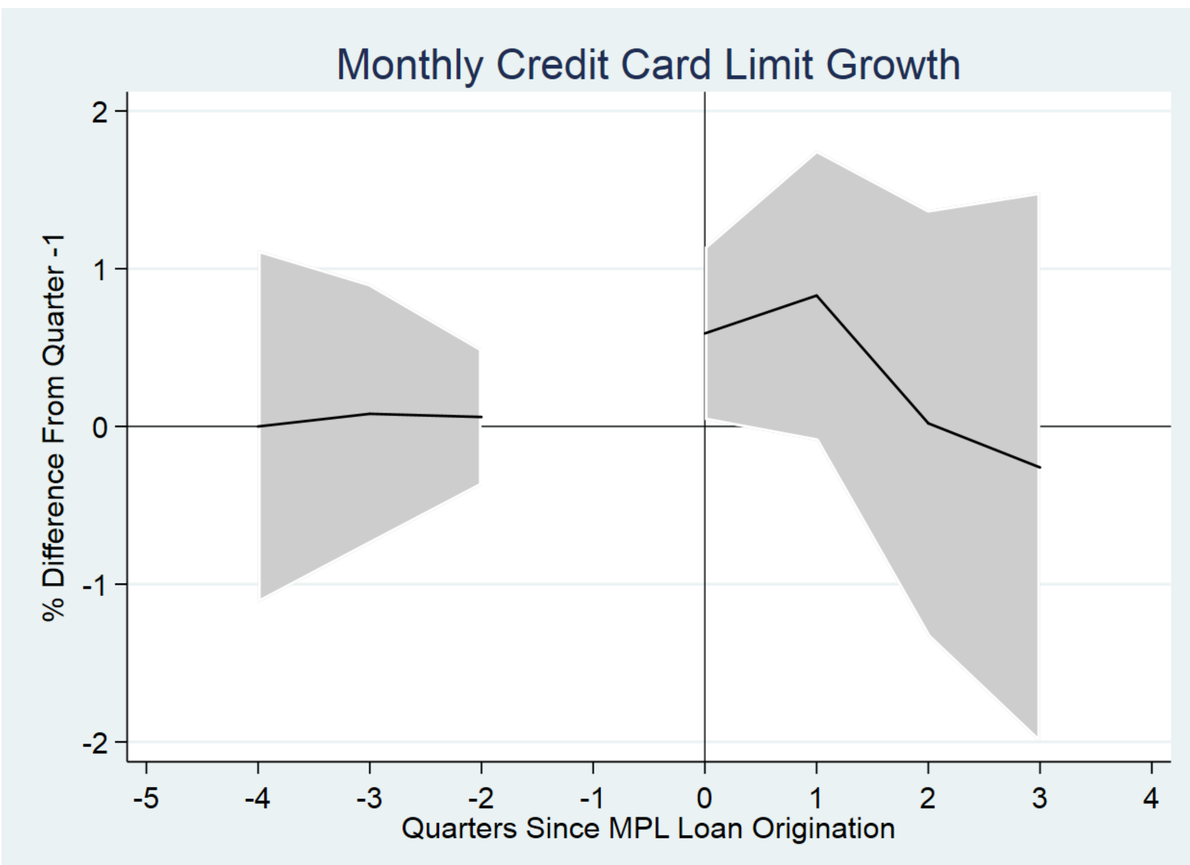


Figure 4: Probability of Default on Credit Card Debt

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 prior (months [-3,-1]) to 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.

