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

Sudheer Chava Nikhil Paradkar Yafei Zhang
Georgia Institute of Technology

Abstract

Using comprehensive credit bureau data, we examine the credit dynamics of borrowers on a major marketplace lending (MPL) platform. Relative to their neighbors with identical ex-ante credit dynamics, but with unmet credit demand (those originating unsecured installment loans) from banks, MPL borrowers' credit card balances decline 42% (13%) post-MPL origination, but revert to pre-MPL levels within 4 quarters. Their credit scores increase 21 (14) points immediately after origination, followed by an increase in credit card limits. In the next two years, MPL borrowers' higher indebtedness results in 96% (65%) higher default likelihood, with the effects more pronounced for constrained borrowers.

*Sudheer Chava can be reached at sudheer.chava@scheller.gatech.edu. Nikhil Paradkar can be reached at nikhil.paradkar@scheller.gatech.edu. Yafei Zhang can be reached at yafei.zhang@scheller.gatech.edu. We thank Rohan Ganduri, Adam Jørring (discussant), Lauren Lambie-Hanson (discussant), Andres Liberman, Elena Loutskina, Jordan Nickerson (discussant), Alex Oettl, Nagpurnanand Prabhala (discussant), Manju Puri, Amiyatosh Purnanandam, Raghavendra Rau, Peter Simasek, Manpreet Singh, Kelly Shue, Fan Yu (discussant), Linghang Zeng, seminar participants at Georgia Tech, Georgia State University, and the Office of the Comptroller of the Currency (OCC), and conference participants at the 2017/2018 Think Forward Initiative Summit, the 2018 Boulder Summer Conference on Consumer Financial Decision Making, the 2018 Cambridge Conference on Alternative Finance, the 2018 Summer Institute of Finance Conference, the 2018 European Finance Association annual meeting, the 2018 FDIC/JFSR Conference, the 2018 Northern Finance Association annual meeting, the Federal Reserve Bank of Atlanta, and the Federal Reserve Bank of Philadelphia for helpful comments and suggestions. We would also like to thank the program committee of the American Finance Association. This work was awarded the 2017 Think Forward Initiative Research Challenge grant sponsored by The ING Group. The views expressed in the paper are our own and do not represent the views of the credit bureau and other data providers.

I. Introduction

Consumer lending constitutes a significant share of the U.S. economy, accounting for $3.6 trillion as of 2017. Banks, the primary providers of credit to most consumers, specialize in the screening and monitoring of borrowers, and enjoy economies of scale in reducing information asymmetries in the credit market. However, significant frictions such as the imperfect pooling of borrowers of varying credit risk (Leland and Pyle, 1977) or even credit rationing (Stiglitz and Weiss, 1981) remain, especially for applicants who are more reliant on soft information. In addition, despite ultra-low short-term interest rates over the last several years, the interest rates charged on credit cards and personal loans are high, even for applicants of high credit quality (Stango and Zinman, 2009).

Partly, as a result of these imperfections, several FinTech innovators, including marketplace lending (MPL) platforms, have entered the credit market in the last decade.[1] These MPLs attempt to differentiate themselves from banks through the use of online platforms, non-traditional data, and alternative algorithms to price consumer risk. These FinTech players, while still a very small segment of the market, have grown rapidly in terms of lending volume. In this paper, we analyze the impact of engaging on MPL platforms on borrowers' credit dynamics, and whether borrowers benefit from this activity.

MPL platforms can either substitute or complement the availability of credit from traditional banks. MPLs can increase credit options, and possibly offer better credit terms, to consumers that normally rely on banks. The possibility of better terms may induce bank consumers to substitute bank credit with MPL funds.[2] On the other hand, MPL platforms, through non-traditional data and underwriting algorithms, may mitigate some frictions in the unsecured consumer credit market. As a result, credit may be available to bank-rationed consumers. Alternately, additional supply of credit through MPLs may result in more credit or better terms being accessible to borrowers than that available through traditional means given their credit profile. Moreover, given the significant weights assigned to credit utilization and balances in the calculation of consumers' credit scores, these loans may have spillover information effects for credit scores, and hence availability of credit from traditional intermediaries that rely more on credit scores.

We first study the characteristics of individuals who borrow on a major U.S. consumer

[1]Other contributors include changes in consumer attitudes, easier availability of alternative consumer data, improvements in analytics, and cheaper cloud processing. Also, in contrast to the original focus on retail peer-to-peer (P2P) lending, MPL platforms increasingly rely on institutional capital.

[2]Among the applicants on MPL platforms in the U.S., approximately 70% state that their primary reason for requesting funds is "expensive debt consolidation," seeking to replace it with monthly amortized payments.

credit MPL platform through anonymized individual-level data available at a monthly frequency from a credit bureau. Using this data, we identify approximately one million borrowers on the platform in the month immediately before MPL loan origination, and we compare these borrowers to a nationally representative 5% random sample of the U.S. population. Our findings suggest that MPL borrowers are more financially constrained relative to the average consumer. These borrowers have twice as many credit cards, over twice the average credit card debt, and a credit utilization ratio of 70% compared to the national average of 30%. Additionally, MPL borrowers have average credit scores that are nearly 20 (80) points below the national (U.S. homeowners') average.

We examine how the origination of MPL loans changes the credit dynamics of borrowers along five broad dimensions: credit balances, utilization, credit scores, credit limits, and default risk. As mentioned before, there are observable differences between MPL borrowers and the average U.S. consumer. So, in order to attribute the subsequent credit dynamics of MPL borrowers to the origination of the MPL loan, we create multiple counterfactuals of non-MPL borrowing neighbors who reside in the same 5-digit (or 9-digit) ZIP code as the MPL borrower.[3]

We use a modified k-nearest neighbors (k-NN) algorithm to construct four matched cohorts of non-MPL borrowers. Across all cohorts, closest neighbors are selected such that they display identical ex ante dynamics in both *levels* and *trends* along several important characteristics such as credit scores, credit utilization ratios, number of open trade accounts, credit card balances, mortgage balances, total balances, personal monthly income, and debt-to-income ratio for each of the three months immediately preceding MPL loan origination. In the first cohort, we identify the sub-sample of MPL borrowers who unsuccessfully apply for bank credit prior to the origination of the MPL loan and match these "bank-unsatisfied" MPL borrowers to similar "bank-unsatisfied" non-MPL borrowing neighbors within the same 5-digit ZIP code.[4] In the second and third cohorts, we do not condition on MPL borrowers being unsuccessful bank applicants prior to MPL loan origination. Rather, in the second (third) cohort, we match the entire sample of MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit) ZIP code. Finally, in the fourth cohort, we match all MPL borrowers to neighbors within the same 5 digit ZIP code who originate unsecured installment loans from traditional banks.

[3]The average 5-digit (9-digit) ZIP code population in the U.S. is approximately 7,500 (under 10) people, which allows us to match on a narrow geographic space. See `https://www.zip-codes.com/zip-code-statistics.asp`.

[4]We observe that the MPL borrower and their neighbor apply for credit from a bank, but do not have a new credit account in their trade file. This can occur due to either the bank declining the credit request or providing credit at terms that are not satisfactory to the consumer.

These different cohorts provide important insights by capturing the various possible roles MPL loans serve for borrowers. By comparing bank-unsatisfied MPL borrowers to bank-unsatisfied neighbors, we arguably capture the "pure" effect of MPL credit, since this sub-sample of MPL borrowers uses MPL funds to make up for restricted access to bank credit. From a credit supply perspective, these MPL loans can be viewed as complementary to bank credit, since a bank-unsatisfied group is receiving access to different forms of credit. Importantly, the counterfactual of observationally-similar, bank-unsatisfied, non-MPL borrowing neighbors identifies potential ex post outcomes in the absence of MPL loans. A shortcoming of this cohort is that we over-sample lower credit quality MPL borrowers. We overcome this problem in the second (third) cohort by comparing the entire unconditioned sample of MPL borrowers to bank-unsatisfied neighbors within the same 5-digit (9-digit) ZIP. Given that people of similar socioeconomic characteristics tend to co-locate together in the U.S., matching on the 9-digit ZIP in the third cohort implicitly accounts for many observable differences between MPL borrowers and their neighbors that we don't otherwise explicitly account for in our matching algorithm.

Lastly, in the fourth cohort, we compare two observationally-identical individuals who both originate the same type of loan, but from different sources. In this cohort, we over-sample higher credit quality MPL borrowers. Thus, from a credit supply perspective, in this cohort, MPL loans can be viewed as a substitute for bank credit. Importantly, any differences in ex post outcomes between MPL borrowers and bank borrowers provide insights into the relative screening capabilities of the originators. Taken together, the very first and last cohorts can be viewed as "bounds," since they test the validity of our findings to MPL funds being used either as substitutes or complements to bank credit. For positive changes in credit profiles – expensive debt consolidation, credit score increases, credit limit increases – the cohort of bank-borrowers serves as a tighter bound, as high-credit quality bank borrowers also consolidate credit card debt. For negative changes in credit profiles – spikes in credit card default rates – the cohort of unsuccessful bank applicants, with a higher propensity for default in general, is a tighter bound.

However, it is still possible that there is a selection on some relevant, omitted MPL borrower-specific unobservable variables. In order to address selection on unobservables, wherein certain individuals choose to borrow from MPLs, we consider event study specifications restricted only to the sample of MPL borrowers. Finally, we attempt to mitigate concerns about the endogeneity of the decision to borrow on MPL platforms by accounting for MPL borrowers' access to technology in an instrumental variables setting.

In our cohort-level specifications, we include vectors of cohort $\times$ year-quarter and individual- fixed effects. These fine grained fixed effects allow us to effectively compare every MPL borrower to her closest neighbor (on all reasonable observable characteristics) within the same cohort over time. Moreover, in all four cohorts, the pairing of MPL borrowers and neighbors is based on narrow geographic definitions. Thus, any time-varying regional shocks are implicitly accounted for through our matching approach.

Our findings suggest that MPL borrowers use MPL funds to consolidate the most expensive debt they face: credit cards. Despite having identical credit card balances and utilization in the quarter preceding MPL loan origination, we find that MPL borrowers' average credit card balances are approximately 42% (13%) lower relative to the matched cohort of unsuccessful bank applicants (unsecured installment loan bank borrowers) in the quarter of origination. Consistently, in the same period, we find that the utilization ratios of MPL borrowers are significantly lower than their neighbors across all four cohorts. Overall, in the immediate term, we document that MPL loans significantly reduce debt burdens and associated financial constraints for borrowers relative to their neighbors.

MPL-induced debt consolidation is relatively transient, however. One quarter after origination, borrowers resume consumption on credit cards. Despite having identical total non-mortgage debt in the quarter preceding MPL loan origination, we find that MPL borrowers' average non-mortgage indebtedness is approximately 30% (6%) higher relative to the matched cohort of unsuccessful bank applicants (bank borrowers) two years following origination. These findings are consistent with the idea that consolidation simply changes the composition of debt, without reducing aggregate indebtedness. Thus, when these borrowers re-accumulate credit card debt after consolidation, their aggregate indebtedness increases, since they are now faced with paying down both borrowed MPL funds and newly re-accrued credit card debt.

Despite the fleeting nature of MPL-induced consolidation, MPL borrowers experience a significant immediate increase in credit scores. Relative to the matched cohort of unsuccessful bank applicants (bank borrowers), MPL borrowers experience an additional 21 point (14 point) increase in credit scores in the quarter of loan origination. More strikingly, we also find that MPL borrowers experience larger increases in credit card limits from traditional banking intermediaries relative to their neighbors following MPL loan origination. It appears that, influenced by the temporary consolidation-induced increase in credit scores, some banks extend additional credit to these borrowers at a greater rate in the months following MPL loan origination.

Importantly, two years after origination, MPL borrowers are 96% (65%) more likely to be in default on credit cards relative to the matched cohort of unsuccessful bank applicants (bank borrowers). Taken together, our findings suggest that the cascading of information from an MPL platform to banking intermediaries potentially results in the extension of credit to an ex ante constrained group of consumers with a high marginal propensity to consume, thus resulting in higher aggregate indebtedness.

We find consistent results when studying just the sample of MPL borrowers. Our *within*-MPL borrower event study estimates suggest that borrowers' credit card balances decline by 47.50% in the quarter of MPL loan origination. Consistently, credit scores rise by 19 points in the same time span, with a notable spike in credit card limit growth. Lastly, we find that MPL borrowers' non-mortgage indebtedness increases by approximately 30% one year following origination, and that they are 12–13 times more likely to default on credit cards. Interestingly, while credit card defaults rise sharply following origination, defaults on the MPL loan itself are not common. It appears that borrowers focus on repaying MPL loans at the expense of loans made by traditional banks.

A potential concern with our analysis is that our results may be driven by certain omitted variables that are specific to the MPL borrower and independent of the origination of the MPL loan. However, our results show that MPL borrowers do consolidate credit after origination, but they default at a higher rate later. So, an omitted borrower-specific variable is unlikely to explain both the immediate positive and subsequent negative results. Also, in our sample, geographically dispersed MPL borrowers originate their loans at different times, which makes a region-specific or a calendar-time-specific unobservable unlikely. Moreover, this unobservable would have to affect a significant fraction of borrowers in an identical manner at different intervals relative to the time of loan origination. Again, such an event-time specific unobservable appears unlikely in our analysis.

We confirm that our results are not driven by negative shocks to non-credit file factors, such as changes in monthly income or occupation. In addition, we find no evidence of negative health shocks, as proxied by medical-related collection activity, in the months following MPL loan origination. Moreover, we control for these factors in our empirical specifications to reduce concerns that omitted variables may be driving our results.

Thus far, our analysis was conducted at a *quarterly* frequency. Our within-MPL borrower analysis at a *monthly* frequency indicates that MPL borrowers credit scores are approximately 32 points higher one month after loan origination. Credit card limits, however, only increase in the 2–6 month window following origination along the intensive margin. This lead-lag relationship between scores and limits suggests that improvements in credit scores *cause* the increase in credit card limits. More importantly, we observe this lead-lag relationship only for the sub-sample of MPL borrowers who consolidate credit card debt and experience a credit score increase. This helps rule out a general credit availability effect of MPL loans on subsequent increases in credit card limits.

The cohort-level comparisons confirm our within-MPL borrower findings. Across all cohorts, we find a positive relationship between credit scores changes and credit card limit changes. More importantly, across all cohorts, we find that subprime (near-prime) MPL borrowers are approximately 22–34% (16–34%) more likely to turn near-prime (prime) in the three months following MPL loan origination when compared to socioeconomically identical non-MPL borrowing neighbors.

Finally, we also implement an instrumental variables approach to establish a causal relationship between MPL borrower status and changes in credit scores and credit card limits. Using broadband access data from the National Telecommunications and Information Administration (NTIA), we compare MPL borrowers to non-MPL borrowers who apply for bank credit. Our first stage regressions indicate that MPL borrowers are 19–36% more likely in areas with broadband download speeds. In the instrumented setting, we find that MPL borrowers experience increased credit scores and credit card limits in the three months following loan origination relative to non-MPL borrowing bank applicants.

Taken together, our findings suggest that bank credit limit extension decisions are heavily influenced by the temporary increase in credit scores of MPL borrowers due to debt consolidation. This increase in credit scores significantly increases MPL borrowers' probability of transitioning from subprime (near-prime) to near-prime (prime). Our findings are thus consistent with Rajan, Seru, and Vig (2015), who document that bank lending decisions have become increasingly credit score-centric over the years. Our evidence is also consistent with Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018), who find that banks' marginal propensity to lend is increasing in borrowers' credit scores. More generally, consistent with Liberman, Paravisini, and Pathania (2018), our results suggest that credit scores mediate a large amount of dynamic responses in credit markets.

Lastly, we identify winners and losers of MPL borrowing on the basis of ex ante borrower constraints. The first constraint we consider is the borrower's credit status prior to origination. We find that credit card debt consolidation activity is weakest (strongest) for the subprime (prime) segment that accounts for 23% (27%) of our sample. The increase in credit card limits is concentrated among borrowers who were subprime before MPL loan origination. The ex post increase in default probabilities is largest (smallest) in the subprime (prime) segment. Consistent with the constraints channel, we also find that MPL borrowers with high ex ante utilization, and low ex ante monthly income, are most likely to default on credit cards one year following MPL loan origination.

Lastly, we identify MPL borrowers with any medical-related collections activity in the year before loan origination (approximately 30% of the sample) as health-constrained borrowers. We find that health-constrained borrowers are quicker to revert to pre-origination levels of credit card debt following consolidation. However, both groups experience significant increases in credit card default rates one year following MPL loan origination.

Our paper adds to the extant MPL literature on consumer credit that deals with investing and borrowing decisions within online lending platforms (Freedman and Jin, 2011; Pope and Sydnor, 2011; Ravina, 2012; Lin et al., 2013; Hildebrand et al., 2016; Paravisini et al., 2016; Hertzberg et al., 2018), and their implications for the optimal level of information provided on such platforms (Vallee and Zeng, 2018), as well as the possible complementary nature of alternative measures of creditworthiness relative to traditional credit scores (Iyer et al., 2015; Berg et al., 2018). Our paper contributes to this literature by studying the credit dynamics of such borrowers. Our paper also contributes to the growing literature on the interaction between banking intermediaries and FinTech lenders (Buchak et al., 2017; Wolfe and Yoo, 2018; Tang, 2018; Fuster et al., 2018) by documenting that traditional banks appear to utilize information generated by MPL platforms, albeit through borrowers' credit scores.

In contemporary papers, Demyanyk et al. (2017) show that MPL funds are not used for debt consolidation purposes but that there is a significant increase in defaults among MPL borrowers, while Balyuk (2018) finds that credit card limits increase post-MPL loan origination, but finds no evidence that increased access to credit results in higher delinquencies. However, Demyanyk et al. (2017) conduct their analysis at the individual-year level, while Balyuk (2018) uses a small portion of MPL borrowers who apply multiple times on the MPL platform tracked only at the time of loan application. In contrast, access to credit bureau data allows us to track MPL borrowers in the months surrounding loan origination when most MPL-induced credit profile changes occur. Our results strongly suggest that credit limit extension decisions are heavily influenced by the short-term improvements in credit scores induced by MPL activity (Rajan et al., 2015; Agarwal et al., 2018; Liberman et al., 2018). Finally, our paper identifies constraints that determine winners and losers among borrowers on online lending platforms.