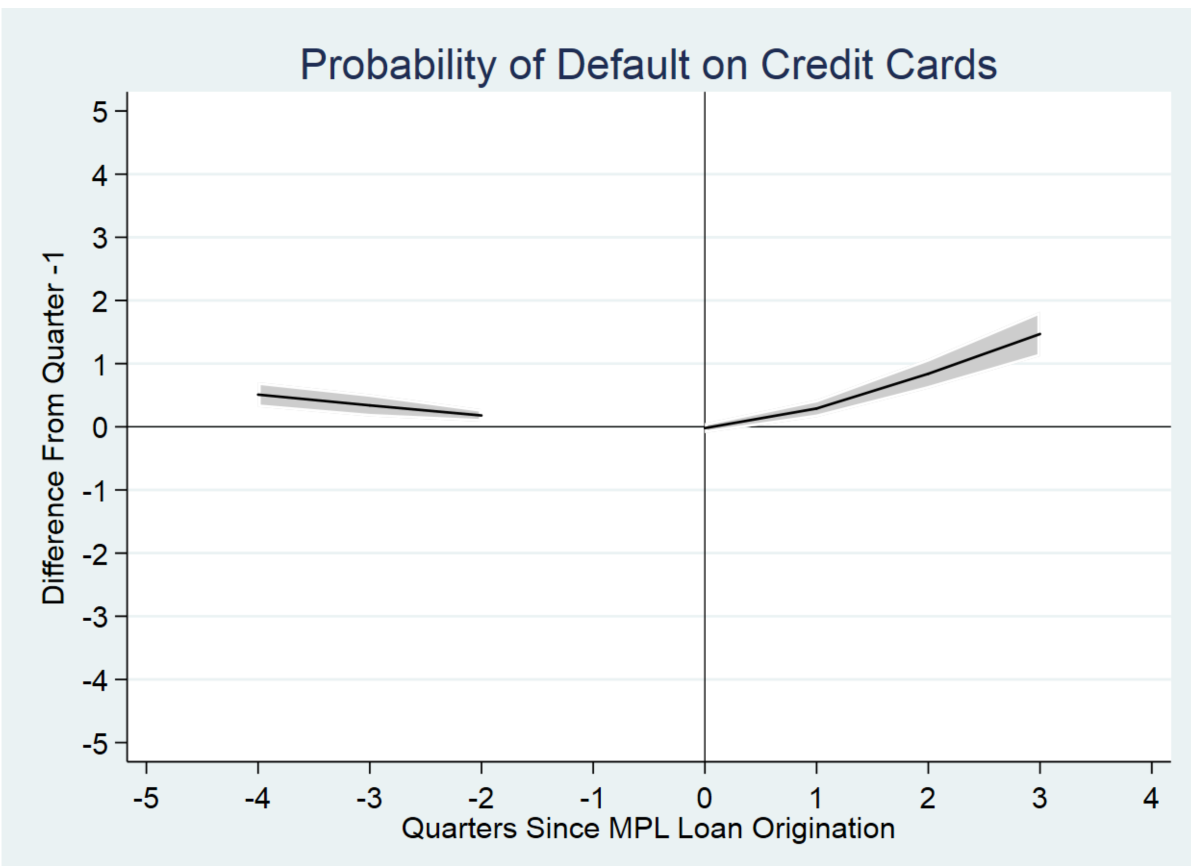


Figure 5: Evolution of Credit Scores

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, and proxy credit scores through the Vantage 3.0 score. 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 prior (months [-3,-1]) to 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.

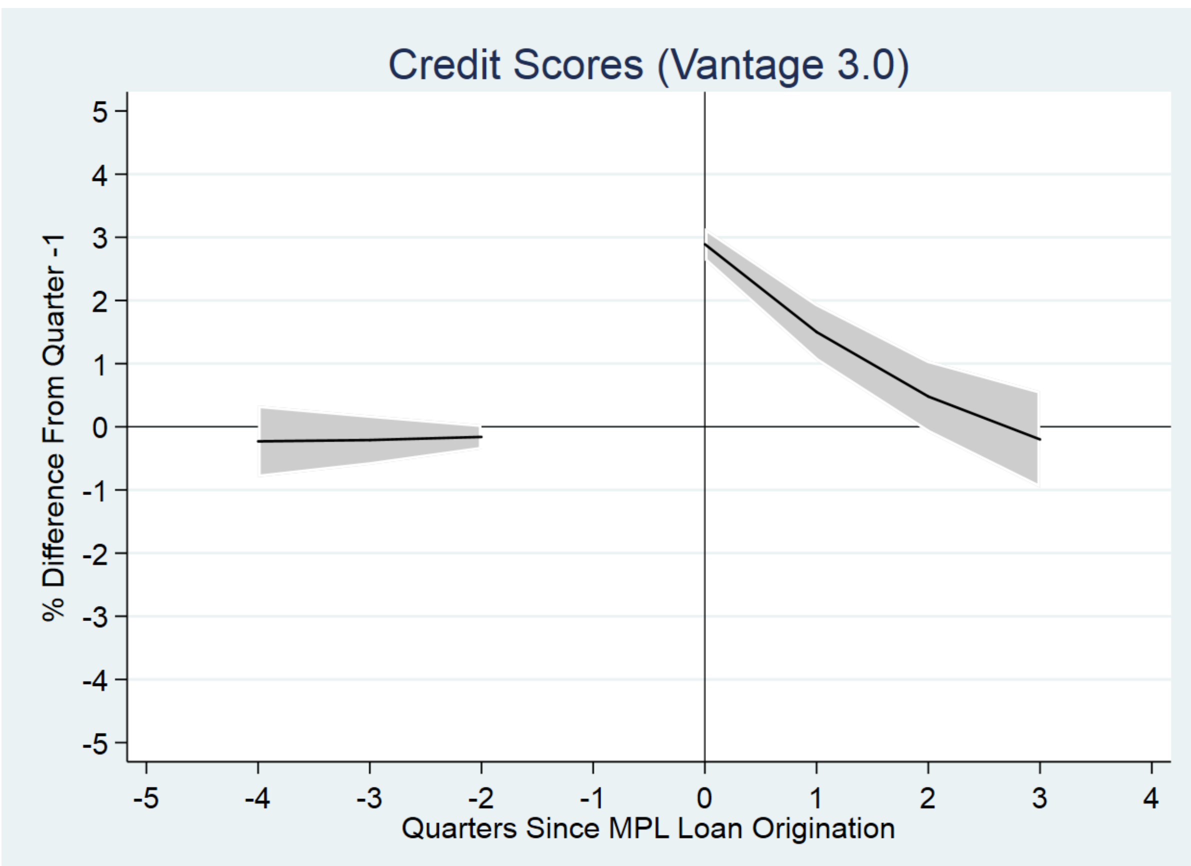
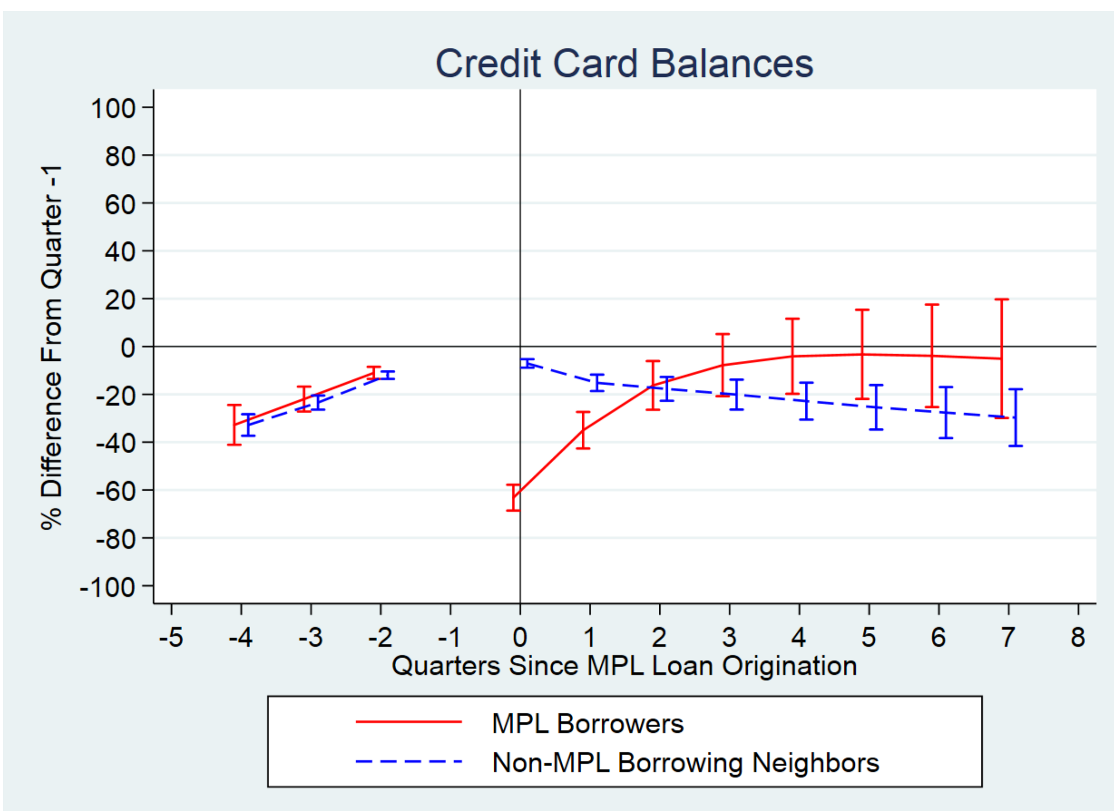