The rest of the paper is organized as follows. We discuss our data sources in Section II and our empirical methodology and identification challenges in Section III. Our main findings and robustness tests are presented in Section IV. In Section V, we discuss whether MPL loans alter the creditworthiness of borrowers. In Section VI, we study winners and losers from MPL borrowing. Finally, we conclude in Section VII.

II. Data Sources

Our primary data is obtained from one of the three major credit bureaus in the United States. All the data sources described below are used purely for academic purposes and contain completely anonymized information. In our identification tests, we supplement credit bureau data with broadband access data gathered from the National Telecommunications and Information Administration (NTIA).

A. Credit Bureau Data

The credit bureau's trade line-level data provides comprehensive, anonymized records of the various lines of credit opened by every U.S. consumer. We use this dataset to identify all individuals who originate unsecured installment loans from a single MPL platform between 2011 and 2016. The MPL platform we consider for our analysis is one of the largest in the consumer credit space in the U.S.

In order to ensure the validity of the records, we consider only those loans associated with non-missing start dates, with positive balances at the time of loan origination, and require that MPL trade line accounts with balances equal to zero are associated with non-missing closing dates. We focus only on one-time MPL platform borrowers and exclude individuals who have borrowed multiple times from this platform. This screen reduces concerns of strategic borrower behavior and eliminates any contamination from our analysis of post-loan origination credit behavior. Ultimately, we are left with approximately one million individuals who originate a single loan from the MPL platform between 2011 and 2016.

Next, we merge in data from the credit bureau's attributes file to study the credit profile evolution of these MPL borrowers in the period of time surrounding the origination of the MPL loan. The attributes file contains monthly snapshots at the individual level on inquiries, balances, utilization ratios, and credit limits in the domains of mortgages, auto loans, student loans, and revolving credit (i.e., credit cards). For every MPL borrower, we gather credit profile information for the 12 months prior to, and the 24 months following, the month of MPL loan origination. Next, we remove any individuals who have invalid information for any variables relevant to our analysis at any point in our event window. For the subset of individuals with valid credit attributes, we winsorize the numerical variables at the 1% and 99% levels.

In addition, we gather MPL borrowers' credit scores at a monthly frequency using Vantage 3.0 score. The MPL platform we study generates its interest rate quotes using

FICO scores. However, FICO scores are owned by the Fair Issac Corporation and credit reporting agencies can incur significant fees by using FICO scores[5] We map every MPL borrower from the trades file to the scores file at a monthly frequency over our analysis window. We exclude individuals with invalid Vantage 3.0 scores (i.e., scores below 300 or above 850) at any point from our analyses.

We also use the demographics file to collect information on individual monthly income, occupation, education level, homeownership status, location, and various other socio-economic measures.[6] The variables gathered from the demographics file serve as control variables in our empirical analysis. Demographics data are only available starting from June 2013. Thus, when conducting multivariate analysis, our sample is restricted to studying individuals who opened MPL trades between June 2013 and December 2016.

The performance file keeps track of the financial well-being of all individuals along broad trade lines at a monthly frequency. For our analysis, we define *default* as being at least 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 in default, and 0 otherwise. For each individual, we aggregate this measure across all open credit lines in four domains: *auto*, *mortgage*, *student debt*, and *credit cards*.

Finally, we make use of the collections file to track the health of individuals. For our analysis, individuals are identified as suffering negative health shocks if they have medical collections against them. We set an indicator variable equal to 1 in the month in which the individual experiences medical-related collections, and 0 otherwise.

B. Broadband Access Data

We gather data on national broadband access from the National Telecommunications and Information Administration (NTIA) website for June 2013, December 2013, and June 2014. The NTIA collaborates with the Federal Communications Commission (FCC), and partners with all fifty states, five territories, and the District of Columbia to track broadband availability in every neighborhood in the United States.

Our analysis relies on comparing MPL share across areas with varying access to broadband internet speeds. Thus, the classification of "high-speed" internet is important for

[5]Vantage 3.0 score is highly positively correlated with all three FICO scores. Correlations across the results of scoring models are high, and generally over 90%. Source: `http://files.consumerfinance.gov/f/201209_Analysis_Differences_Consumer_Credit.pdf`

[6]Unlike the attributes and scores files, demographic information is available at the individual level every 6 weeks. For months in which we do not find a direct match between the demographics file and the merged trades-attributes-scores file, we impute using the most recently available year-month.

our identification tests. According to official FCC guidelines, connections with download speeds of 25 megabits per second (mbps) or faster qualify as broadband.[7]

We make use of the NTIA census block file to identify maximum advertised internet download speeds at the census block level, which we aggregate up to the census tract level. Using the Housing and Urban Development (HUD) crosswalk files, we map census tracts to 5-digit ZIP codes on the basis of population weights, such that there is a unique 5-digit ZIP – census tract pair. We thus identify the maximum advertised download speeds within each 5-digit ZIP. The NTIA data is categorical, and following the FCC definition, we classify residents of 5-digit ZIP codes with maximum advertised download speeds in excess of 25 mbps as having access to broadband internet.

A shortcoming of using maximum advertised download speeds is that such speeds may only be available to the wealthier section of the neighborhood, and is thus not truly reflective of broadband availability. Thus, we make use of NTIA analyze tables, which measure the percentage of households within a county with access to different download speeds. Thus, for each county, we gather the percentage of households with access to download speeds of at least 25 mbps. We document the robustness of our analysis to both the "advertisement" measure, as well as this "county population access" measure.

C. Descriptive Statistics

In Panel A of Table I, we compare the profile characteristics of all MPL borrowers in the month before MPL loan origination to a 5% random sample of the total U.S. population and to a 33% random sample of homeowners. The results highlight that MPL borrowers have more open trades compared to the national average and to the sample of homeowners. Importantly, MPL borrowers have more than twice as many open credit cards relative to the two comparison groups. Consistently, MPL borrowers owe more than twice the national average in credit card debt, and their average credit card utilization ratio is approximately 70%, which is over twice the national average of 30%. We find that MPL borrowers have credit scores that are approximately 20 (80) points lower than the national (homeowners') average, and this is consistent with higher indebtedness being positively linked to a higher probability of default. Finally, MPL borrowers have debt-to-income (DTI) ratios that are comparable to the U.S. homeowners sample despite having an average mortgage balance that is approximately $85,000 lower. This indicates that their high DTI ratios can be attributed to lower income and higher non-mortgage debt.

[7]Source: `https://www.nbcnews.com/tech/internet/faster-internet-fcc-sets-new-definition-broadband-speeds-n296276`

III. Empirical Methodology And Threats To Identification

In our data, we are able to identify consumers as MPL borrowers when the MPL platform reports the origination of the MPL loan to the credit bureau. However, as highlighted in the descriptive statistics, there are observable differences between MPL borrowers and the average U.S. consumer. In addition, selection on unobservables is also an issue with some borrowers endogenously choosing to engage on MPL platforms. In this section, we describe our empirical approach that attempts to address the potential threats to our identification, and attribute the subsequent credit dynamics of MPL borrowers to the origination of the MPL loan itself.

A. Cohort-Level Analysis

In order to mitigate some of the aforementioned identification concerns, as counterfactuals, we create matched cohorts of non-MPL borrowers that are similar in *levels* and *trends* on several observable dimensions to MPL borrowers, with the only differentiating factor between the two groups being the origination of the MPL loan. We implement a modified k-nearest neighbors (k-NN) algorithm in order to construct four such matched cohorts of non-MPL borrowers. The details of the cohort-creation process are provided in the Online Appendix.

<u>Cohort I</u>: Bank-Unsatisfied MPL Borrowers matched to Bank-Unsatisfied Neighbors in the same 5-digit ZIP Code

In our first cohort, we create a matched sample of MPL borrowers and their closest non-MPL borrowing neighbors within the same 5-digit ZIP code such that both groups have first unsuccessfully applied for bank credit in the same calendar month.[8] Subsequently, MPL borrowers access MPL platforms for credit, whereas their neighbors do not. The initial bank application is identified through hard credit checks performed by banks against the applicants. Consumers who do not originate bank loans following the hard credit check are identified as unsuccessful applicants, or "bank-unsatisfied" consumers.[9]

Next, we filter the sample to only include MPL borrower-neighbor pairs that display identical credit dynamics in the months leading up to MPL loan origination by the MPL borrower. Assuming that an individual's credit score is a sufficient statistic of creditwor-

[8]Given that the average population of a 5-digit ZIP code in the United States is approximately 7,500 people, this filter allows us to select neighbors from a relatively narrow geographic space.

[9]Our approach is similar to Jiménez et al. (2012, 2014), in the sense that it allows us to identify individuals who have a serious interest in obtaining bank credit, but 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.

thiness, we first match MPL borrowers and neighbors on this dimension in both *levels* and *trends*. Thus, we restrict the sample to only include MPL borrowers and neighbors who display identical credit scores for each of the three months leading up to MPL loan origination by the MPL borrower. Subsequently, we further match MPL borrowers and neighbors on both levels and trends along the credit card utilization ratio and credit card balance dimensions.[10] In the final step, we use a k-NN algorithm to identify closest neighbors based on credit score, utilization, the number of open trade accounts, credit card balance, mortgage balance, total individual balance, personal monthly income, and DTI. Our approach thus facilitates a cohort-level analysis, in which a cohort refers to each matched pair of an MPL borrower and her geographically proximate, socio-economically identical neighbor. Moreover, we create the cohorts in calendar time, which ensures that the pre- and post-MPL loan origination time periods are the same for both MPL borrowers and their non-borrowing neighbors within the same cohort.

This cohort arguably assists in identifying the "pure" effect of the MPL loan on ex post credit profile characteristics, since bank-unsatisfied MPL borrowers use MPL funds to make up for restricted access to bank credit. Moreover, by creating counterfactuals of identical bank-unsatisfied non-MPL borrowing neighbors, this cohort provides insight into potential ex post credit profile trends in the absence of MPL loans.

<u>Cohort II</u>: *All MPL Borrowers matched to Bank-Unsatisfied Neighbors in the same 5-digit ZIP Code*

In the second cohort, we do not condition MPL borrowers on being unsuccessful bank applicants prior to MPL loan origination. Rather, we match the entire sample of MPL borrowers to socio-economically similar, bank-unsatisfied neighbors within the same 5-digit ZIP code. We also require that MPL borrowers originate their MPL loans and non-borrowing neighbors file their unsuccessful bank application in the same calendar month. Compared to the first cohort, this approach allows us to use a significantly larger sample of MPL borrowers. The remaining steps in the matching process are identical to the first cohort.

<u>Cohort III</u>: *All MPL Borrowers matched to Bank-Unsatisfied Neighbors in the same 9-digit ZIP Code*

In the more stringent third cohort, we match the entire sample of MPL borrowers to bank-unsatisfied neighbors residing in the same 9-digit ZIP code. According to credit

[10] We choose to match on credit scores, utilization, and credit card balances because the summary statistics presented in Panel A of Table I indicate that MPL borrowers differ most from the national average on these dimensions.

bureau statistics, the average population of a 9-digit ZIP code in the United States is fewer than 10 people. Moreover, individuals of similar socioeconomic characteristics tend to co-locate in the United States. Thus, this process identifies a much more homogeneous set of MPL borrowers and matched neighbors. The remaining steps in the matching process are identical to the first cohort.

<u>*Cohort IV*</u>*: All MPL Borrowers matched to Bank-Borrowing Neighbors in the same 5-digit ZIP Code*

In the fourth variant, we create cohorts of MPL borrowers matched to neighbors within the same 5-digit ZIP code who originate unsecured installment loans from traditional banks. We ensure that the loans issued to this neighboring group are non-mortgage, non-auto, and non-student debt. The cohorts are created such that MPL borrowers and their bank-borrowing neighbors originate their respective loans in the same calendar month. The remaining steps in the matching process are identical to the first cohort.

Since MPL platforms also provide unsecured, amortized loans, in this last cohort, we are comparing two observationally-equivalent neighboring individuals who receive the same type of loan, but from different sources. Thus, any differences in the ex post credit profile trends of bank borrowers relative to MPL borrowers provide insights into possible differences in screening between banks and MPL platforms.

In Panel B of Table I, we present descriptive statistics of our matched cohorts. In columns (I) and (II), we compare bank-unsatisfied MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP. We find that both groups of individuals have credit scores of approximately 652 for each of the three months leading up to MPL loan origination by the MPL borrower. In addition, we document that both groups have utilization ratios of approximately 70% prior to MPL loan origination. Most importantly, we note that MPL borrowers and their neighbors display approximately identical and increasing *trends* in both utilization and credit card balances in the three months immediately preceding MPL loan origination. Moreover, we document that both groups have nearly identical mortgage debt and total debt. Lastly, even though we do not explicitly match on education and occupation, we find that there is not a significant difference in the percentage of college graduates or individuals with sophisticated jobs in this matched sample. Our inferences remain unchanged when we compare all MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP (columns (III) and (IV)).

In columns (V) and (VI), we compare MPL borrowers to the matched cohort of bank borrowers. We find that MPL borrowers in this cohort have slightly higher credit scores and lower utilization relative to the cohorts discussed above. However, even in this bank-borrower cohort, we confirm that MPL borrowers are identical to their bank borrowing neighbors in terms of credit scores, utilization, indebtedness, education, and occupation in both levels and trends.

In order to study differences between MPL borrowers and non-MPL borrowing neighbors, we use the following event study specification on each of the four cohorts:

$$Y_{i,c,t} = \sum_{\tau=-4,\tau\neq-1}^{+7} \beta_\tau Quarter_{i,c,\tau} + \sum_{\tau=0}^{+7} \lambda_\tau Quarter_{i,c,\tau} \times MPL\_Borrower_{i,c} \qquad (1)$$
$$+ \gamma \mathbf{X}_{i,c,t} + \alpha_i + \delta_{ct} + \epsilon_{i,t}.$$

In the above specification, $MPL\_Borrower$ is an indicator variable that equals 1 for MPL borrowers and 0 for non-MPL borrowing neighbors. The subscripts i, t, and c identify individuals, year-months, and cohorts of matched MPL borrowers and their closest non-MPL borrowing neighbors. We construct $Quarter_0$ as months [0,+3] in relation to the month of MPL loan origination. The variable τ indicates quarters relative to $Quarter_0$. We choose τ to vary from -4 to +7, 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. 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 the Online Appendix.

In our specification, $Quarter_{-1}$ serves as the absorbed period. By construction, and as verified by Panel B of Table I, MPL borrowers and non-MPL borrowing neighbors have identical credit characteristics in this absorbed period. The β coefficients in the above specification represent differences from $Quarter_{-1}$ for non-MPL borrowing neighbors. In the post-MPL loan origination period (i.e, when $\tau \geq 0$), the λ coefficients capture the *differential* response of MPL borrowers relative to non-borrowing neighbors *within* the same cohort in the monthly interval captured by the quarter indicator.

The specification includes vectors of individual and cohort-time fixed effects; thus, this specification induces within-cohort variation over time by comparing outcomes for MPL borrowers relative to their neighbors. Moreover, since the cohorts are created in *calendar* time over a narrow geographical space, any time-varying regional shocks are implicitly accounted for through this tight fixed effects specification. The outcome variables we study using the above specification are individual-level monthly balances along five broad trade lines: auto, mortgage, student debt, credit cards, and total non-mortgage debt. We also study how credit utilization ratios, credit limits, probabilities of default, and credit scores are influenced by the origination of MPL loans. Standard errors are double clustered at the cohort- and year-quarter levels.

B. Within-MPL Borrower Analysis

One shortcoming of our cohort-level analysis is that we are unable to account for any unobservable differences that influence participation on MPL platforms. In order to circumvent this "matching-on-observables" problem, we use an event study methodology similar to Agarwal, Pan, and Qian (2016) and Agarwal, Qian, and Zou (2017), where we study MPL borrowers in the 25-month window centered on the month in which the MPL loan is originated.

We use the following regression model to estimate fluctuations in average credit profile characteristics in the period of time surrounding MPL loan origination:

$$ln(Y_{i,t}) = \sum_{\tau \neq -1} \beta_\tau Quarter_{i,\tau} + \gamma \mathbf{X}_{i,t} + \alpha_i + \delta_t + \epsilon_{i,t}. \quad (2)$$

Our analysis includes observations at the individual level at a monthly frequency. As before, the quarter indicators represent monthly intervals in relation to the month of MPL loan origination. α_i represents a vector of individual fixed effects, and δ_t indicates a vector of year-quarter fixed effects. As before, we study how credit balances, credit utilization ratios, credit limits, probabilities of default, and credit scores are influenced by the origination of MPL loans. In all our analyses, we double cluster our estimates at the individual and year-quarter level, unless specified otherwise.

C. Regional Economic Factors

The within-borrower specification includes vectors of fixed effects capturing time-invariant, individual-specific trends and individual-invariant, time-specific trends. However, one possible issue is that our results could be driven by shocks at the geographic level that are exogenous to borrowers on MPL platforms. This could especially pose a problem for our results regarding credit expansion or credit contraction, since these practices are heavily dependent on the profitability estimates of bank branches at the local regional level. Moreover, negative region-specific economic shocks could explain default patterns unrelated to MPL borrowing activity. Thus, we re-estimate Equation (2) 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.

IV. Post-MPL Loan Origination Borrower Dynamics

In this section, we present our main empirical results, which examine the impact of MPL loans on borrowers' consolidation activity, credit utilization, total indebtedness, credit scores, and ex post delinquencies and defaults.

A. Do MPL Borrowers Use MPL Funds To Consolidate Expensive Credit Card Debt?

In Table II, we first analyze whether MPL borrowers consolidate expensive credit card debt in the aftermath of MPL loan origination. The dependent variable in our specification is logged monthly credit card balances at the individual level.

The results of the cohort-level analysis are presented in columns (I)–(IV). In column (I), we present results comparing bank-unsatisfied MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP, where both parties need credit in the same calendar month. The pre-MPL loan origination trends reveal increasing average credit card balances for both MPL borrowers and their neighbors. However, starting from the quarter of MPL loan origination, there appears to be a significant divergence in the credit card balance trends of MPL borrowers and their neighbors. In the quarter of the unsuccessful bank application, non-borrowing neighbors experience a 4.57% increase in credit card balances. In contrast, MPL borrowers have credit card balances that are nearly 42% lower in the same time span.[11] This divergence is stark given that both groups have nearly identical balances in the preceding quarter.