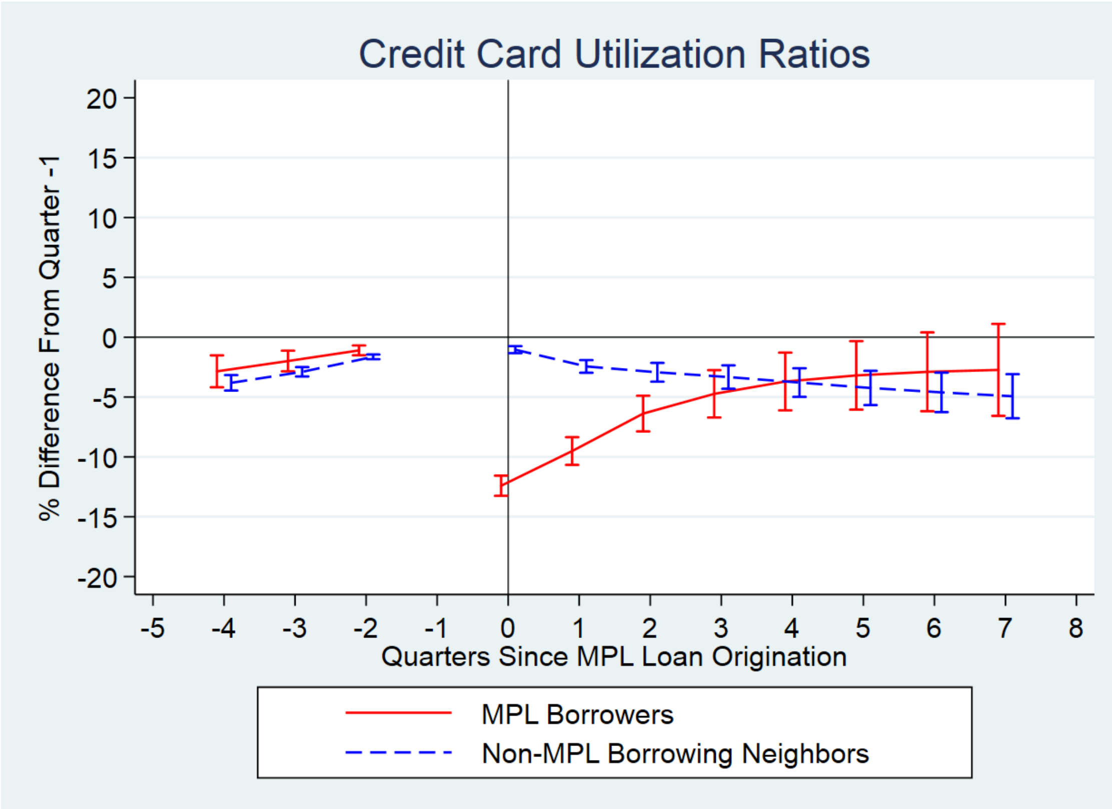