In the following quarters, we note that the difference in credit card balances between the two groups shrinks, and even reverses sign. This occurs partly because the non-borrowing neighbors steadily reduce credit card debt starting from two quarters after the unsuccessful bank loan application. Two years following the unsuccessful application, their average credit card balances are approximately 17% lower. However, the main driver appears to be the short-lived consolidation phase of MPL borrowers. Despite the significant immediate consolidation activity, three quarters after origination, MPL borrowers and their neighbors have nearly identical credit card balances, and subsequently, MPL borrowers start carrying higher balances relative to their neighbors.

In column (II), we report results for cohorts of the entire sample of MPL borrowers matched to bank-unsatisfied neighbors within the same 5-digit ZIP code. As described

[11] The coefficient on the interaction term, $Quarter_0 \times MPL\_Borrower$, captures the differential response of MPL borrowers relative to their neighbors within the same cohort in the quarter of MPL loan origination. The percentage change equivalent of estimate provided is $100 \times [exp(-0.5365) - 1] = -41.52\%$.

earlier, the cohorts are created such that the MPL borrower originates her loan and the neighbor files their unsuccessful bank loan application in the same calendar month. Again, our findings suggest that MPL borrowers consolidate credit card debt in the immediate aftermath of MPL loan origination. Subsequently, they revert to consumption, such that two quarters following origination, they carry higher credit card balances than their neighbors. Our inferences remain unchanged when we compare all MPL borrowers to bank-unsatisfied neighbors within the same 9-digit ZIP code (column (III)).

Lastly, we match MPL borrowers to neighbors within the same 5-digit ZIP code who originate an unsecured installment loan issued by a traditional bank. The cohort is created such that the MPL borrower and the neighboring bank borrower originate their respective loans in the same month. The results of this analysis are presented in column (IV). Our findings highlight that the bank-borrowing neighbors use their installment loans to pay off credit card debt – their credit card balances are approximately 30% lower in the quarter of bank loan origination. However, MPL borrowers, consolidate an additional 13% of their credit card debt relative to their bank borrowing neighbors in the same time span. The neighboring group's consolidation activity is more permanent, and their average credit card balances remain approximately 19% lower two years following the origination of the bank loan. In contrast, MPL borrowers' consolidation is transitory, such that one quarter post-origination, MPL borrowers carry higher credit card balances than their bank-borrowing neighbors, and this difference increases over time.

To assuage self-selection concerns not addressed by our cohort-level analysis, in column (V), we report the *within*-MPL borrower event study estimates generated using Equation (2) restricted only to the sample of MPL borrowers. MPL borrowers accrue credit card debt in the months leading up to MPL loan origination. In the quarter of origination, however, credit card balances are approximately 47.50% lower relative to preceding quarter, which is consistent with the consolidation of credit card debt.[12] More importantly, we also note that this consolidation phase appears to be short lived. In subsequent quarters, these borrowers resume consumption on credit cards. As a result, three quarters after origination, credit card balance levels are not significantly different from pre-origination levels. In column (VI), we report the robustness of our findings in column (V) by controlling for regional time-trends through 5-digit ZIP code $\times$ year-quarter fixed effects. We note that this tighter specification does not alter our earlier inferences.[13]

[12]The estimate on $Quarter_0$ is -0.6432. However, as the dependent variable is the logged monthly credit card balance, the percentage change equivalent is given by $100 \times [exp(-0.6432) - 1] = -47.44\%$.

[13]In supplemental findings presented in Online Appendix Table OA.I, we show that MPL funds are not used to consolidate auto debt, mortgages, or student loans.

Taken together, our findings suggest that borrowers utilize MPL funds in a manner consistent with the vast majority of stated reasons on MPL loan applications. Given how MPL platforms have no mechanism in place to enforce the appropriate use of borrowed funds, this finding suggests that the commonly stated aim of debt consolidation is not frequently misreported on loan applications. Moreover, these borrowers only focus on consolidating their most expensive debt. The average interest rates on auto, mortgage, and student debt are significantly lower than the 15–20% rates charged on unsecured credit cards, which is the focus of MPL loan-induced consolidation activity.

We also note that the short-lived consolidation of credit card debt is factored into the credit card utilization ratios of MPL borrowers. In the quarter of origination, the utilization of MPL borrowers is approximately 18 pp lower relative to the preceding quarter, which significantly reduces financial constraints. These findings hold when MPL borrowers are compared to each of the four cohorts described above. The results of this analysis are presented in Appendix Table OA.II.

B. How Is Total Non-Mortgage Indebtedness Affected?

In this section, we study how the relatively short-lived consolidation of credit card debt affects the total non-mortgage indebtedness of MPL borrowers. The dependent variable in this analysis is logged individual-level total non-mortgage balance at the monthly frequency. The results of this analysis are presented in Table III.

In column (I), bank-unsatisfied MPL borrowers are compared to bank-unsatisfied neighbors within the same 5-digit ZIP. We find that in the quarter of the unsuccessful bank loan application, these neighbors experience a 2.85% decline in total non-mortgage indebtedness. In comparison, MPL borrowers experience a 7.53% decline in non-mortgage indebtedness during the same time period.[14] However, two quarters following MPL loan origination, we find that MPL borrowers have higher non-mortgage debt than their neighbors. Two years following MPL loan origination, we note that MPL borrowers have 26.75% higher non-mortgage debt than their neighbors. We find similar magnitudes when comparing the entire sample of MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP) in column (II) (column (III)).

In column (IV), the entire sample of MPL borrowers is compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In

[14]The impact on the total non-mortgage indebtedness of MPL borrowers in the quarter of MPL loan origination is captured by summing up the coefficients on $Quarter_0$ and $Quarter_0 \times MPL$ $((-2.85) + (-4.68) = -7.53)$.

the quarter of loan origination, bank borrowers experience a 6.13% increase in total non-mortgage indebtedness. In contrast, MPL borrowers experience a 17.12% decrease in non-mortgage indebtedness. Over time, however, both groups trend in opposite directions, such that by the two year mark following origination, MPL borrowers have approximately 6% higher total debt relative to bank borrowers.

Within-MPL borrower event study estimates, presented in column (V), suggest that MPL borrowers have approximately 30% more total non-mortgage debt one year following the origination of the MPL loan. Our inferences remain unchanged when we account for time-varying regional trends in column (VI).

Taken together, our credit card balance and total non-mortgage balance results highlight the transience of MPL-induced debt consolidation activity wherein expensive credit card debt is replaced with relatively less expensive MPL debt. However, MPL borrowers end up just as indebted in credit card debt three quarters after origination as they were before receiving the loan. These borrowers are already burdened with the monthly payments associated with amortized MPL loans when they begin consuming credit card debt again. Thus, this "double dipping" activity increases the aggregate indebtedness of MPL borrowers in the months following MPL loan origination.

C. Does MPL Induced Debt Consolidation Impact Borrowers' Credit Scores?

Next, we study the impact of MPL loans on the credit scores of borrowers, since credit utilization ratios and credit balances are important ingredients to credit scores. The dependent variable in this section is logged credit scores at the monthly frequency. The results of this analysis are presented in Table IV.

Across all cohorts, we find that, in the initial aftermath of MPL loan origination, MPL borrowers experience a larger increase in credit scores relative to their neighbors. However, over time, as MPL borrowers revert to consumption, their credit scores decline, such that 1–2 years after origination, they have lower credit scores relative to their neighbors. In column (I), bank-unsatisfied MPL borrowers are compared to bank-unsatisfied neighbors. Following the unsuccessful bank application, the constrained neighbor group experiences an immediate 0.78% decline in credit scores. In contrast, MPL borrowers have credit scores that are approximately 3% (approximately 20 points) higher during the same time period. Similarly, when we compare the full sample of MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP or 9-digit ZIP code (columns (II) and (III)), we find that MPL borrowers have credit scores that are 2.99–3.31% (approximately 21 points) higher in the quarter of loan origination. As column (IV) shows, due to their consolidation activity, bank borrowers experience a 0.33% increase in average credit scores in the quarter of loan origination. Relative to this group from the same 5-digit ZIP code, MPL borrowers have an additional 2% (approximately 14 point) larger increase in average credit scores in the same time span.

In column (V), within-borrower event study estimates indicate that the credit scores of MPL borrowers remain steady in the year prior to loan origination. In the quarter of MPL loan origination, credit scores are approximately 2.97%, or 19 points, higher relative to the absorbed period (significant at the 1% level).[15] Our estimates for $Quarter_{+1}$ ($Quarter_{+2}$) indicate that average credit scores are 1.59% (0.55%) higher one quarter (two quarters) following origination. However, three quarters after origination, average credit scores are insignificantly different relative to pre-origination levels. The interpretation remains consistent when we account for time-varying regional trends (column (VI)).

D. Do Short-Term Credit Profile Improvements Trigger Bank Lending Actions?

Thus far, we have documented that MPL-induced credit card debt consolidation temporarily elevates credit scores. In this section, we document whether these short-term improvements in credit profiles trigger bank lending actions in the form of increased credit limits on credit cards. The dependent variable under consideration is logged monthly credit card limit growth. The results of this analysis are presented in Table V.

In our cohort-level analysis, we document that relative to non-MPL borrowing neighbors, MPL borrowers experience higher credit card limit growth for up to 6 months following MPL loan origination. Subsequently, however, the credit card limit growth of the neighboring group dominates. This finding remains consistent when bank-unsatisfied MPL borrowers are compared to bank-unsatisfied neighbors (column I)), and even when the unconditioned set of MPL borrowers is compared to bank-unsatisfied neighbors in the same 5-digit ZIP (column (II)), bank-unsatisfied neighbors in the same 9-digit ZIP (column (III)), or bank borrowers within the same 5-digit ZIP (column (IV)).

In columns (V), we report within-MPL borrower event study estimates. We find that monthly credit card limit growth is stagnant in the quarters leading up to MPL loan origination. However, our estimate on $Quarter_0$ ($Quarter_{+1}$) indicates that monthly credit limit growth is approximately 0.55% (0.78%) higher in the quarter of (the quarter

[15]Descriptive statistics presented in Table I show that the average credit score of MPL borrowers in the month immediately prior to loan origination is approximately 656. Thus, our coefficient estimate of 2.97% suggests that in the quarter of MPL loan origination, borrowers' credit scores increase by 19 points ($\approx 0.0297 \times 656$).

immediately following) MPL loan origination. This interpretation remains consistent when we account for time-varying regional trends (column (VI)).

E. Impact Of MPL Funds On Credit Card Default Rates

Lastly, we study the impact of MPL funds on credit card default rates. The results of this analysis are presented in Table VI.

In column (I), we report results for cohorts of bank-unsatisfied MPL borrowers matched to bank-unsatisfied neighbors within the same 5-digit ZIP. We find that in the absence of additional credit, the neighbor group experiences a steady increase in credit card default rates, such that seven quarters following the unsuccessful application, their default rates are 2.10 pp higher relative to the absorbed period. In comparison, upon receiving MPL funds, MPL borrowers initially have lower default rates relative to their neighbors. However, as they revert to consumption, their credit card default rates surpasses that of the neighbor group by four quarters following origination. Seven quarters following origination, MPL borrowers are 1.82 pp (or 86.67%) more likely to default on credit cards than their neighbors. Similarly, when the entire sample of MPL borrowers is compared to bank-unsatisfied neighbors within the same 5-digit ZIP (column (II)), we note that MPL borrowers are 1.96 pp (or 96.55%) more likely to default on credit cards two years following origination. Lastly, when compared to unsecured installment bank loan borrowers within the same 5-digit ZIP (column (IV)), MPL borrowers are 1.31 pp (or 65.17%) more likely to default on credit cards two years following loan origination.

In column (V), we present within-MPL borrower event study estimates. Our results highlight an approximate U-shape in credit card default probabilities that bottoms out near the quarter of MPL loan origination. Default probabilities are declining in the quarters leading up to MPL loan origination. However, following origination, credit card default probabilities begin to increase again. The estimate on $Quarter_{+3}$ indicates that default probabilities are 1.55 pp higher three quarters following MPL loan origination (significant at the 1% level). Given average credit card default occurrences of 0.12% in the absorbed period, this indicates that the probability of defaulting on credit cards is 13 times higher at the 1-year mark after MPL loan origination. Our interpretation remains unchanged when accounting for time-varying regional trends (column (VI)).

These findings lead us to conclude that traditional banking intermediaries over-extrapolate the temporary decrease in credit card debt facilitated by MPL-induced debt consolidation. Our findings from the previous sections suggest that credit card limit growth is strongest when credit card debt (and associated utilization ratios) are lowest.

Thus, credit extension decisions are made before observing the subsequent upturn in credit accumulation. As a result, these borrowers, faced with paying down borrowed MPL funds as well as re-accumulated credit card debt, begin to default at higher rates in the quarters following MPL loan origination.

F. Do MPL Borrowers Default On All Kinds Of Debt?

In Table VII, we study whether MPL loan origination is associated with higher default rates in other forms of debt besides credit cards. In column (I) of Table VII, we display the default rates on credit cards, as shown in column (V) of Table VI. As before, we note that credit card default rates are 1.55 pp higher three quarters after MPL loan origination. On the other hand, our estimates in columns (II), (III), and (IV) suggest that default rates on auto loans, mortgage loans, and student loans, respectively, are not significantly higher (in an economic sense). In column (V), we report results for default rates on installment loans, and we note that, here too, the origination of MPL loans is not associated with an economically significant rise in default rates after origination. The findings reported in column (V) are interesting because MPL loans, given their amortized repayment schedule, are recorded as installment loans. Thus, taken together, our findings in columns (I) and (V) suggest that, after MPL loan origination, default rates spike for credit cards, but not for the MPL loan itself.

G. Do Changes In Employment, Income, or Health Outcomes Explain These Findings?

In this section, we study whether our ex post results regarding credit card limit growth and credit card defaults are explained through a change in the employment or health outcomes of MPL borrowers. It is important to note, however, that MPL loans differ from traditional loans only in means of origination, and thus, it is unlikely that they can impact the job profiles of individuals engaging in MPL platforms. In addition, for health outcomes to play a significant role in explaining ex post credit card defaults, a significant portion of MPL borrowers would have to receive a negative health shock within one year of MPL loan origination. However, in our sample, MPL borrowers are geographically dispersed, and originate their MPL loans at different times. More importantly, our findings also suggest that defaults on credit cards spike in the post-origination period, while default rates on amortized MPL loans (and other forms of debt) are economically negligible. Therefore, this style of 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 (2), and replace the dependent variable with a dummy 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 presented in column (I) of Table VIII show that in the 25-month window centered on the month of MPL loan origination, the probability of income change remains stable. We also study Equation (2), with job change as the dependent variable. This variable 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. The results presented in column (II) of Table VIII show that occurrences of job changes remain negligible in the months following MPL loan origination. Taken together, these findings indicate that job or income loss cannot explain the ex post increase in credit card default rates.

Lastly, in column (III), we study whether the likelihood of MPL borrowers facing medical collections changes over the 25-month window centered on the month of MPL loan origination. We find that the probability of facing medical collections is *lower* in the post-origination period, which indicates that ex post negative health shocks cannot explain the rise in credit card default rates following MPL loan origination.

V. What Factors Influence the Extension of Additional Credit?

In this section, we attempt to identify whether MPL loans improve the perceived credit quality of borrowers, which could potentially explain the increase in credit card limits following MPL loan origination. Our findings thus far establish that both credit scores and credit card limits increase following origination. We now look to study whether improvements in credit scores explain increases in credit limits in a *causal* sense.

A. What Increases First – Credit Scores or Credit Card Limits?

For the ease of exposition, our earlier event study findings use quarterly indicators in relation to the quarter of MPL loan origination. This approach masks within-quarter variation, and possibly understates our findings. Thus, in this section, we present event study plots of the evolution of credit scores and credit card limit growth using *monthly* indicators instead. The findings are presented in Appendix Figure A.II.

Our findings reveal that our prior analysis indeed provides a conservative estimate. MPL borrowers experience a moderate increase in credit scores in the month of MPL loan origination, before experiencing a near 4% increase in scores in the following month.[16]

[16]This near-month long lag in increased credit scores possibly reflects the delay in reporting from

More importantly, credit card limit growth remains stagnant for up to two months *following* the origination of the MPL loan. In fact, credit limits show a significant increase only *after* the MPL-induced improvement in credit scores. While credit scores increase immediately, credit limit growth is 1–2% stronger in the 2–4 month window following origination, which highlights a clear lead–lag and possibly causal relationship.

Lastly, we find that credit card account growth is not significantly different following MPL loan origination, which suggests that these post-origination credit card limit increases occur largely along the intensive margin. According to descriptive statistics presented in Panel A of Table I, MPL borrowers have nearly four open credit cards prior to MPL loan origination, with an average utilization of approximately 70%. Even after debt consolidation, MPL borrowers' average utilization is nearly 50%. Thus, it would be unlikely that banks issue an additional credit card to such a constrained group. However, these findings also indicate that existing creditors are still heavily reliant on credit scores. These banks already have information on the credit card consumption patterns of MPL borrowers for many months. However, they too, appear to be influenced by the MPL-induced drop in utilization, and associated credit score increase, that is completely at odds with consumption patterns in the year leading up to MPL loan origination.

B. What Matters More – Higher Credit Scores or Higher Credit Availability?

While higher credit scores could explain the increase in credit card limits, it is also possible that this limit growth occurs in response to the general increase in the MPL borrower's credit availability because of MPL loans. Thus, it is possible that traditional banks perceive the origination of MPL loans as a signal of increased creditworthiness of the MPL borrower, and respond by increasing limits on issued credit cards.[17] If this increase in general credit availability is indeed the key determinant, we should find increased credit card limits for all MPL borrowers, irrespective of debt consolidation.

We partition our sample of MPL borrowers into "credit card debt consolidators" and "non-consolidators." Consolidators (non-consolidators) refer to MPL borrowers who's average credit card balances in the quarter of MPL loan origination are lower (greater) than that in the preceding quarter. Consolidators and non-consolidators account for approximately 68% and 32% of our sample, respectively.

Our findings are presented in the form of event study plots in Figure A.III. In Panel A, we study the differential credit score trends of consolidators and non-consolidators.

creditors to the credit bureau.

[17]This is similar to the discussion of fads and informational cascades in Bikhchandani et al. (1992).

We note that consolidators experience a near 6% increase in credit scores in the 1–2 months following MPL loan origination. On the other hand, non-consolidators experience a steady decline in credit scores following origination, such that their credit scores are approximately 4% lower one year following origination.

In Panel B, we study credit card limit growth. We find that the credit card limit growth of consolidators is stagnant prior to origination. However, in the 2–8 month window following origination, consolidators experience a 2.5–3% increase in credit card limit growth. Most tellingly, this spike in limits occurs *after* the immediate increase in consolidators' credit scores. In contrast, we find that non-consolidators experience increasing credit limits in the months preceding MPL loan origination. In the month of, and the month immediately following origination, non-consolidators continue to experience 1% higher credit card limit growth, but there appears to be no deviation from pre-origination trends. Subsequently, non-consolidators have stagnant limit growth, which is in stark contrast to the ex post experience of consolidators.

Taken together, our findings suggest that the increase in general credit availability following MPL loan origination cannot fully explain the ex post increase in credit card limits. MPL borrowers who do not consolidate credit card debt do not experience higher credit scores and markedly higher credit card limit growth. Credit card debt consolidators, on the other hand, experience both an increase in credit scores and a subsequent spike in credit card limits following MPL loan origination.

C. Cohort-Level Analysis

Our earlier analysis focuses on within-MPL borrower variation. Now, we utilize the different cohorts described earlier to implement the following fixed effects cross-sectional regression:

$$log\left(\frac{Y_{[+1,+3]}}{Y_{[-3,-1]}}\right)_{i,c} = MPL\_Borrower_{i,c} + \gamma\overline{\mathbf{X}}_{i,c} + \alpha_c + \epsilon_{i,c}. \tag{3}$$

As before, $MPL\_Borrower$ is an indicator that equals 1 if the individual is an MPL borrower, and 0 otherwise. $Y_{i,c}$ is the outcome variable, represented in the form of logged changes. For our analysis, we study changes in average outcomes in the three months following MPL loan origination relative to the three months immediately preceding origination. $\mathrm{X}_{i,c}$ represents control variables, and α_c is a vector of cohort fixed effects, which induces within-cohort comparisons between the MPL borrower and her neighbor. 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 Sub-Panel A.1, we compare bank-unsatisfied MPL borrowers to bank-unsatisfied non-MPL borrowing neighbors. In column (I), the dependent variable is credit score growth, defined as the logged average credit score of the individual in months [+1,+3] less her logged average score in months [-3,-1], where month 0 refers to the month of MPL loan origination. The estimate on the MPL borrower dummy indicates that, relative to their bank-unsatisfied neighbors, bank-unsatisfied MPL borrowers experience a 3.69% larger increase (significant at the 1% level) in average credit scores in three months following MPL loan origination.

In column (II), we study changes in credit card limits. Our findings suggest that relative to bank-unsatisfied neighbors, bank-unsatisfied MPL borrowers experience a 3.53% larger increase (significant at the 1% level) in average credit card limits in the three months following MPL loan origination. In column (III), we regress change in credit card limits on change in credit scores. In this matched sample, we find that a 1% increase in an individual's credit score is associated with a 0.08% increase in the individual's credit card limits (significant at the 1% level).

In Sub-Panel A.2, we conduct the same analysis as earlier, but on the cohort of all MPL borrowers matched to bank-unsatisfied neighbors within the same 5-digit ZIP. We find that MPL borrowers experience a 4.14% larger increase in credit scores (column (I)), and a 4.47% larger increase in credit card limits (column (II)) in the three months following origination. Moreover, in this larger matched sample, we document a 0.07% increase in credit card limits for a 1% increase in credit scores (column (III)).

Lastly, in Sub-Panel A.3, we repeat the above analysis on cohorts of MPL borrowers matched to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. Relative to bank borrowers, MPL borrowers experience a 2.12% larger increase in credit scores (column (I)), and a 1.75% larger increase in credit card limits (column (II)) in the three months following MPL origination. Our findings in column (III) suggest that in this matched sample, a 1% increase in credit scores is associated with a 0.01% increase in credit card limits (significant at the 10% level).

Our findings in Panel A suggest that MPL borrowers experience large increases in credit scores in the immediate aftermath of loan origination, which substantially reduces financial constraints. Thus, in Panel B, we study the relative probability of subprime (near-prime) MPL borrowers crossing industry-standard credit score thresholds of 620 (680) in the three months following MPL loan origination, and thus turning near-prime (prime) as compared to their socioeconomically-identical non-MPL borrowing neighbors. This comparison is conducted across all three cohorts discussed in Panel A. In Sub-Panel

B.1, we compare bank-unsatisfied MPL borrowers matched to bank-unsatisfied neighbors within the same 5-digit ZIP. In column (I), we study the subprime segment of the sample. We find that following MPL loan origination, subprime MPL borrowers are 34.20% more likely to turn near-prime than their neighbors. Similarly, in column (II), we find that near-prime MPL borrowers are 31.12% more likely to turn prime than their neighbors following MPL loan origination. Our findings do not change materially when we compare the entire sample of MPL borrowers to bank-unsatisfied neighbors within the same 5-digit ZIP (Sub-Panel B.2). Lastly, in Sub-Panel B.3, we compare MPL borrowers to bank borrowers within the same 5-digit ZIP. We find that relative to subprime (near-prime) bank borrowers, subprime (near-prime) MPL borrowers are 22.73% (15.71%) more likely to turn near-prime (prime) in the three months following MPL loan origination.

D. Addressing Causality Concerns

The previous set of tests were conducted on matched cohorts of MPL borrowers and their geographically and socioeconomically proximate non-MPL borrowing neighbors. Despite the tight matching criteria of levels and trends of credit attributes, however, there could still be a "selection-on-unobservables" concern. Moreover, directly regressing credit outcomes on an MPL borrower dummy (as we do in Equation (3)) could be problematic because MPL borrower status is partly determined by unobservables. Thus, in this section, we tackle the endogeneity of the decision to borrow on MPL platforms by accounting for MPL borrowers' access to technology in an instrumental variables setting.

The thought experiment relies on the fact that the MPL paradigm is completely online-technology based. Thus, areas with better access to internet can reasonably be expected to have a larger MPL share relative to areas with poor internet access, which satisfies the relevance condition for the first stage. Moreover, since our analysis relies on identifying the role of internet access on MPL share at a point of time, as opposed to a rollout or extension of additional technology services, there are no clear reasonable explanations as to why the credit outcomes of residents will *change* at that specific point in time other than through the decision to take up an MPL loan. i.e., internet availability at a given point in time will influence the decision to engage on MPL platforms at that specific point of time. However, internet access at a static point in time cannot directly explain *changes* in credit outcomes in the surrounding window, other than through the MPL borrower channel. Thus, the exclusion restriction is satisfied.

In order to conduct our analysis, we use broadband data from the NTIA internet access maps. This data is available for June 2013, December 2013, and June 2014.[18] Next, we identify cross-sections of MPL borrowers who have originated MPL loans between June 2013 and November 2014. Over the same time span, we identify non-MPL borrowers who apply for bank credit from a 1% random sample of the U.S. population.

Our first stage specification is defined as follow:

$$MPL\_Borrower_{i,z,s,t} = \beta Broadband\_Access_{z,t} + \gamma \mathbf{X}_{i,z,s,t} + \alpha_{st} + \epsilon_{i,z,s,t} \tag{4}$$

where the subscripts i, z, s, and t identify individual, 5-digit ZIP, state, and year-month, respectively. $MPL\_Borrower$ is a dummy which takes the value of 1 if individual i originated an MPL loan in year-month t, and 0 otherwise. $Broadband\_Access$ is a dummy indicating whether the 5-digit ZIP, z, in which individual i resides has access to broadband internet speeds at time t. Following the FCC's 2015 definition of "high-speed" internet, this dummy takes the value of 1 if the maximum advertised download speed exceeds 25 mbps, and 0 otherwise. α_{st} represents state $\times$ year-month fixed effects; we thus compare MPL borrowers to non-MPL borrowers residing in the same state, such that both parties require credit in the same year-month (i.e., MPL borrowers originate their MPL loans and non-MPL borrowers file their bank loan application in the same year-month). Lastly, $\mathbf{X}_{i,z,s,t}$ is a vector of individual-level control variables.

One shortcoming of using the maximum advertised download speed in an area as a measure of broadband access is that it fails to accurately capture how accessible these speeds are to the local population. For example, if the maximum advertised download speed is only available to a small, wealthy subsection of the population, then the relevance condition required for the first stage may not be satisfied. Thus, we supplement our analysis by looking at an alternate first stage specification as follows:

$$MPL\_Borrower_{i,c,s,t} = \beta \ HH/CountyPop_{c,t} + \gamma \mathbf{X}_{i,c,s,t} + \alpha_{st} + \epsilon_{i,c,s,t} \tag{5}$$

where the subscripts i, c, s, and t identify individual, county, state, and year-month, respectively. $HH/CountyPop_{c,t}$ is the percentage of households in a given county, c, at time t that have access to broadband download speeds. All other variables are defined as in Equation (4).

The instrumented specification is defined as follows:

$$log\left(\frac{Y_{[+1,+3]}}{Y_{[-3,-1]}}\right)_{i,z,s,t} = \beta \widehat{MPL\_Borrower}_{i,z,s,t} + \gamma \mathbf{X}_{i,z,s,t} + \alpha_{st} + \epsilon_{i,z,s,t} \tag{6}$$

where $\widehat{MPL\_Borrower}$ is the fitted value from Equation (4) or Equation (5), and the

[18] In our tests, we assume that the broadband access data as identified in June 2013 is valid through November 2013. Similarly, we assume that internet access data in December 2013 (June 2014) is valid through May 2014 (November 2014).

dependent variable is the logged change in credit score or logged change in credit card limits. The numerical subscripts in the outcome variable identify monthly intervals in relation to the monthly cross-section, t, under consideration.

The first stage results are presented in Panel A of Table X. In column (I), the coefficient on the intercept suggests that in 5-digit ZIP codes with maximum advertised download speeds less than 25 mbps, the probability of being an MPL borrower is 3.08%. However, in 5-digit ZIPs with broadband download speeds, the probability of being an MPL borrower is 35.71% higher.[19] In column (II), we include controls, and find that the probability of being an MPL borrower is 18.83% greater in 5-digit ZIPs with broadband download speeds. Next, we measure high-speed internet availability in terms of the percentage of county population with access to broadband download speeds. In column (III) (column (IV)), we find that the probability of being an MPL borrower is approximately 21.08% higher (8.83% higher) in counties with a one standard deviation higher percentage of population with access to high-speed internet.

In Panel B, we study the impact of borrowing on MPL platforms on credit score growth where MPL borrower status is instrumented with broadband access. The OLS results presented in column (I) indicate that MPL borrowers experience a 4.74% larger increase in credit scores relative to non-MPL borrowers residing in the same state, where both groups have a need for credit in the same year-month. In column (III), we instrument MPL borrower status with an indicator for whether the individual's 5-digit ZIP has maximum advertised download speeds greater than 25 mbps. In this instrumented setting, we find that MPL borrowers experience an 11.62% (significant at the 1% level) larger increase in credit scores relative to non-MPL borrowers with a need for credit. In column (V), we instrument MPL borrower status with the standardized continuous variable which identifies the percentage of county population with access to broadband download speeds. In this setting, MPL borrowers experience a 14.70% (significant at the 1% level) larger increase in credit scores relative to non-MPL borrowers with credit need.

Finally, in Panel C, we study credit card limit growth. In the OLS setting, we note that MPL borrowers experience a 7.12% larger increase in credit card limits relative to non-MPL borrowers with a need for credit residing in the same state (column (I)). In the instrumented setting, we find that MPL borrowers experience a 34.75–60.15% larger credit card limit increase relative to non-MPL borrowers (columns (III) and (V)).

Across all instrumented specifications discussed thus far, the F-statistic of the ex-

[19] 5-digit ZIPs with broadband (or high-speed internet) access are $\frac{1.10}{3.08} = 35.71\%$ more likely to produce MPL borrowers.

cluded instruments is well over 10, indicating that it is a strong instrument (Bound, Jaeger, and Baker, 1995; Staiger and Stock, 1997). The instrumented estimates of the credit card limit growth regressions are approximately 5–8 times larger than their OLS counterpart, which raises some concerns of our instrument capturing a local average treatment effect (LATE). However, according to the channel established in the previous sections, borrowing from MPL platforms doesn't directly translate to increased credit card limits from traditional banks. Rather, MPL-induced debt consolidation inflates borrower credit scores, which in turn induce increased credit card limits.

These results suggest that MPL platforms may not necessarily be generating any new soft information about borrowers on their platforms that are unavailable to their banks. MPL loans initially help borrowers through lower credit card balances, lower utilization, and higher credit scores. It appears that banks possibly overweight the credit score increase induced through MPL loans, even though the associated consolidation activity is both short-lived and at odds with their (very recent) historical consumption patterns. Thus, our results suggest that bank credit extension decisions are strongly influenced by credit scores, consistent with the arguments posed in Rajan, Seru, and Vig (2015) and Agarwal, Chomsisengphet, Mahoney, and Stroebel (2018).

VI. Who Wins Or Loses From Borrowing On MPL Platforms?

In this section, we discuss if there are systematic differences among the borrowers who benefit from borrowing from MPL platforms and those that don't benefit by analyzing how our results vary across different cross-sections of our sample.

A. Role Of MPL Borrower Credit Quality

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

In Panel A of Table XI, we present regression results for our analysis of credit card balances separately for the subprime (column (I)), near-prime (column (II)), and prime segments (column (III)). 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 two quarters (three quarters) after origination, average subprime (near-prime) credit card indebtedness is not significantly different relative to pre-origination levels. On the other hand, three quarters after origination, prime MPL borrowers appear to have 16.11% less credit card debt relative to pre-origination levels. Results in Panel B suggest that all three segments have lower credit utilization ratios after MPL loan origination relative to the baseline period.

Panel C shows that all three segments benefit from credit card debt consolidation, as reflected by an immediate increase credit scores. However, three quarters after origination, the subprime and near-prime segments have credit scores that are not significantly different from pre-origination levels. Moreover, the prime segment has credit scores that are actually 0.53% *lower* relative to the baseline period. In Panel D, we study credit card limit growth. Subprime MPL borrowers experience approximately 1.3% higher monthly credit card limit growth for up to 6 months following origination. Near-prime borrowers experience a marginally significant 0.50% higher increase in credit growth in the quarter of loan origination. Finally, prime borrowers don't seem to experience a change in credit limit growth in the 25-month window centered on loan origination.

Panel E shows our analysis of credit card default rates. The results indicate that three quarters after origination, the subprime segment has a 2.80 pp higher default rate relative to the baseline period. The subprime MPL borrower segment has an average credit card default rate of 0.25% in the three months immediately preceding MPL loan origination. Thus, the coefficient estimate at the one-year mark suggests that credit card default rates are approximately 12–13 times higher for the subprime group one year following origination relative to the quarter immediately preceding origination. The near-prime and prime segments experience a 1.48 pp and 0.63 pp increase in default rates, respectively, one year following MPL loan origination.

Taken together, our findings suggest that regardless of the borrower's credit quality at the time of loan origination, MPL loans are used to consolidate credit card debt. In doing so, these loans relax financial constraints for all borrowers through lower utilization ratios and higher credit scores. Banks appear to react to this new information as well, since credit card limits increase significantly when debt is being consolidated. This growth in credit limits is strongest for the most constrained borrowers – the subprime segment. However, this segment is also the quickest to revert to consumption behavior; within six months of origination, subprime MPL borrowers are as indebted in credit card debt as they were before origination. Given the increased aggregate debt burden, credit card default rates rise dramatically for subprime borrowers in the post-origination period.

B. Role of Borrower Pre-MPL Credit Card Utilization

We also study the role of MPL borrowers' pre-loan origination credit card utilization on ex post outcomes. We group all borrowers in our sample into three groups based on their utilization in the month immediately preceding MPL loan origination: *low* (<= 50%), *high* (50–90%), and *very high* (>= 90%). We then re-run our within-MPL borrower event study specifications on these three subgroups (Appendix Table OA.III).

In Panel A, we study the evolution of credit card balances for the three subgroups of MPL borrowers. We find that the 'low' utilization group consolidates the least amount of credit card debt using MPL funds. Moreover, two quarters following origination, these borrowers are as indebted in credit card debt as they were prior to the origination of the MPL loan. On the other hand, we note that the 'high' and 'very high' utilization groups of borrowers consolidate the most amount of credit card. While both these latter groups of borrowers also display a tendency to resume consumption on credit cards following consolidation, these sets of borrowers enjoy significantly lower credit card indebtedness one year following origination. These findings thus highlight that low utilization MPL borrowers, who are relatively less constrained, maybe seek out MPL funds for reasons other than expensive debt consolidation. Moreover, our findings also suggest that even the most heavily indebted borrowers use MPL funds to alleviate financial constraints temporarily, thus further mitigating concerns of misreporting on MPL loan applications.

In Panel B, we study credit card defaults. We note that ex post credit card default propensities are positively related to ex ante borrower constraints. The low utilization group experiences the smallest increase in credit card default rates despite being the least likely to use MPL funds for credit card debt consolidation purposes. On the other hand, our findings suggest that the ex ante 'high' and 'very high' utilization borrowers experience a significant increase in credit card default rates in the months following MPL loan origination despite using MPL funds for debt consolidation purposes.

C. Role of Borrower Income

We also identify financial constraints through the monthly income of MPL borrowers. We group all MPL borrowers into quintiles on the basis of their monthly income in the month immediately preceding MPL loan origination, where the lowest (highest) quintile corresponds to the least (most) well off group of MPL borrowers. We then re-run our baseline event study specification on these five subgroups. The results of this analysis are presented in Appendix Table OA.IV.

Our findings in Panel A suggest that borrowers of all incomes appear to use MPL funds to pay off credit card debt. However, the borrowers falling in the lowest income quintile are quickest to revert to pre-origination credit card indebtedness levels. On the other hand, the most well off MPL borrowers are, on average, approximately 17% less indebted in credit card debt one year following origination.

Consistent with the findings in Panel A, we note that the increase in credit card default rates at the one year mark following origination declines monotonically in the monthly income of MPL borrowers. The least well off MPL borrowers are 2.80 pp more likely to default on credit cards, whereas the most well off MPL borrowers experience a 0.75 pp increase in credit card default rates.