Figure 6: KNN: MPL Borrower to Closest Non-MPL Borrowing Neighbor

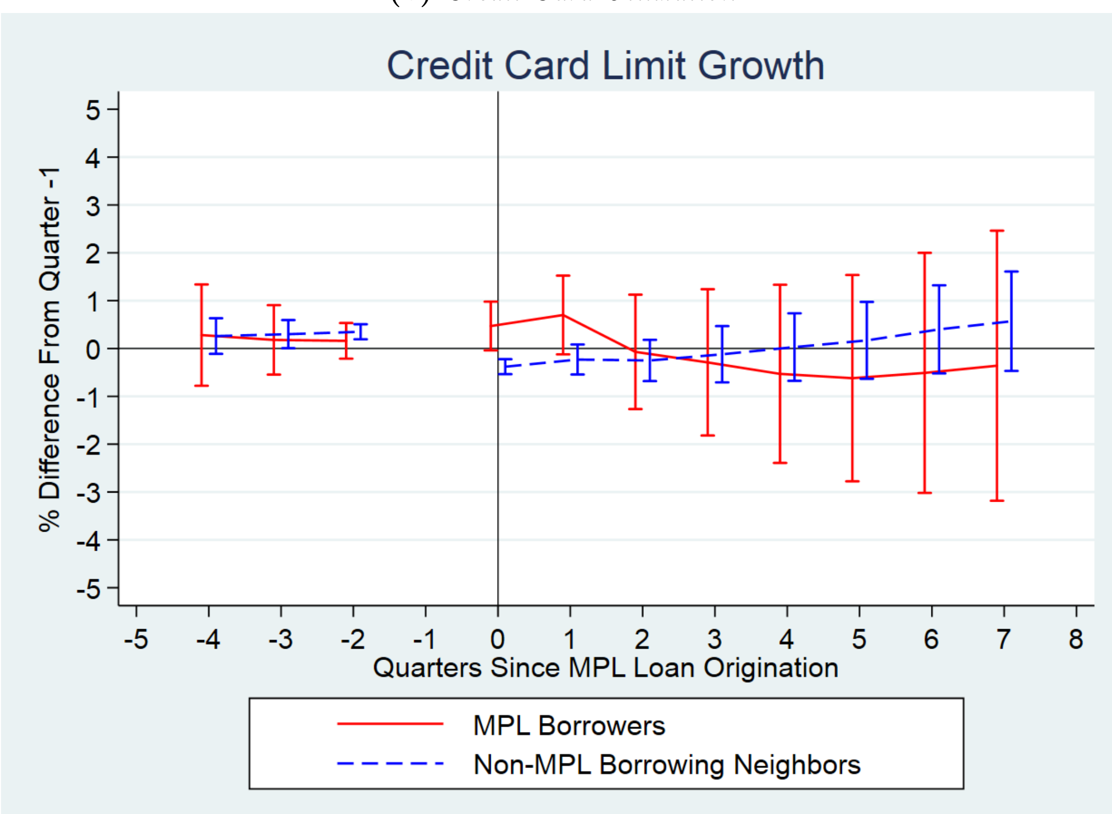
In this set of figures, we present event study plots documenting the differential trends in credit profile characteristics of marketplace lending (MPL) platform borrowers and their geographically- and socioeconomically-proximate non-MPL borrowing neighbors in the months surrounding the origination of 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. In Panels A, B, C, D, and E, we study 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 prior (months [-3,-1]) to 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.



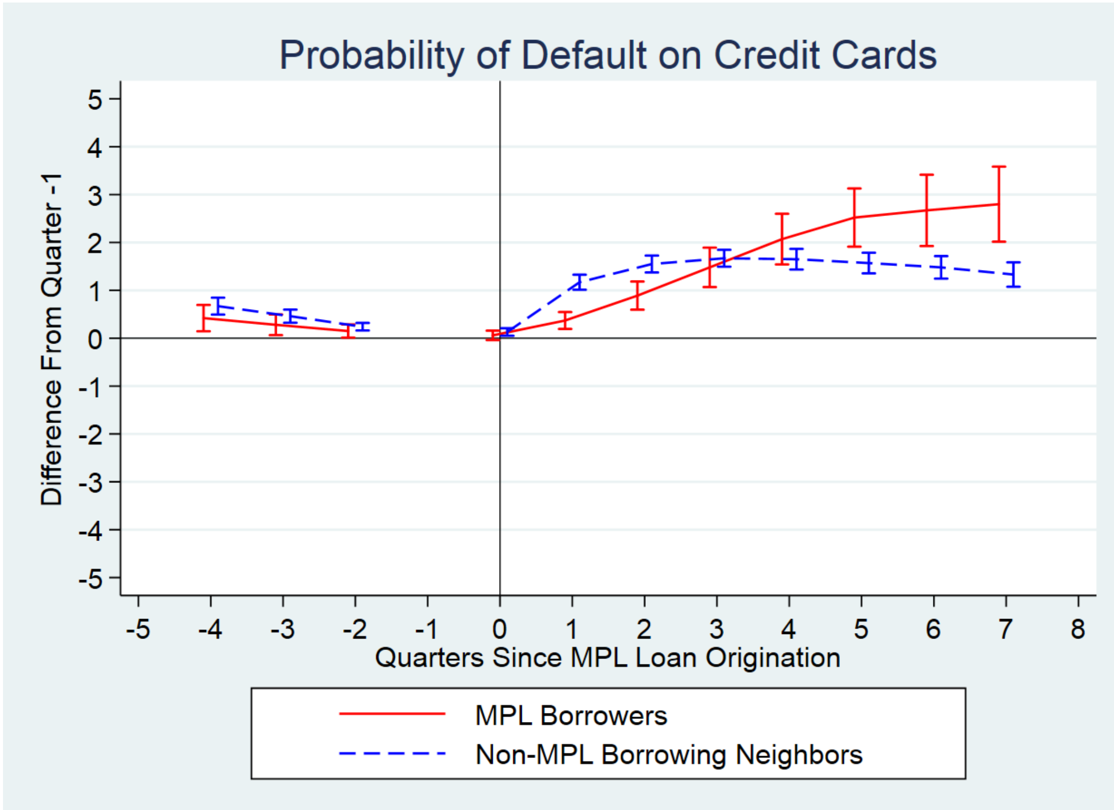
(a) *Credit Card Balances*



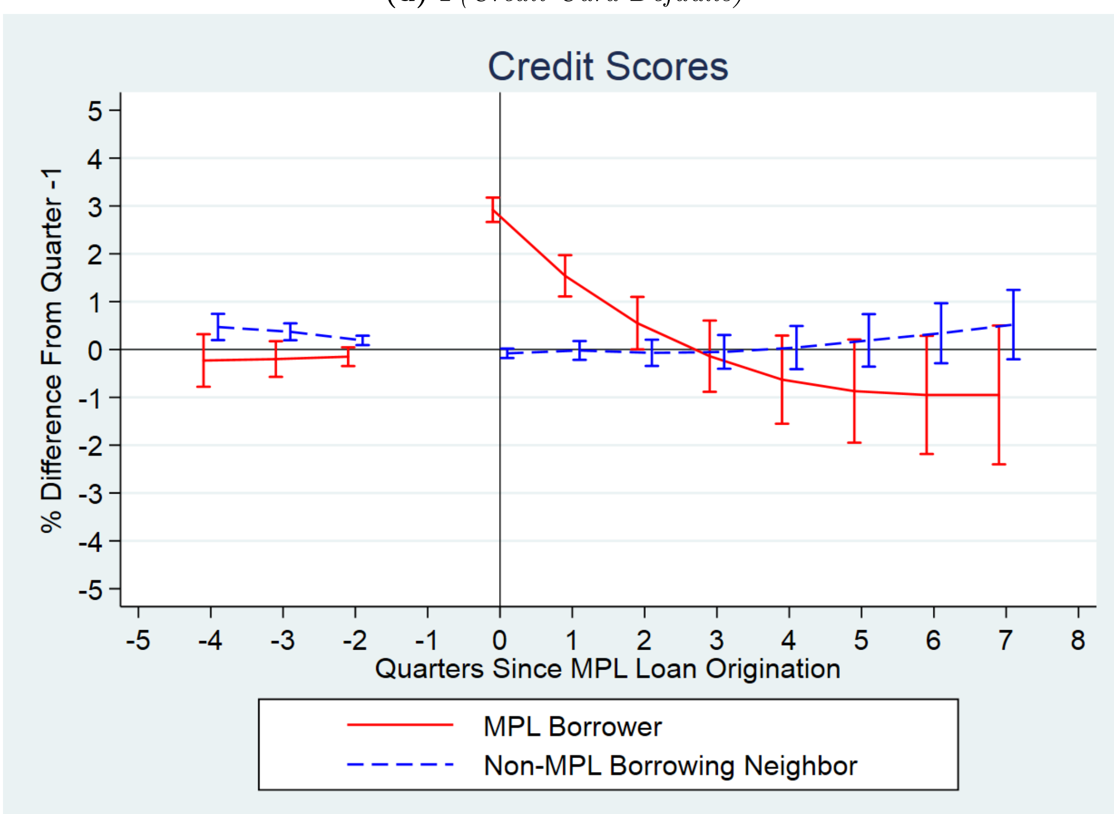
(b) *Credit Card Utilization*



(c) *Credit Card Limits*