D. Role of Borrower Health

In results presented in column (III) of Table VIII, we rule out that the increase in ex post credit card defaults is caused by a spike in negative health shocks after MPL loan origination. However, we do document that MPL borrowers are *more* likely to have medical-related accounts in collection *before* the origination of the MPL loan relative to the post-origination period. Thus, we create two sub-samples of MPL borrowers – those with at least one medical-related account in collection before MPL loan origination, and those with no such ex ante collections activity. These sub-samples account for approximately 30% and 70% of our sample, respectively. The results of this analysis are presented in Online Appendix Table OA.V.

In Panel A, we report results for credit card balances. We find that MPL borrowers with pre-origination health shocks are quicker to revert to pre-origination credit card debt levels. In fact, two quarters after origination, MPL borrowers with ex ante health shocks have as much credit card debt as they did before MPL loan origination. In contrast, MPL borrowers with no ex ante health shocks are approximately 12% less indebted by one year after origination (marginally significant at the 10% level).

In Panel B, we report results for credit card defaults. We find that MPL borrowers with pre-origination health shocks are 1.67 pp more likely to be delinquent on credit cards one year after origination. Moreover, we find that even MPL borrowers with no pre-existing health condition (as proxied by medical collections) are 0.94 pp more likely to be delinquent on credit cards one year following origination.

Overall, these results reveal that for a subset of the MPL borrower base, the decision to turn to MPL platforms may be due to negative health shocks. Thus, while MPL funds help in temporarily alleviating financial constraints, the recurring nature of medical bills results in the reversion to credit card consumption, which eventually results in increased occurrences of credit card default. However, we also find that individuals with no prior health shocks revert to consumption following the immediate consolidation of debt. Moreover, even this larger sub-sample of non-health shocked MPL borrowers default at a significantly higher rate following the origination of the MPL loan.

VII. Conclusion

In this paper, we document some of the benefits and drawbacks of MPL borrowing for consumers. Our results indicate that MPL funds help reduce credit card debt by approximately 47%, on average, in the quarter of loan origination. The associated decline in utilization results in a 19 point increase in credit scores. Thus, at least in the short run, MPL borrowers benefit through a relaxation in financial constraints, even when compared to socioeconomically identical non-MPL borrowing neighbors.

Our results suggest that banks respond to this temporary elevation in credit scores by increasing credit card limits to MPL borrowers. Thus, to the extent that credit card debt consolidation through MPLs influences credit scores and thereby alters bank behavior, our results have broader implications for credit extension decisions by banks.

Importantly, our findings suggest that MPL loans fail to change the consumption behavior of such borrowers. In the longer horizon, the benefits to MPL borrowers depend on their subsequent credit utilization. Borrowers with the financial discipline to avoid drawing down on their higher credit limits benefit, but borrowers who lack this financial discipline, or who are too financially stressed to avoid drawing down on their higher credit limits, end up in a worse financial condition, even when compared to their non-MPL borrowing neighbors with similar ex ante credit dynamics. Thus, MPL borrowers have higher probabilities of credit card default in the months after MPL loan inception, with ex ante constrained borrowers being most negatively affected. Thus, there are winners and losers among MPL borrowers.

References

Agarwal, S., S. Chomsisengphet, N. Mahoney, and J. Stroebel. 2018. Do banks pass through credit expansions? The marginal profitability of consumer lending during the great recession. *The Quarterly Journal of Economics* 133:129–190.

Agarwal, S., C. Liu, and N. S. Souleles. 2007. The reaction of consumer spending and debt to tax rebates—evidence from consumer credit data. *Journal of Political Economy* 115:986–1019.

Agarwal, S., J. Pan, and W. Qian. 2016. Age of decision: Pension savings withdrawal and consumption and debt response. *Working Paper* .

Agarwal, S., W. Qian, and X. Zou. 2017. Thy neighbor's misfortune: Peer effect on consumption. *Working Paper* .

Akerlof, G. A. 1970. The market for" lemons": Quality uncertainty and the market mechanism. *Quarterly Journal of Economics* pp. 488–500.

Balyuk, T. 2018. Financial innovation and borrowers: Evidence from peer-to-peer lending. *Working Paper* .

Banerjee, A. V. 1992. A simple model of herd behavior. *The Quarterly Journal of Economics* 107:797–817.

Bartlett, R., A. Morse, R. Stanton, and N. Wallace. 2018. Consumer-lending discrimination in the FinTech era. *Working Paper* .

Berg, T., V. Burg, M. Puri, and A. Vanjak. 2018. On the rise of FinTechs – Credit scoring using digital footprints. *Working Paper* .

Bikhchandani, S., D. Hirshleifer, and I. Welch. 1992. A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy* 100:992–1026.

Bound, J., D. A. Jaeger, and R. M. Baker. 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *Journal of the American statistical association* 90:443–450.

Buchak, G., G. Matvos, T. Piskorski, and A. Seru. 2017. Fintech, regulatory arbitrage, and the rise of shadow banks. Tech. rep., National Bureau of Economic Research.

Demyanyk, Y., E. Loutskina, and D. Kolliner. 2017. The taste of peer-to-peer loans. *Working Paper* .

Duarte, J., S. Siegel, and L. Young. 2012. Trust and credit: The role of appearance in peer-to-peer lending. *Review of Financial Studies* 25:2455–2484.

Freedman, S. M., and G. Z. Jin. 2011. Learning by doing with asymmetric information: Evidence from Prosper.com. Tech. rep., National Bureau of Economic Research.

Fuster, A., M. Plosser, P. Schnabl, and J. Vickery. 2018. The role of technology in mortgage lending. Tech. rep., National Bureau of Economic Research.

Gross, D. B., and N. S. Souleles. 2002. Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data. *The Quarterly Journal of Economics* 117:149–185.

Hasan, I., Q. He, and H. Lu. 2018. Stereotypes and lending: Evidence from person-to-person transactions. *Working Paper* .

Hertzberg, A., A. Liberman, and D. Paravisini. 2018. Screening on Loan Terms: Evidence from Maturity Choice in Consumer Credit. *Review of Financial Studies* .

Hildebrand, T., M. Puri, and J. Rocholl. 2016. Adverse incentives in crowdfunding. *Management Science* 63:587–608.

Iyer, R., A. I. Khwaja, E. F. Luttmer, and K. Shue. 2015. Screening peers softly: Inferring the quality of small borrowers. *Management Science* 62:1554–1577.

Jagtiani, J., and C. Lemieux. 2017. FinTech lending: Financial inclusion, risk pricing, and alternative information. *Working Paper* .

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina. 2012. Credit supply and monetary policy: Identifying the bank balance-sheet channel with loan applications. *American Economic Review* 102:2301–26.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina. 2014. Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects of Monetary Policy on Credit Risk-Taking? *Econometrica* 82:463–505.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig. 2010. Did securitization lead to lax screening? Evidence from subprime loans. *The Quarterly Journal of Economics* 125:307–362.

Leland, H. E., and D. H. Pyle. 1977. Informational asymmetries, financial structure, and financial intermediation. *Journal of Finance* 32:371–387.

Liberman, A., D. Paravisini, and V. Pathania. 2018. High-cost debt and perceived creditworthiness: Evidence from the UK .

Lin, M., N. R. Prabhala, and S. Viswanathan. 2013. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science* 59:17–35.

Michels, J. 2012. Do unverifiable disclosures matter? Evidence from peer-to-peer lending. *The Accounting Review* 87:1385–1413.

Paravisini, D., V. Rappoport, and E. Ravina. 2016. Risk aversion and wealth: Evidence from person-to-person lending portfolios. *Management Science* 63:279–297.

Phillippon, T. 2015. Has the US finance industry become less efficient? On the theory and measurement of financial intermediation. *American Economic Review* 105:1408–1438.

Pope, D. G., and J. R. Sydnor. 2011. What's in a picture? Evidence of discrimination from Prosper.com. *Journal of Human Resources* 46:53–92.

Rajan, U., A. Seru, and V. Vig. 2015. The failure of models that predict failure: Distance, incentives, and defaults. *Journal of Financial Economics* 115:237–260.

Ravina, E. 2012. Love & loans: The effect of beauty and personal characteristics in credit markets. *Working Paper* .

Staiger, D., and J. H. Stock. 1997. Instrumental variables regression with weak instruments. *Econometrica* 65:557–586.

Stango, V., and J. Zinman. 2009. What do consumers really pay on their checking and credit card accounts? Explicit, implicit, and avoidable costs. *American Economic Review* 99:424–429.

Stiglitz, J. E., and A. Weiss. 1981. Credit rationing in markets with imperfect information. *American Economic Review* 71:393–410.

Tang, H. 2018. Peer-to-peer lenders versus banks: substitutes or complements? *Review of Financial Studies* .

Vallee, B., and Y. Zeng. 2018. Marketplace Lending: A New Banking Paradigm? .

Wolfe, B., and W. Yoo. 2018. Crowding out banks: Credit substitution by peer-to-peer lending. *Working Paper* .

Table I: Descriptive Statistics

In this table, we present descriptive statistics of the credit and income characteristics of individuals who borrow funds from marketplace lending (MPL) platforms. In Panel A, we compare MPL borrowers to the average U.S. population. In column (I), we present descriptive statistics of MPL borrowers in the month immediately preceding MPL loan origination. 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, respectively. In Panel B, we present descriptive statistics comparing MPL borrowers to a matched cohort of socioeconomically identical non-MPL borrowing neighbors. In columns (I) and (II), bank-unsatisfied MPL borrowers are compared to a matched cohort of bank-unsatisfied neighbors within the same 5-digit ZIP code. In columns (III) and (IV), the entire sample of MPL borrowers is compared to a matched cohort of bank-unsatisfied neighbors within the same 5-digit ZIP code. In columns (V) and (VI), the entire sample of MPL borrowers is compared to a matched cohort of neighbors within the same 5-digit ZIP, who originate unsecured installment loans from traditional banks. Details of the cohort-creation process are provided in the Online Appendix.

Panel A: Comparing MPL Borrowers to Average American Consumer

	MPL Platform Borrowers	National Average	Homeowners' Average
	(I)	(II)	(III)
A.1: Credit Characteristics			
# Open Trades	10.49	4.68	7.58
# Auto Trades	1.02	0.66	0.84
# Mortgage Trades	0.86	0.79	1.07
# Student Loan Trades	2.23	1.66	1.49
# Credit Card Trades	3.84	1.97	2.74
Credit Score	656.44	675.47	733.84
Total Balance	$232,463	$208,195	$310,142
Auto Balance	$20,659	$17,038	$20,648
Mortgage Balance	$189,597	$186,237	$274,244
Student Loan Balance	$24,425	$19,122	$20,210
Credit Card Balance	$9,821	$4,197	$5,994
Credit Card Utilization	69.42%	30.89%	28.55%
A.2: Income Characteristics			
Monthly Income	$3,602	$3,437	$5,232
Debt-to-Income	41.03%	27.82%	45.39%
A.3: Socio-Economic Characteristics			
% College Graduates	26.85%	32.30%	33.39%
% Sophisticated Job	19.64%	19.52%	21.08%

Panel B: Relative to Matched Cohort

	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP		All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP		All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	
	Borrower	Neighbor	Borrower	Neighbor	Borrower	Neighbor
	(I)	(II)	(III)	(IV)	(V)	(VI)
B.1: Credit Characteristics						
Credit Score$_{(-3)}$	652.03	654.60	654.47	656.10	665.86	671.39
Credit Score$_{(-2)}$	652.37	654.21	654.79	655.74	666.60	670.99
Credit Score$_{(-1)}$	652.91	654.04	655.21	655.98	667.77	670.36
Credit Card Util.$_{(-3)}$	68.99%	69.23%	69.69%	69.73%	66.64%	66.27%
Credit Card Util.$_{(-2)}$	69.49%	69.78%	70.27%	70.30%	67.14%	66.80%
Credit Card Util.$_{(-1)}$	69.78%	70.03%	70.60%	70.53%	67.57%	67.27%
Log(Total Balance)$_{(-3)}$	12.29	12.27	12.22	12.23	12.22	12.24
Log(Total Balance)$_{(-2)}$	12.29	12.28	12.23	12.23	12.22	12.25
Log(Total Balance)$_{(-1)}$	12.30	12.28	12.23	12.24	12.22	12.25
Log(Mortgage Balance)$_{(-3)}$	11.99	11.98	11.93	11.95	11.92	11.93
Log(Mortgage Balance)$_{(-2)}$	11.99	11.99	11.93	11.95	11.92	11.93
Log(Mortgage Balance)$_{(-1)}$	12.00	11.99	11.93	11.95	11.92	11.93
Log(Credit Card Balance)$_{(-3)}$	8.66	8.66	8.64	8.64	8.70	8.76
Log(Credit Card Balance)$_{(-2)}$	8.70	8.69	8.68	8.67	8.73	8.78
Log(Credit Card Balance)$_{(-1)}$	8.74	8.73	8.72	8.69	8.76	8.81
B.2: Income Characteristics						
Log(Monthly Income)$_{(-3)}$	8.16	8.23	8.14	8.23	8.17	8.24
Log(Monthly Income)$_{(-2)}$	8.16	8.24	8.14	8.23	8.17	8.24
Log(Monthly Income)$_{(-1)}$	8.16	8.24	8.14	8.24	8.17	8.24
Debt-to-Income$_{(-3)}$	43.79%	49.01%	41.04%	47.14%	41.31%	46.22%
Debt-to-Income$_{(-2)}$	43.63%	49.52%	41.07%	47.43%	41.22%	46.33%
Debt-to-Income$_{(-1)}$	43.86%	49.36%	41.23%	47.44%	41.39%	46.57%
B.3: Other Socio-Economic Characteristics (Not used in cohort creation)						
% College Graduates$_{(-1)}$	28.60%	29.37%	26.84%	27.82%	26.88%	27.13%
% Sophisticated Job$_{(-1)}$	19.60%	20.35%	19.64%	20.36%	20.12%	19.26%

Table II: Are MPL Funds Used To Consolidate Credit Card Debt?

This table reports results documenting the evolution of credit card balances in the period of time 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In columns (I)–(IV), we report event study estimates for the cohort-level analysis. In column (I), bank-unsatisfied MPL borrowers are compared to socioeconomically identical bank-unsatisfied neighbors within the same 5-digit ZIP. In column (II) (column (III)), the entire sample of MPL borrowers is compared to socioeconomically similar bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP). In column (IV), all MPL borrowers are compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In columns (V) and (VI), we report estimates for event study specifications that capture within-borrower and time-varying regional trends, respectively. Standard errors are clustered at the cohort and year-quarter levels (columns (I)–(IV)), at the individual- and year-quarter levels (column (V)), and at the 5-digit ZIP and year-quarter levels (column (VI)). The cohort-creation process is described in the Online Appendix. All control variables included in the analysis are defined in the Online Appendix. *I*, *C*, *Z*, and *Y-Q* refer to individual, cohort, 5-digit ZIP code, and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Log(Credit Card Balance)					
	Cohort-Level Analysis				Within-MPL Analysis	
	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 9-Digit ZIP	All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	Individual Trends	Regional Trends
	(I)	(II)	(III)	(IV)	(V)	(VI)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-19.30***	-19.61***	-16.95***	-18.66***	-33.65***	-35.60***
	(4.13)	(4.08)	(4.08)	(3.76)	(4.37)	(4.00)
$Quarter_{-3}$	-14.23***	-14.54***	-12.10***	-13.22***	-21.94***	-24.10***
	(2.54)	(2.44)	(2.76)	(2.36)	(2.72)	(2.32)
$Quarter_{-2}$	-7.69***	-7.93***	-6.48***	-7.08***	-10.56***	-11.60***
	(1.11)	(1.09)	(1.36)	(1.05)	(1.29)	(1.16)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	4.57***	4.81***	6.74***	-36.08***	-64.32***	-64.00***
	(1.20)	(1.24)	(1.39)	(1.39)	(2.77)	(2.45)
$Quarter_{+1}$	-4.09	-4.42	-0.32	-27.36***	-35.93***	-36.50***
	(2.78)	(2.90)	(3.15)	(2.99)	(4.05)	(3.54)
$Quarter_{+2}$	-10.90**	-11.07**	-5.77	-24.81***	-16.90***	-18.40***
	(4.47)	(4.47)	(4.73)	(4.49)	(5.41)	(-4.30)
$Quarter_{+3}$	-14.15**	-13.94***	-6.83	-22.19***	-8.53	-9.76
	(5.65)	(5.39)	(5.82)	(5.71)	(7.12)	(6.12)
$Quarter_{+4}$	-15.37**	-15.51**	-6.99	-20.39***		
	(6.44)	(6.46)	(7.21)	(6.65)		
$Quarter_{+5}$	-16.45**	-16.71**	-7.26	-20.38***		
	(7.74)	(7.64)	(8.30)	(7.83)		
$Quarter_{+6}$	-17.64**	-17.73**	-7.11	-21.09**		
	(8.61)	(8.70)	(9.49)	(9.08)		
$Quarter_{+7}$	-17.23*	-18.00*	-6.97	-21.21**		
	(9.56)	(9.45)	(9.91)	(9.91)		
Differential Post-Trends of MPL Borrowers						
$Quarter_{0} \times$ MPL	-53.65***	-57.17***	-57.58***	-12.89***		
	(1.93)	(1.89)	(2.13)	(2.39)		
$Quarter_{1} \times$ MPL	-17.62***	-19.34***	-24.64***	6.48***		
	(2.44)	(2.21)	(2.51)	(1.98)		
$Quarter_{2} \times$ MPL	4.43**	2.99*	-4.24*	16.55***		
	(2.11)	(1.58)	(2.42)	(1.25)		
$Quarter_{3} \times$ MPL	15.88***	14.12***	3.91*	21.12***		
	(1.81)	(1.34)	(2.20)	(1.13)		
$Quarter_{4} \times$ MPL	21.26***	20.06***	10.02***	23.75***		
	(1.78)	(1.39)	(2.48)	(1.16)		
$Quarter_{5} \times$ MPL	24.84***	22.87***	12.54***	24.90***		
	(1.81)	(1.55)	(2.66)	(1.34)		
$Quarter_{6} \times$ MPL	27.29***	24.66***	12.29***	24.95***		
	(1.79)	(1.79)	(2.66)	(1.53)		
$Quarter_{7} \times$ MPL	27.57***	26.04***	12.94**	24.88***		
	(1.97)	(1.82)	(3.14)	(1.66)		
Observations	5,922,513	44,486,001	1,363,022	14,759,812	15,710,940	15,710,940
Adjusted R^2	0.71	0.71	0.73	0.67	0.56	0.61
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ Y\text{-}Q$	$I,\ Z\times Y\text{-}Q$

Table III: Impact of MPL Funds on Total Non-Mortgage Indebtedness

This table reports results documenting the evolution of total individual non-mortgage balances in the period of time 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In columns (I)–(IV), we report event study estimates for the cohort-level analysis. In column (I), bank-unsatisfied MPL borrowers are compared to socioeconomically identical bank-unsatisfied neighbors within the same 5-digit ZIP. In column (II) (column (III)), the entire sample of MPL borrowers is compared to socioeconomically similar bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP). In column (IV), all MPL borrowers are compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In columns (V) and (VI), we report estimates for event study specifications that capture within-borrower and time-varying regional trends, respectively. Standard errors are clustered at the cohort and year-quarter levels (columns (I)–(IV)), at the individual- and year-quarter levels (column (V)), and at the 5-digit ZIP and year-quarter levels (column (VI)). The cohort-creation process is described in the Online Appendix. All control variables included in the analysis are defined in the Online Appendix. *I*, *C*, *Z*, and *Y-Q* refer to individual, cohort, 5-digit ZIP code, and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Log(Total Non-Mortgage Balance)					
	Cohort-Level Analysis				Within-MPL Analysis	
	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 9-Digit ZIP	All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	Individual Trends	Regional Trends
	(I)	(II)	(III)	(IV)	(V)	(VI)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-6.48***	-6.97***	-6.17***	-5.64***	-9.14***	-8.59***
	(1.52)	(1.48)	(1.53)	(1.30)	(1.17)	(1.10)
$Quarter_{-3}$	-4.31***	-4.78***	-4.04***	-3.66***	-5.67***	-4.99***
	(0.97)	(0.92)	(1.00)	(0.82)	(1.12)	(1.02)
$Quarter_{-2}$	-2.13***	-2.44***	-1.95***	-1.79***	-2.55***	-2.45***
	(0.46)	(0.46)	(0.50)	(0.40)	(0.75)	(0.62)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	-2.85***	-3.42***	-2.55**	6.13***	-4.82***	-4.55***
	(0.86)	(0.97)	(1.02)	(0.95)	(1.45)	(1.30)
$Quarter_{+1}$	-14.38***	-15.76***	-14.50***	0.71	28.90***	28.00***
	(1.03)	(1.13)	(1.17)	(1.22)	(1.27)	(1.13)
$Quarter_{+2}$	-15.31***	-16.63***	-15.30***	-0.58	29.98***	28.76***
	(1.50)	(1.55)	(1.75)	(1.55)	(1.22)	(1.11)
$Quarter_{+3}$	-15.57***	-16.87***	-15.24***	-1.84	29.19***	28.56***
	(1.73)	(1.77)	(2.12)	(1.75)	(1.53)	(1.42)
$Quarter_{+4}$	-15.69***	-17.03***	-14.55***	-3.16		
	(2.03)	(2.11)	(2.42)	(1.97)		
$Quarter_{+5}$	-15.99***	-17.12***	-14.28***	-4.50**		
	(2.34)	(2.47)	(2.65)	(2.18)		
$Quarter_{+6}$	-16.35***	-17.37***	-14.48***	-6.17***		
	(2.56)	(2.74)	(3.08)	(2.37)		
$Quarter_{+7}$	-16.56***	-17.57***	-14.31***	-7.56***		
	(2.70)	(2.88)	(3.63)	(2.53)		
Differential Post-Trends of MPL Borrowers						
$Quarter_{0}\times$ MPL	-4.68***	-4.60**	-5.80***	-23.25***		
	(1.65)	(1.87)	(1.80)	(1.48)		
$Quarter_{1}\times$ MPL	30.38***	32.91***	30.47***	1.12*		
	(0.67)	(0.67)	(1.00)	(0.67)		
$Quarter_{2}\times$ MPL	32.72***	35.35***	32.38***	4.19***		
	(0.52)	(0.41)	(0.96)	(0.39)		
$Quarter_{3}\times$ MPL	32.69***	35.34***	31.35***	5.58***		
	(0.64)	(0.48)	(0.92)	(0.49)		
$Quarter_{4}\times$ MPL	31.96***	34.47***	29.57***	6.34***		
	(0.77)	(0.61)	(1.15)	(0.51)		
$Quarter_{5}\times$ MPL	30.56***	32.70***	27.62***	6.30***		
	(0.76)	(0.79)	(1.21)	(0.54)		
$Quarter_{6}\times$ MPL	28.81***	30.85***	25.24***	6.21***		
	(0.67)	(0.81)	(1.24)	(0.54)		
$Quarter_{7}\times$ MPL	26.75***	29.05***	22.56***	5.94***		
	(0.71)	(0.66)	(1.70)	(0.60)		
Observations	6,010,266	45,147,655	1,380,017	14,967,041	16,731,511	16,731,511
Adjusted R^2	0.87	0.86	0.87	0.85	0.84	0.87
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ Y\text{-}Q$	$I,\ Z\times Y\text{-}Q$

Table IV: Do MPL Funds Impact Credit Scores?

This table reports results documenting the evolution of credit scores in the period of time 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In columns (I)–(IV), we report event study estimates for the cohort-level analysis. In column (I), bank-unsatisfied MPL borrowers are compared to socioeconomically identical bank-unsatisfied neighbors within the same 5-digit ZIP. In column (II) (column (III)), the entire sample of MPL borrowers is compared to socioeconomically similar bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP). In column (IV), all MPL borrowers are compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In columns (V) and (VI), we report estimates for event study specifications that capture within-borrower and time-varying regional trends, respectively. Standard errors are clustered at the cohort and year-quarter levels (columns (I)–(IV)), at the individual- and year-quarter levels (column (V)), and at the 5-digit ZIP and year-quarter levels (column (VI)). The cohort-creation process is described in the Online Appendix. All control variables included in the analysis are defined in the Online Appendix. *I*, *C*, *Z*, and *Y-Q* refer to individual, cohort, 5-digit ZIP code, and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Log(Credit Score)					
	Cohort-Level Analysis				Within-MPL Analysis	
	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 9-Digit ZIP	All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	Individual Trends	Regional Trends
	(I)	(II)	(III)	(IV)	(V)	(VI)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	0.11	0.11	-0.02	0.05	-0.04	-0.01
	(0.29)	(0.30)	(0.27)	(0.26)	(0.27)	(0.24)
$Quarter_{-3}$	0.11	0.12	0.00	0.04	-0.09	0.01
	(0.18)	(0.19)	(0.18)	(0.18)	(0.19)	(0.16)
$Quarter_{-2}$	0.07	0.08	-0.01	0.03	-0.11	-0.10
	(0.09)	(0.09)	(0.08)	(0.08)	(0.10)	(0.07)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	-0.78***	-0.79***	-0.74***	0.33***	2.97***	2.85***
	(0.10)	(0.11)	(0.11)	(0.08)	(0.14)	(0.12)
$Quarter_{+1}$	-0.44**	-0.49**	-0.50**	0.19	1.59***	1.45***
	(0.18)	(0.19)	(0.21)	(0.16)	(0.22)	(0.19)
$Quarter_{+2}$	-0.14	-0.23	-0.30	0.13	0.55*	0.45*
	(0.28)	(0.30)	(0.31)	(0.23)	(0.28)	(0.26)
$Quarter_{+3}$	0.10	-0.02	-0.23	0.04	-0.19	-0.27
	(0.35)	(0.36)	(0.36)	(0.29)	(0.39)	(0.33)
$Quarter_{+4}$	0.24	0.10	-0.20	-0.05		
	(0.40)	(0.42)	(0.42)	(0.34)		
$Quarter_{+5}$	0.39	0.22	-0.07	-0.05		
	(0.48)	(0.49)	(0.49)	(0.40)		
$Quarter_{+6}$	0.51	0.32	0.03	0.02		
	(0.55)	(0.56)	(0.59)	(0.46)		
$Quarter_{+7}$	0.58	0.42	0.05	0.08		
	(0.59)	(0.60)	(0.63)	(0.50)		
Differential Post-Trends of MPL Borrowers						
$Quarter_{0}\times$ MPL	3.09***	3.31***	2.99***	2.06***		
	(0.09)	(0.09)	(0.09)	(0.13)		
$Quarter_{1}\times$ MPL	1.45***	1.76***	1.53***	1.04***		
	(0.10)	(0.09)	(0.09)	(0.10)		
$Quarter_{2}\times$ MPL	0.31***	0.69***	0.64***	0.46***		
	(0.11)	(0.09)	(0.10)	(0.09)		
$Quarter_{3}\times$ MPL	-0.57***	-0.17*	0.08	0.03		
	(0.11)	(0.10)	(0.11)	(0.10)		
$Quarter_{4}\times$ MPL	-1.24***	-0.83***	-0.40***	-0.36***		
	(0.12)	(0.11)	(0.11)	(0.11)		
$Quarter_{5}\times$ MPL	-1.65***	-1.22***	-0.73***	-0.58***		
	(0.14)	(0.11)	(0.13)	(0.12)		
$Quarter_{6}\times$ MPL	-1.89***	-1.48***	-0.92***	-0.76***		
	(0.16)	(0.11)	(0.17)	(0.11)		
$Quarter_{7}\times$ MPL	-2.06***	-1.73***	-1.01***	-0.93***		
	(0.16)	(0.13)	(0.14)	(0.11)		
Observations	6,031,910	45,305,650	1,384,832	15,005,899	15,710,940	15,710,940
Adjusted R^2	0.78	0.78	0.82	0.77	0.66	0.70
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ Y\text{-}Q$	$I,\ Z\times Y\text{-}Q$

Table V: Do MPL Funds Impact Credit Card Limit Growth?

This table reports results documenting the evolution of credit card limit growth in the period of time 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In columns (I)–(IV), we report event study estimates for the cohort-level analysis. In column (I), bank-unsatisfied MPL borrowers are compared to socioeconomically identical bank-unsatisfied neighbors within the same 5-digit ZIP. In column (II) (column (III)), the entire sample of MPL borrowers is compared to socioeconomically similar bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP). In column (IV), all MPL borrowers are compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In columns (V) and (VI), we report estimates for event study specifications that capture within-borrower and time-varying regional trends, respectively. Standard errors are clustered at the cohort and year-quarter levels (columns (I)–(IV)), at the individual- and year-quarter levels (column (V)), and at the 5-digit ZIP and year-quarter levels (column (VI)). The cohort-creation process is described in the Online Appendix. All control variables included in the analysis are defined in the Online Appendix. *I*, *C*, *Z*, and *Y-Q* refer to individual, cohort, 5-digit ZIP code, and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Log(Credit Card Limit Growth)					
	Cohort-Level Analysis				Within-MPL Analysis	
	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 9-Digit ZIP	All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	Individual Trends	Regional Trends
	(I)	(II)	(III)	(IV)	(V)	(VI)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	0.15	0.14	0.51	0.28	0.08	-0.01
	(0.62)	(0.64)	(0.57)	(0.57)	(0.55)	(0.58)
$Quarter_{-3}$	0.04	0.04	0.56	0.20	0.14	0.03
	(0.44)	(0.45)	(0.37)	(0.42)	(0.41)	(0.34)
$Quarter_{-2}$	0.05	0.09	0.48*	0.14	0.08	0.04
	(0.21)	(0.22)	(0.28)	(0.19)	(0.21)	(0.16)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	-0.42***	-0.25	0.09	0.70***	0.55**	0.61**
	(0.16)	(0.16)	(0.21)	(0.19)	(0.24)	(0.23)
$Quarter_{+1}$	-0.70**	-0.23	0.01	0.45	0.78*	0.82*
	(0.31)	(0.36)	(0.44)	(0.39)	(0.45)	(0.44)
$Quarter_{+2}$	-0.44	0.11	0.37	0.59	-0.01	0.05
	(0.47)	(0.53)	(0.62)	(0.56)	(0.68)	(0.60)
$Quarter_{+3}$	-0.21	0.35	0.83	0.81	-0.29	-0.24
	(0.62)	(0.68)	(0.79)	(0.68)	(0.88)	(0.79)
$Quarter_{+4}$	-0.07	0.53	1.08	0.90		
	(0.71)	(0.79)	(0.97)	(0.80)		
$Quarter_{+5}$	-0.02	0.61	1.41	0.94		
	(0.80)	(0.89)	(0.99)	(0.90)		
$Quarter_{+6}$	0.17	0.59	1.58	0.90		
	(0.90)	(0.99)	(1.15)	(0.99)		
$Quarter_{+7}$	0.21	0.57	1.64	0.91		
	(1.02)	(1.08)	(1.16)	(1.07)		
Differential Post-Trends of MPL Borrowers						
$Quarter_{0} \times$ MPL	0.37**	0.63***	0.50***	-0.12		
	(0.13)	(0.12)	(0.11)	(0.12)		
$Quarter_{1} \times$ MPL	0.79***	0.68***	0.57***	0.37***		
	(0.09)	(0.08)	(0.12)	(0.08)		
$Quarter_{2} \times$ MPL	-0.13**	-0.14*	-0.13	-0.17***		
	(0.07)	(0.08)	(0.15)	(0.06)		
$Quarter_{3} \times$ MPL	-0.66***	-0.61***	-0.46***	-0.44***		
	(0.09)	(0.09)	(0.15)	(0.07)		
$Quarter_{4} \times$ MPL	-1.15***	-1.12***	-0.69***	-0.80***		
	(0.11)	(0.11)	(0.16)	(0.10)		
$Quarter_{5} \times$ MPL	-1.39***	-1.39***	-1.04***	-0.98***		
	(0.14)	(0.10)	(0.15)	(0.10)		
$Quarter_{6} \times$ MPL	-1.61***	-1.52***	-1.22***	-1.10***		
	(0.16)	(0.15)	(0.15)	(0.08)		
$Quarter_{7} \times$ MPL	-1.56***	-1.56***	-1.19***	-1.14***		
	(0.17)	(0.17)	(0.23)	(0.10)		
Observations	5,883,819	44,229,078	1,354,559	14,677,657	15,026,940	15,026,940
Adjusted R^2	0.02	0.02	0.02	0.02	0.01	0.02
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	$I,\ C \times Y\text{-}Q$	$I,\ C \times Y\text{-}Q$	$I,\ C \times Y\text{-}Q$	$I,\ C \times Y\text{-}Q$	$I,\ Y\text{-}Q$	$I,\ Z \times Y\text{-}Q$

Table VI: Impact Of MPL Funds On Credit Card Default Rates

This table reports results documenting the evolution of credit card default rates in the period of time 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In columns (I)–(IV), we report event study estimates for the cohort-level analysis. In column (I), bank-unsatisfied MPL borrowers are compared to socioeconomically identical bank-unsatisfied neighbors within the same 5-digit ZIP. In column (II) (column (III)), the entire sample of MPL borrowers is compared to socioeconomically similar bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP). In column (IV), all MPL borrowers are compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In columns (V) and (VI), we report estimates for event study specifications that capture within-borrower and time-varying regional trends, respectively. Standard errors are clustered at the cohort and year-quarter levels (columns (I)–(IV)), at the individual- and year-quarter levels (column (V)), and at the 5-digit ZIP and year-quarter levels (column (VI)). The cohort-creation process is described in the Online Appendix. All control variables included in the analysis are defined in the Online Appendix. *I*, *C*, *Z*, and *Y-Q* refer to individual, cohort, 5-digit ZIP code, and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Credit Card Default Rates					
	Cohort-Level Analysis				Within-MPL Analysis	
	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 9-Digit ZIP	All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	Individual Trends	Regional Trends
	(I)	(II)	(III)	(IV)	(V)	(VI)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-0.09	-0.08	-0.04	-0.11*	0.43***	0.50***
	(0.09)	(0.09)	(0.08)	(0.07)	(0.09)	(0.09)
$Quarter_{-3}$	-0.06	-0.05	0.01	-0.08**	0.29***	0.31***
	(0.06)	(0.05)	(0.04)	(0.04)	(0.08)	(0.07)
$Quarter_{-2}$	-0.02	-0.02	0.02	-0.03	0.15***	0.16***
	(0.03)	(0.02)	(0.04)	(0.02)	(0.05)	(0.05)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	0.17***	0.15***	0.06	0.14**	0.04	0.07**
	(0.06)	(0.05)	(0.07)	(0.05)	(0.04)	(0.03)
$Quarter_{+1}$	0.91***	0.93***	0.88***	0.54***	0.36***	0.38***
	(0.09)	(0.08)	(0.09)	(0.07)	(0.08)	(0.07)
$Quarter_{+2}$	1.18***	1.27***	1.14***	0.99***	0.96***	0.90***
	(0.16)	(0.14)	(0.15)	(0.12)	(0.13)	(0.11)
$Quarter_{+3}$	1.29***	1.35***	1.39***	1.23***	1.55***	1.57***
	(0.19)	(0.20)	(0.18)	(0.14)	(0.20)	(0.18)
$Quarter_{+4}$	1.32***	1.45***	1.68***	1.41***		
	(0.25)	(0.25)	(0.27)	(0.18)		
$Quarter_{+5}$	1.50***	1.62***	1.81***	1.69***		
	(0.32)	(0.29)	(0.36)	(0.23)		
$Quarter_{+6}$	1.74***	1.80***	2.00***	1.88***		
	(0.38)	(0.34)	(0.44)	(0.26)		
$Quarter_{+7}$	2.10***	2.03***	2.28***	2.01***		
	(0.47)	(0.39)	(0.53)	(0.30)		
Differential Post-Trends of MPL Borrowers						
$Quarter_0\times$ MPL	-0.10	-0.02	0.07	0.05		
	(0.10)	(0.09)	(0.09)	(0.10)		
$Quarter_1\times$ MPL	-0.65***	-0.62***	-0.52***	-0.17		
	(0.11)	(0.11)	(0.12)	(0.11)		
$Quarter_2\times$ MPL	-0.30*	-0.45***	-0.38**	-0.24*		
	(0.17)	(0.16)	(0.15)	(0.13)		
$Quarter_3\times$ MPL	0.31	0.20	0.02	0.05		
	(0.21)	(0.24)	(0.21)	(0.16)		
$Quarter_4\times$ MPL	1.17***	0.92***	0.20	0.54***		
	(0.31)	(0.31)	(0.27)	(0.20)		
$Quarter_5\times$ MPL	1.66***	1.49***	0.87***	0.97***		
	(0.35)	(0.34)	(0.32)	(0.21)		
$Quarter_6\times$ MPL	1.90***	1.76***	1.27***	1.18***		
	(0.38)	(0.35)	(0.29)	(0.18)		
$Quarter_7\times$ MPL	1.82***	1.96***	1.13***	1.31***		
	(0.37)	(0.36)	(0.40)	(0.18)		
Observations	5,796,560	43,693,086	1,335,247	14,545,467	16,143,093	16,143,093
Adjusted R^2	0.39	0.39	0.44	0.39	0.13	0.20
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ Y\text{-}Q$	$I,\ Z\times Y\text{-}Q$