(d) *ℙ(Credit Card Defaults)*

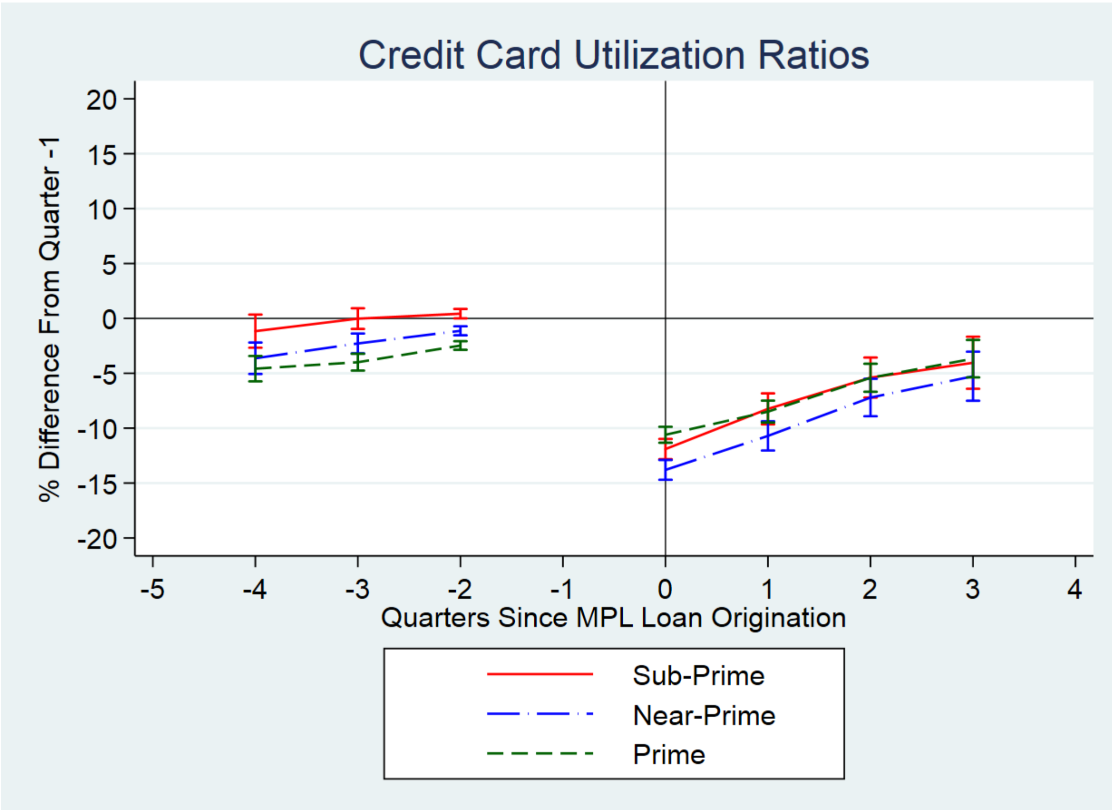


(e) *Credit Scores*

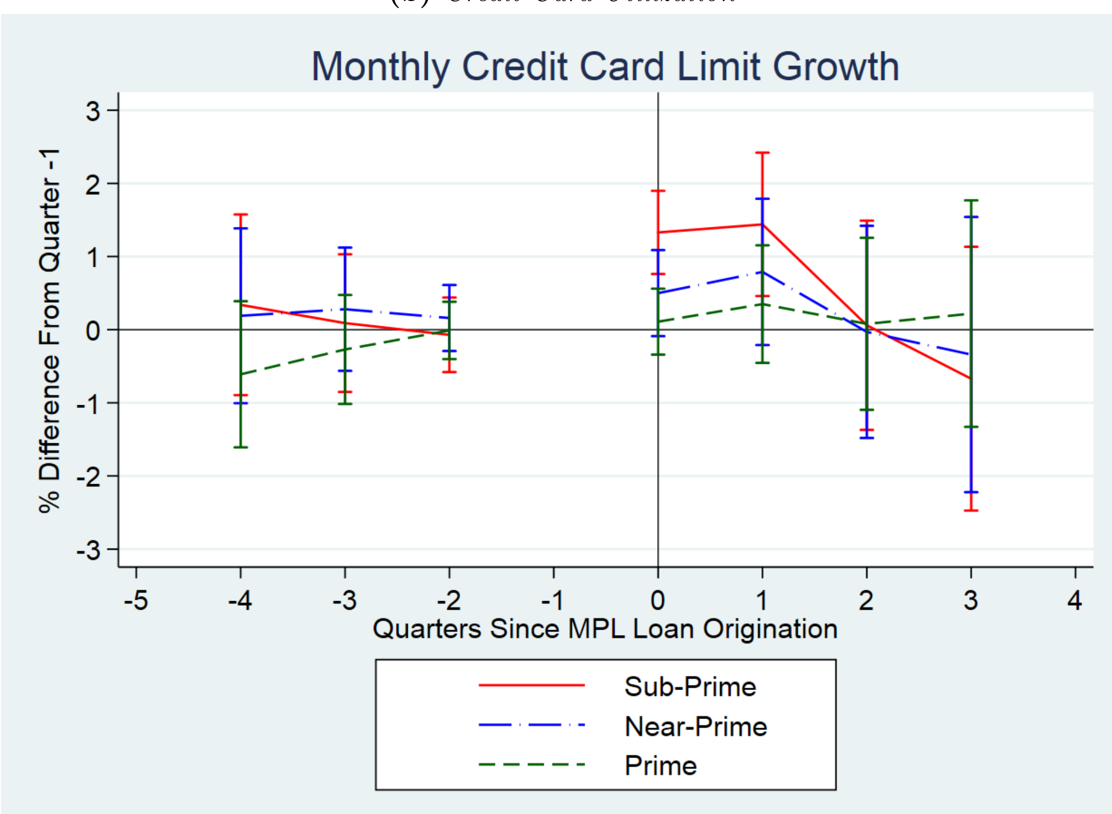
Figure 7: Impact of Credit Quality of MPL Borrowers