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

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

	Credit Cards	Auto Loans	Mortgage Loans	Student Loans	Installment Loans (+ MPL Loan)
	(I)	(II)	(III)	(IV)	(V)
Pre-MPL Loan Origination Trends					
$Quarter_{-4}$	0.43***	0.10***	0.15***	0.47***	0.55***
	(0.09)	(0.01)	(0.02)	(0.03)	(0.04)
$Quarter_{-3}$	0.29***	0.08***	0.18***	0.43***	0.38***
	(0.08)	(0.01)	(0.01)	(0.03)	(0.03)
$Quarter_{-2}$	0.15***	0.05***	0.11***	0.26***	0.21***
	(0.05)	(0.01)	(0.01)	(0.02)	(0.02)
Post-MPL Loan Origination Trends					
$Quarter_0$	0.04	-0.01**	-0.04***	0.10***	0.04***
	(0.04)	(0.005)	(0.01)	(0.02)	(0.01)
$Quarter_{+1}$	0.36***	0.01	-0.00	0.20***	0.15***
	(0.08)	(0.01)	(0.01)	(0.02)	(0.03)
$Quarter_{+2}$	0.96***	0.03***	0.04**	0.26***	0.28***
	(0.13)	(0.01)	(0.02)	(0.04)	(0.04)
$Quarter_{+3}$	1.55***	0.08***	0.06***	0.23***	0.35***
	(0.20)	(0.01)	(0.02)	(0.04)	(0.05)
Observations	16,143,093	10,593,829	6,628,411	4,822,720	8,815,419
Adjusted R^2	0.13	0.32	0.42	0.19	0.18
Controls	✓	✓	✓	✓	✓
Fixed Effects	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

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

In this table, we report regression results that document fluctuations in non-credit profile factors in the period of time 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 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. In column (III), the dependent variable is an indicator which equals 1 if the MPL borrower experiences a medical-related collection in a given month, and 0 otherwise. 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 the Online Appendix. *I* and *Y-Q* refer to individual and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	$\mathbb{P}$(Income Change)	$\mathbb{P}$(Job Change)	$\mathbb{P}$(Health Collections)
	(I)	(II)	(III)
Pre-MPL Loan Origination Trends			
$Quarter_{-4}$	-0.02	1.63*	2.09***
	(0.14)	(0.86)	(0.16)
$Quarter_{-3}$	0.17	0.28	1.53***
	(0.11)	(0.32)	(0.09)
$Quarter_{-2}$	0.06	0.16	0.89***
	(0.06)	(0.16)	(0.06)
Post-MPL Loan Origination Trends			
$Quarter_0$	-0.15*	-0.52**	-0.38***
	(0.08)	(0.20)	(0.07)
$Quarter_{+1}$	-0.15	-0.55	-0.49***
	(0.12)	(0.39)	(0.15)
$Quarter_{+2}$	-0.20	-0.62	-0.48**
	(0.16)	(0.54)	(0.19)
$Quarter_{+3}$	-0.27	-0.75	-0.31
	(0.21)	(0.69)	(0.25)
Observations	16,174,176	16,174,176	15,711,799
Adjusted R^2	0.01	0.01	0.82
Controls	✓	✓	✓
Fixed Effects	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

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

In this table, we present results documenting the effects of MPL-induced credit card debt consolidation activities on the perceived credit quality of MPL borrowers. In Panel A, we study the impact of MPL borrower status on credit score growth and credit card limit growth. In Panel B, we study the impact of MPL borrower status on the probability of crossing industry-standard credit score thresholds. In both panels, our analysis relies on comparing outcomes for MPL borrowers relative to their geographically and socioeconomically proximate non-MPL borrowing neighbors. We consider three cohorts: bank-unsatisfied MPL borrowers matched to bank-unsatisfied neighbors, all MPL borrowers matched to bank-unsatisfied neighbors, and all MPL borrowers matched to unsecured installment loan bank borrowers. In all three cohorts, MPL borrowers and neighbors are chosen from the same 5-digit ZIP. In column (I) (columns (II) and (III)) of all sub-panels of Panel A, the dependent variable is credit score growth (credit card limit growth). In column (I) (column (II)) of all sub-panels of Panel B, we study subprime (near-prime) cohorts. In column (I) (column (II)), the dependent variable is an indicator variable which equals 1 if the subprime (near-prime) consumer crosses the credit score threshold of 620 (680) in the three months following the origination of the MPL loan. 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, along with the matching process used to generate the cohorts, are described in the Online Appendix. C refers to cohort. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Effect of MPL Borrower Status on Credit Scores and Credit Card Limits

	A.1: Bank-Unsatisfied MPL Borrowers to Bank-Unsatisfied Neighbors			**A.2**: All MPL Borrowers to Bank-Unsatisfied Neighbors			**A.3**: All MPL Borrowers to Bank-Borrowing Neighbors		
	Δ(Credit Score) (I)	Δ(CC Limits) (II)	Δ(CC Limits) (III)	Δ(Credit Score) (I)	Δ(CC Limits) (II)	Δ(CC Limits) (III)	Δ(Credit Score) (I)	Δ(CC Limits) (II)	Δ(CC Limits) (III)
MPL Borrower	3.69***	3.53***		4.14***	4.47***		2.12***	1.75***	
	(0.04)	(0.18)		(0.02)	(0.07)		(0.04)	(0.14)	
Δ(Credit Score)			0.08***			0.07***			0.01*
			(0.02)			(0.01)			(0.006)
Observations	181,962	181,567	181,567	1,374,056	1,370,908	1,370,908	420,273	419,246	419,246
Adjusted R^2	0.12	0.05	0.05	0.06	0.06	0.04	0.06	0.03	0.03
Fixed Effects	C	C	C	C	C	C	C	C	C
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓

Panel B: Effect of MPL Borrower Status on Credit Status Transitions

	B.1: Bank-Unsatisfied MPL Borrowers to Bank-Unsatisfied Neighbors		**B.2**: All MPL Borrowers to Bank-Unsatisfied Neighbors		**B.3**: All MPL Borrowers to Bank-Borrowing Neighbors	
	$\mathbb{P}$(Subprime – Near-prime) (I)	$\mathbb{P}$(Near-prime – Prime) (II)	$\mathbb{P}$(Subprime – Near-prime) (I)	$\mathbb{P}$(Near-prime – Prime) (II)	$\mathbb{P}$(Subprime – Near-prime) (I)	$\mathbb{P}$(Near-prime – Prime) (II)
MPL Borrower	34.20***	31.12***	36.81***	34.30***	22.73***	15.71***
	(1.11)	(0.58)	(0.43)	(0.22)	(0.15)	(0.48)
Observations	31,337	90,329	219,379	677,454	34,726	205,290
Adjusted R^2	0.18	0.15	0.19	0.16	0.06	0.05
Fixed Effects	C	C	C	C	C	C
Controls	✓	✓	✓	✓	✓	✓

Table X: Does Broadband Access Influence MPL Participation?

This table reports results documenting the impact of broadband access on participation on marketplace lending platforms. For each month between June 2013 and November 2014, MPL borrowers originating MPL loans in a given month are paired with a 1% random sample of non-MPL borrowers (nationally) who have a need for bank credit (as proxied through hard credit checks) in the same month. The results of the first stage regressions are reported in Panel A. In columns (I) and (II), broadband access is an indicator which equals 1 if the maximum advertised download speeds in the individual's 5-digit ZIP is greater than 25 mbps, and 0 otherwise. In columns (III) and (IV), broadband access is defined in terms of percentage of county population that has access to download speeds greater than 25 mbps. In Panel B, we report instrumented regression results for the effect of MPL borrower status on credit scores using both the advertised download speed measure (columns (II) and (III)) and the county-access download speed measure (columns (IV) and (V)). In Panel C, we report instrumented regression results for the effect of MPL borrower status on credit card limits using both the advertised download speed measure (columns (II) and (III)) and the county-access download speed measure (columns (IV) and (V)). In Panels B and C, column (I) reports results for the OLS specification, columns (II) and (IV) report results for the reduced form regressions, and columns (III) and (V) report results for the instrumented specification. All control variables included in the analysis are described in the Online Appendix. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: First Stage Regressions

	Advertisement Measure		Access Measure	
	(I)	(II)	(III)	(IV)
(Intercept)	3.08***		3.51***	
	(0.11)		(0.09)	
Broadband Access	1.10***	0.58***		
	(0.11)	(0.06)		
% HH/County Pop. (Std.)			0.74***	0.31***
			(0.06)	(0.02)
Observations	2,832,123	2,832,123	2,832,123	2,832,123
Controls		✓		✓

Panel B: Effect on Credit Scores

		Instrument: Advertisement Measure		Instrument: Access Measure	
	OLS	RF	2SLS	RF	2SLS
	(I)	(II)	(III)	(IV)	(V)
MPL Borrower	4.74***				
	(0.03)				
Instrument Variable		0.07***		0.05***	
		(0.02)		(0.004)	
MPL Borrower (Instr.)			11.62***		14.70***
			(3.35)		(1.48)
Observations	2,832,123	2,832,123	2,832,123	2,832,123	2,832,123
Controls	✓	✓	✓	✓	✓
F-stat (Excl. Instr.)			105		261

Panel C: Effect on Credit Card Limits

		Instrument: Advertisement Measure		Instrument: Access Measure	
	OLS	RF	2SLS	RF	2SLS
	(I)	(II)	(III)	(IV)	(V)
MPL Borrower	7.12***				
	(0.13)				
Instrument Variable		0.20**		0.19***	
		(0.10)		(0.03)	
MPL Borrower (Instr.)			34.75**		60.15***
			(17.32)		(10.49)
Observations	2,832,123	2,832,123	2,832,123	2,832,123	2,832,123
Controls	✓	✓	✓	✓	✓
F-stat (Excl. Instr.)			105		261

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

This table reports results documenting the evolution of credit profile characteristics in the period of time surrounding the origination of MPL loans, separately for the subprime, near-prime, and prime segments of MPL borrowers. An MPL borrower is deemed subprime, near-prime, or prime if their credit score is below 620, between 620 and 680, or greater than or equal to 680, respectively, in the month immediately before 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A, B, C, D, and E focus on credit card balances, utilization, credit scores, credit card limit growth, and credit card default rates, respectively. In each panel, columns (I), (II), and (III) report results for 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 the Online Appendix. I and Y-Q refer to individual and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

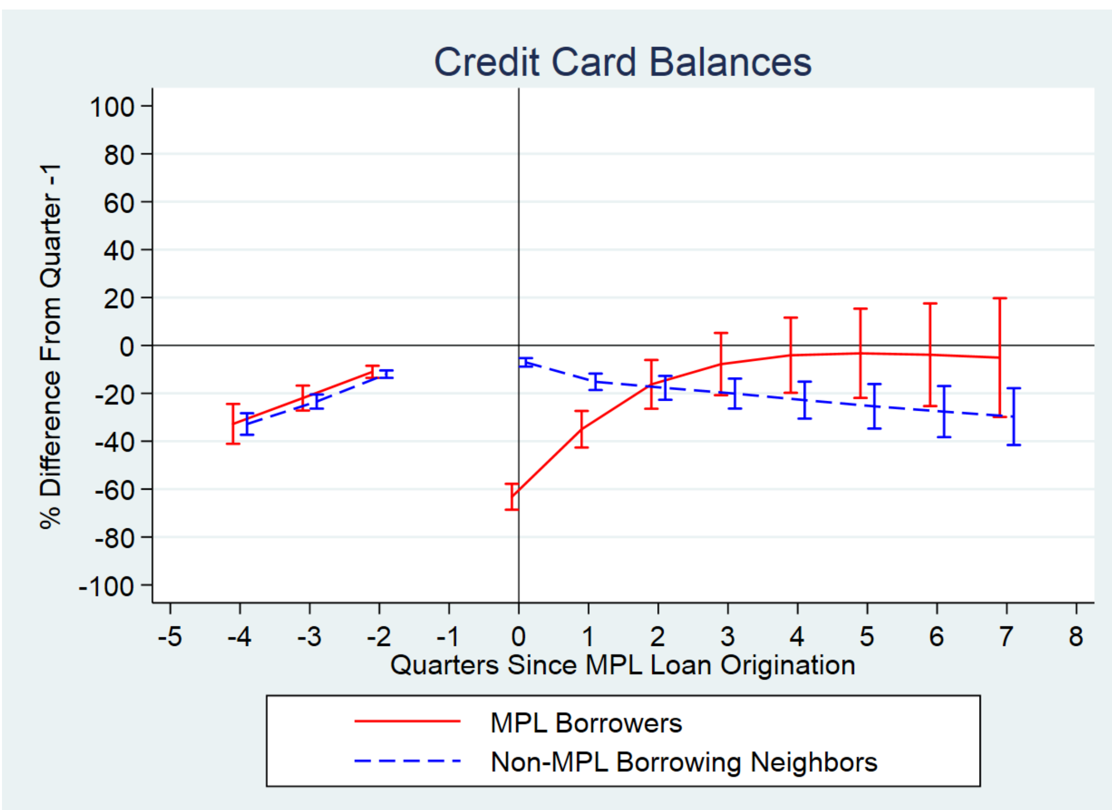
	Panel A: Credit Card Balances			**Panel B**: Credit Card Utilization		
	Sub-Prime	Near-Prime	Prime	Sub-Prime	Near-Prime	Prime
	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-13.90***	-33.59***	-51.23***	-2.04*	-5.70***	-6.41***
	(3.65)	(4.36)	(5.38)	(1.21)	(1.07)	(0.79)
$Quarter_{-3}$	-6.05**	-20.70***	-38.29***	-0.10	-3.65***	-5.78***
	(2.32)	(2.69)	(3.47)	(0.74)	(0.66)	(0.53)
$Quarter_{-2}$	-1.56	-9.57***	-20.39***	0.68**	-1.83***	-3.68***
	(1.12)	(1.25)	(1.70)	(0.33)	(0.30)	(0.27)
Post-MPL Loan Origination Trends						
$Quarter_0$	-45.16***	-67.22***	-75.99***	-18.53***	-20.30***	-14.41***
	(2.16)	(2.75)	(2.99)	(0.75)	(0.70)	(0.50)
$Quarter_{+1}$	-16.97***	-38.07***	-48.83***	-12.99***	-15.85***	-11.49***
	(3.52)	(4.01)	(4.26)	(1.15)	(1.00)	(0.66)
$Quarter_{+2}$	-2.68	-18.44***	-26.58***	-8.33***	-10.45***	-7.02***
	(4.71)	(5.33)	(5.94)	(1.50)	(1.28)	(0.86)
$Quarter_{+3}$	2.58	-9.71	-16.11**	-5.96***	-7.33***	-4.33***
	(5.83)	(7.07)	(8.15)	(1.96)	(1.74)	(1.19)
Observations	3,712,533	7,841,500	4,147,726	3,712,533	7,841,500	4,147,726
Adjusted R^2	0.66	0.56	0.51	0.49	0.52	0.56
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

	Panel C: Credit Scores			**Panel D**: Credit Card Limit Growth			**Panel E**: Credit Card Default Rate		
	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									
$Quarter_{-4}$	-1.02***	0.23	0.47***	0.51	0.25	-0.58	1.08***	0.31***	0.11
	(0.38)	(0.27)	(0.18)	(0.58)	(0.59)	(0.52)	(0.15)	(0.09)	(0.07)
$Quarter_{-3}$	-1.37***	0.10	0.77***	0.22	0.30	-0.22	0.80***	0.18***	0.05
	(0.27)	(0.18)	(0.13)	(0.45)	(0.41)	(0.39)	(0.14)	(0.07)	(0.06)
$Quarter_{-2}$	-1.07***	-0.01	0.58***	-0.03	0.17	0.02	0.40***	0.10**	0.03
	(0.14)	(0.09)	(0.07)	(0.23)	(0.22)	(0.21)	(0.08)	(0.04)	(0.03)
Post-MPL Loan Origination Trends									
$Quarter_{0}$	3.68***	3.23***	1.84***	1.29***	0.50*	0.05	0.04	0.05	0.03
	(0.19)	(0.15)	(0.10)	(0.28)	(0.30)	(0.23)	(0.06)	(0.04)	(0.03)
$Quarter_{+1}$	2.34***	1.80***	0.54***	1.38***	0.77	0.30	0.59***	0.36***	0.16**
	(0.31)	(0.23)	(0.15)	(0.47)	(0.51)	(0.43)	(0.13)	(0.07)	(0.06)
$Quarter_{+2}$	1.02***	0.73**	-0.14	-0.02	-0.04	0.05	1.75***	0.87***	0.43***
	(0.39)	(0.29)	(0.18)	(0.69)	(0.72)	(0.61)	(0.20)	(0.12)	(0.10)
$Quarter_{+3}$	0.03	-0.04	-0.53**	-0.71	-0.34	0.21	2.80***	1.48***	0.63***
	(0.52)	(0.41)	(0.26)	(0.88)	(0.94)	(0.80)	(0.30)	(0.19)	(0.14)
Observations	3,712,533	7,841,500	4,147,726	3,550,721	7,499,627	3,967,828	3,777,796	8,066,450	4,289,238
Adjusted R^2	0.45	0.41	0.50	0.01	0.01	0.00	0.15	0.13	0.12
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$	$I, Y\text{-}Q$