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 prior to peer-financed loan origination. In Panels A, B, C, D, and E, we study 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 prior (months [-3,-1]) to 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.

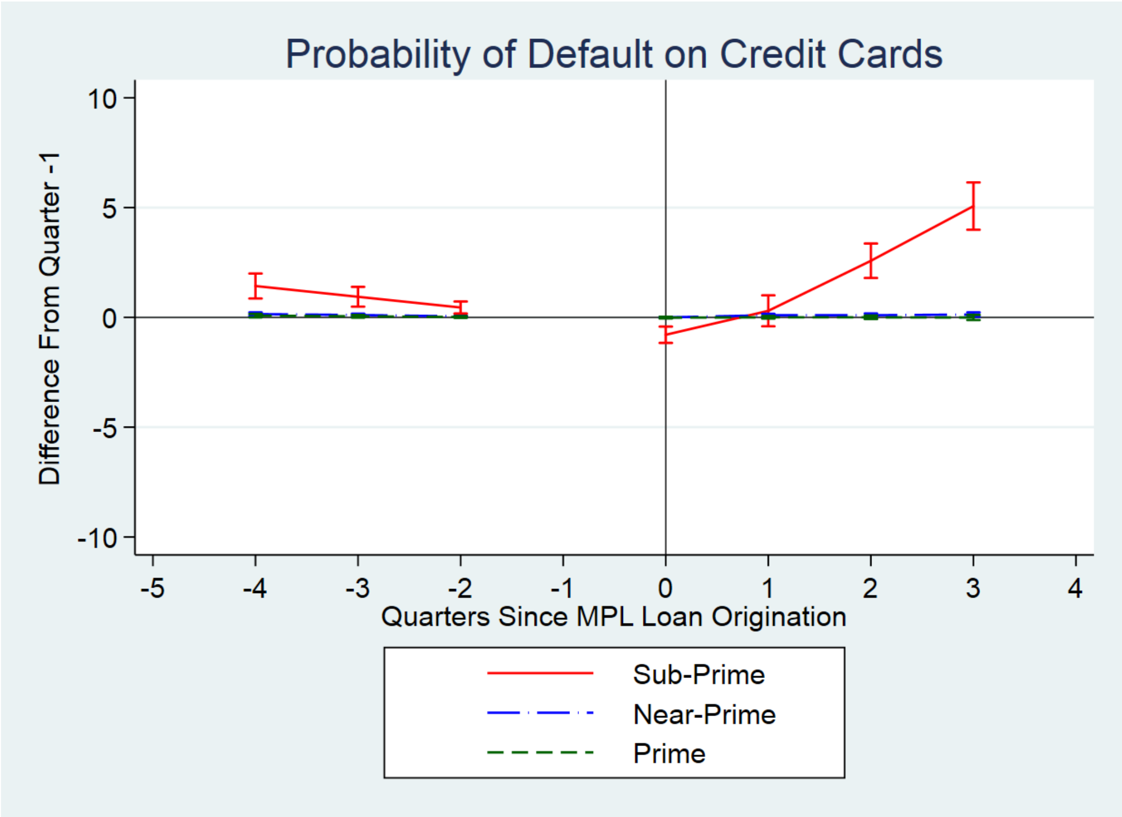
(a) *Raw Credit Card Balance*



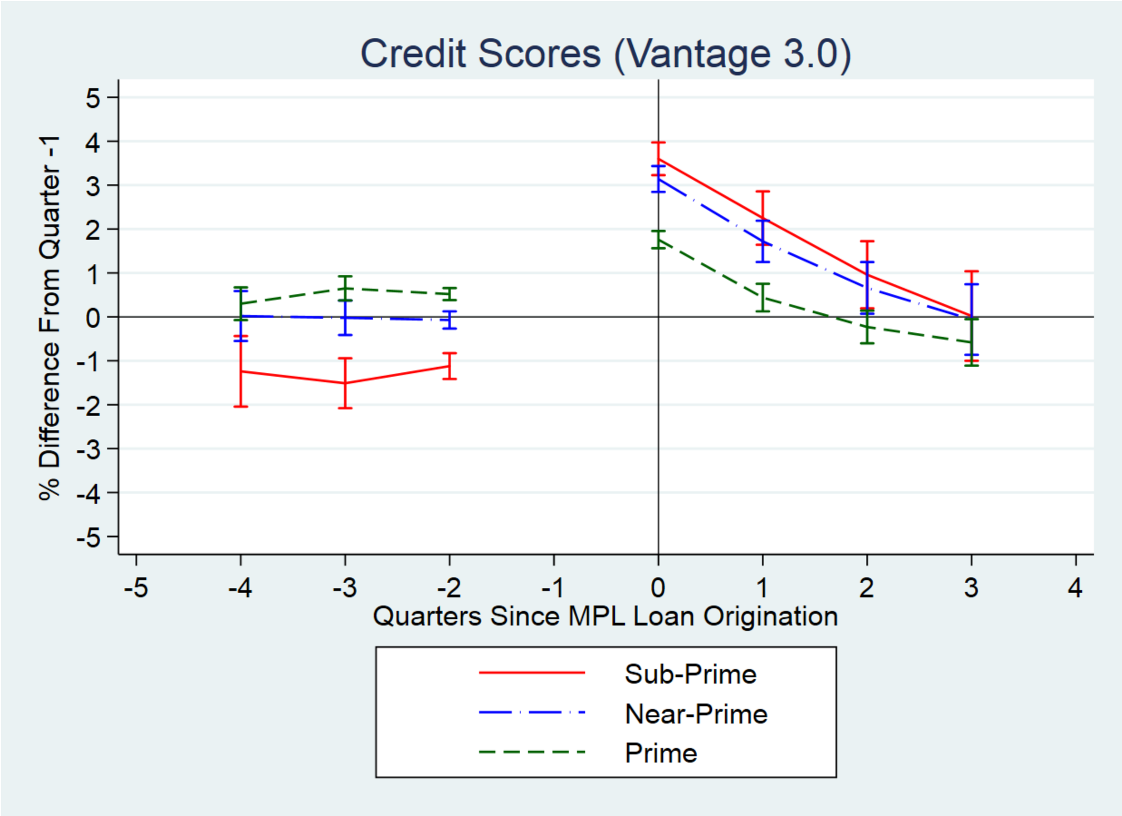
(b) *Credit Card Utilization*



(c) *Credit Card Limit Growth*



(d) *Probability of Default on Credit Cards*



(e) *Credit Scores (Vantage 3.0)*

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 is a minor variant of the k-nearest neighbors (kNN) algorithm. We do 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:

Baseline Matching Approach

- 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 that has 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.[16] This disaggregated geographic level allows for the optimal tradeoff 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 only include those neighbors that have had a non-utilities, bank hard credit check performed against them in the quarter prior to the MPL borrower originating 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 only consider neighbors that fail to obtain traditional bank credit. In effect, we are able to identify non-MPL borrowing neighbors that have a "need" for credit, which 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 people that have no need for additional credit from banks.

- 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 that have

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

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. The credit profile characteristics that we require to display trends for both the non-borrowing neighbor at the MPL borrower 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 show the robustness of our results to two additional matching techniques:

Bank-Unsatisfied Matching Approach

- Step 01: Identical to first step from baseline matching approach
- Step 02: MPL borrowers and their neighbors are both subsetted such that both groups only contain individuals have applied for, and both 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 that 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.
- Step 03: Identical to third step from baseline matching approach
- Step 04: Identical to fourth step from baseline matching approach

Narrow Neighborhood Matching Approach

- Step 01: Similar to the first step from 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 under 10 people, and that individuals of similar socio-economic characteristics tend to co-locate in the United States, we are able to 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.
- Step 02: Identical to second step from baseline matching approach

- Step 03: Identical to third step from baseline matching approach
- Step 04: Identical to fourth step from baseline matching approach

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 part of the paper due to space considerations.

A brief summary of the additional tests is presented below:

- In Appendix Table C.I, we present results which document the robustness of our findings to the implementation of the "bank-unsatisfied" matching algorithm described in Appendix B.
- In Appendix Table C.II, we show that our results presented in Table VII hold even when creating a matched sample of MPL borrowers and socio-economically similar non-MPL borrowing neighbors selected from MPL borrowers' same 9-digit ZIP code. The baseline analysis in Table VII creates the matched sample at the 5-digit ZIP code level.
- In Appendix Table C.III, 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.IV, 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 Check IIa: Bank-Unsatisfied Algorithm

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 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, 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 “strict” matching algorithm, which is described in detail in Appendix B.

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 Vantage 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 Check IIb: Narrow Neighbor Matching Algorithm

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 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, 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 "narrowest neighborhood" matching algorithm, which is described in detail in Appendix B.

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 Vantage 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: Cuts by Interest Rates on MPL Loans

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 specification include individual and year-quarter 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	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

	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.IV: Cuts by MPL Loan Amounts

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 specification include individual and year-quarter 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	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

	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	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$