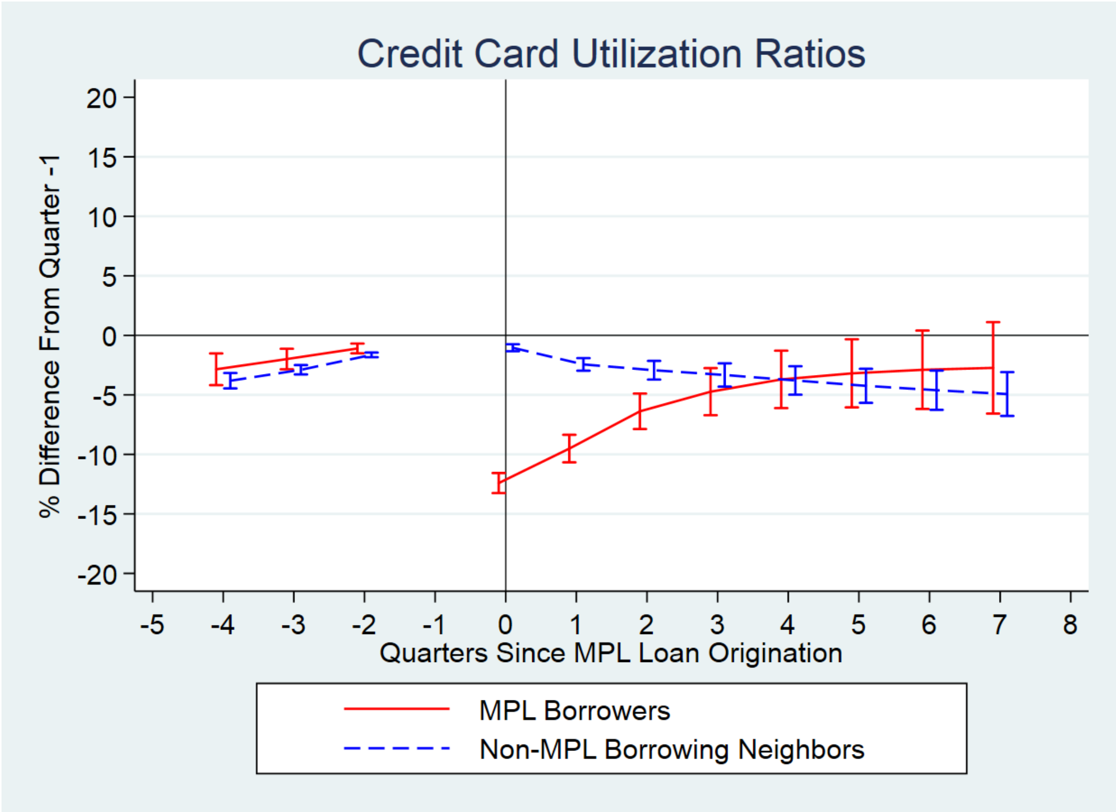
Appendix

Figure A.I: MPL Borrower v. Closest Non-MPL Borrowing Neighbor

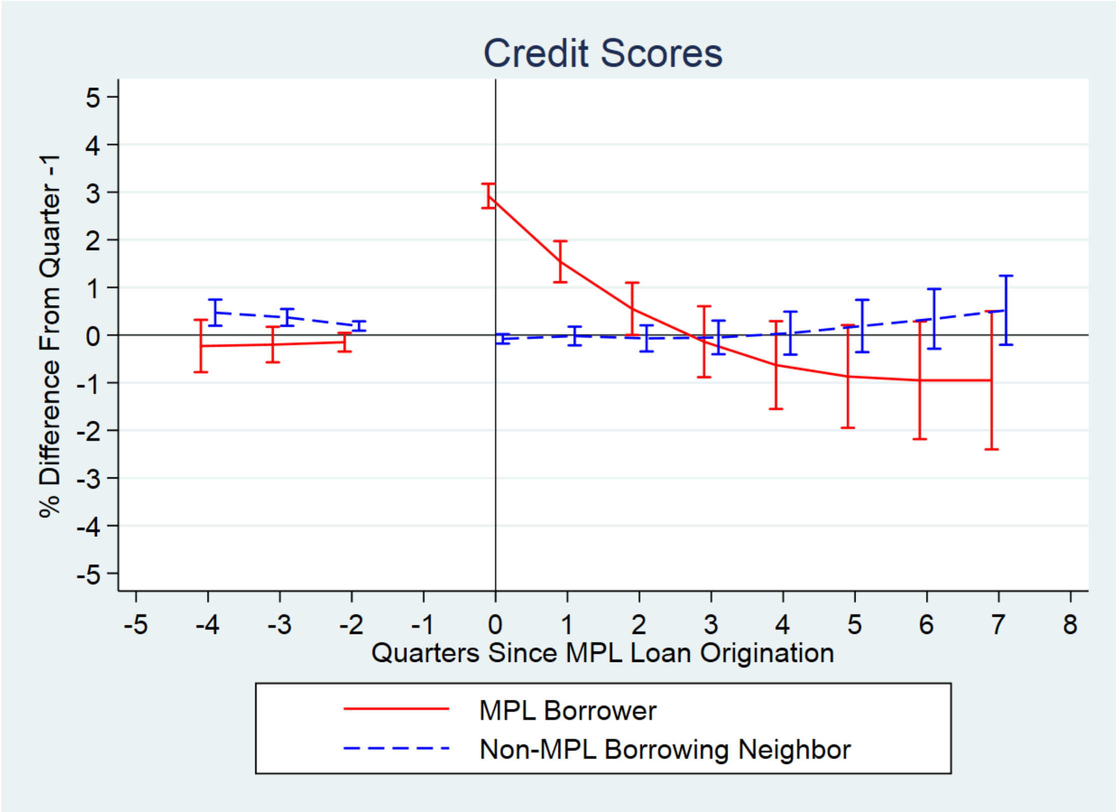
In this set of figures, we present event study plots documenting the differential trends in credit profile characteristics of marketplace lending (MPL) platform borrowers and their geographically- and socioeconomically-proximate non-MPL borrowing neighbors in the months surrounding the origination of MPL loans by MPL borrowers. Every matched pair of MPL borrower and their nearest non-borrowing neighbor is referred to as a cohort. The analysis is conducted separately for MPL borrowers and non-borrowers. Panels A, B, C, D, and E show the analysis of credit card balances, credit card utilization, credit scores, credit card limit growth, and credit card default occurrences, respectively. The x-axis displays quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays 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, along with the matching process used to generate the cohorts, are described in the Online Appendix.



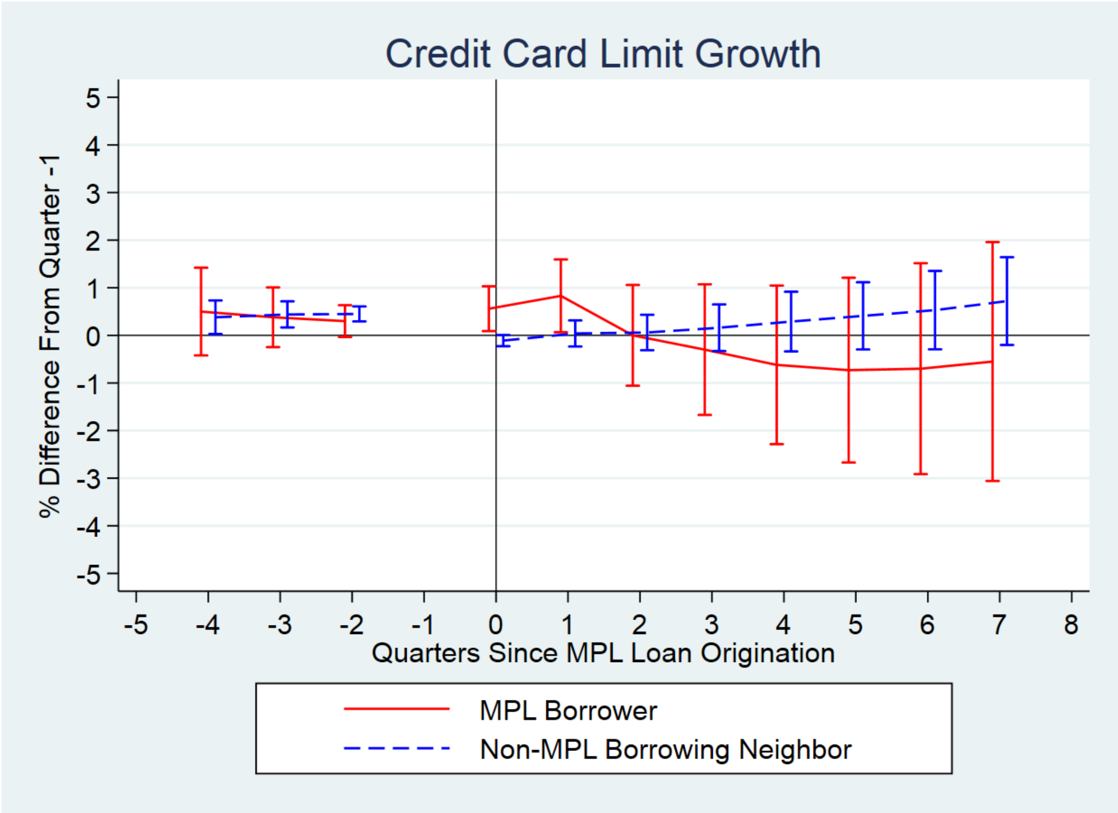
(a) *Credit Card Balances*



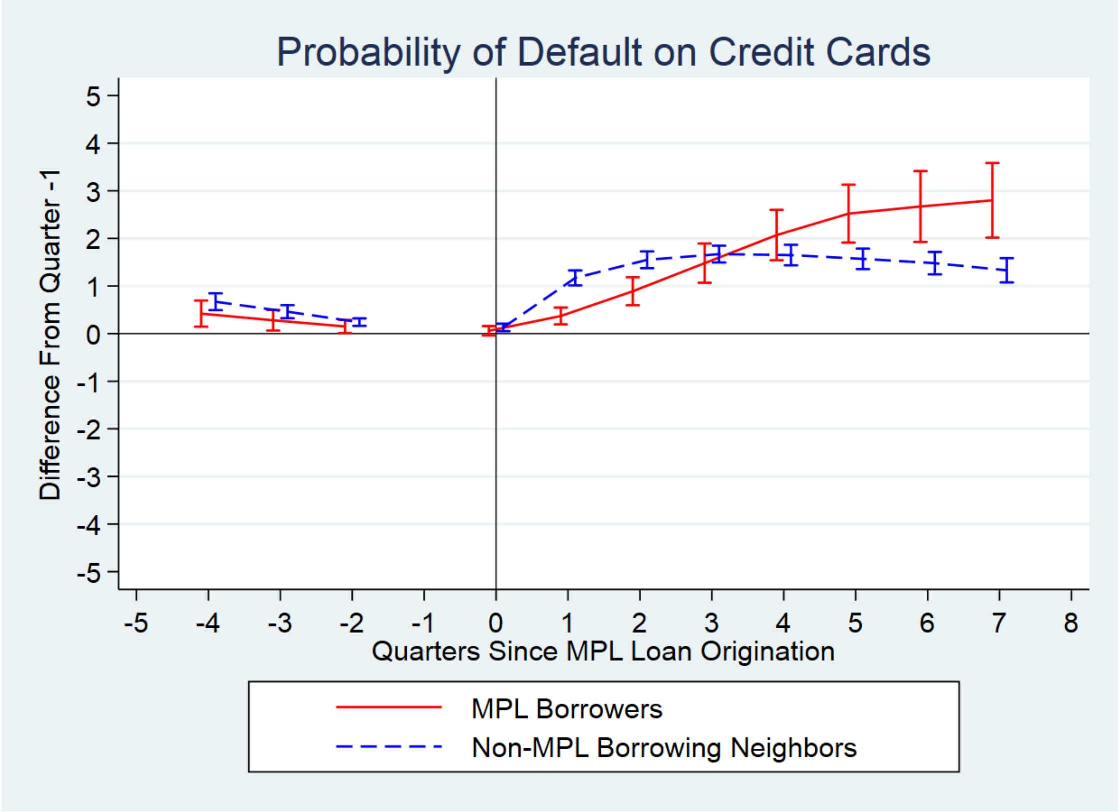
(b) *Credit Card Utilization*



(c) *Credit Scores*



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



(e) *Credit Card Defaults*

Figure A.II: Do Credit Score Improvements Cause Credit Card Limit Growth?

In this figure, we study the relationship between credit scores and credit card limit growth. The x-axis displays the months since loan inception, where $Month_0$ refers to the month in which the MPL trade is opened. $Month_{-1}$ and $Month_{+1}$ refer to the month before and the month immediately following the month of origination, respectively. All other monthly indicators are defined in an analogous manner. The y-axis displays differences relative to $Month_{-1}$, 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 solid, red line displays the evolution of credit scores. The dash-dot, blue line displays the evolution of credit card limit growth. Lastly, the dashed, green line displays the evolution of credit card account growth. 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 the Online Appendix.

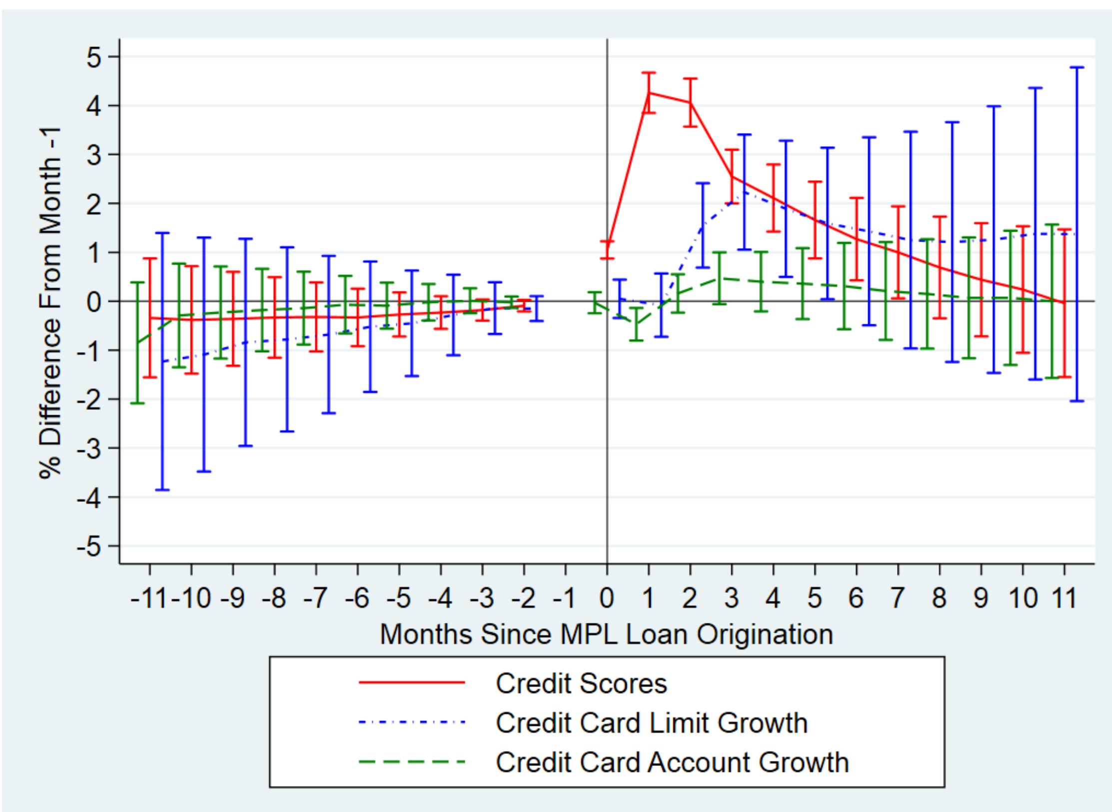
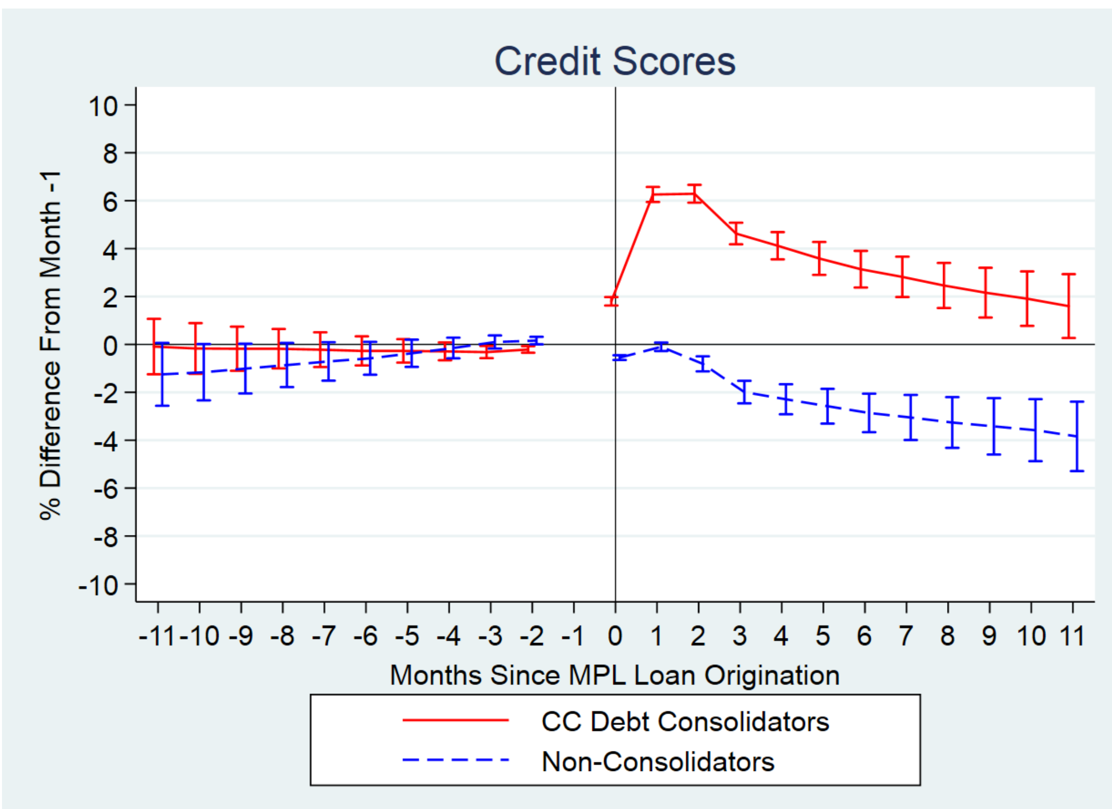
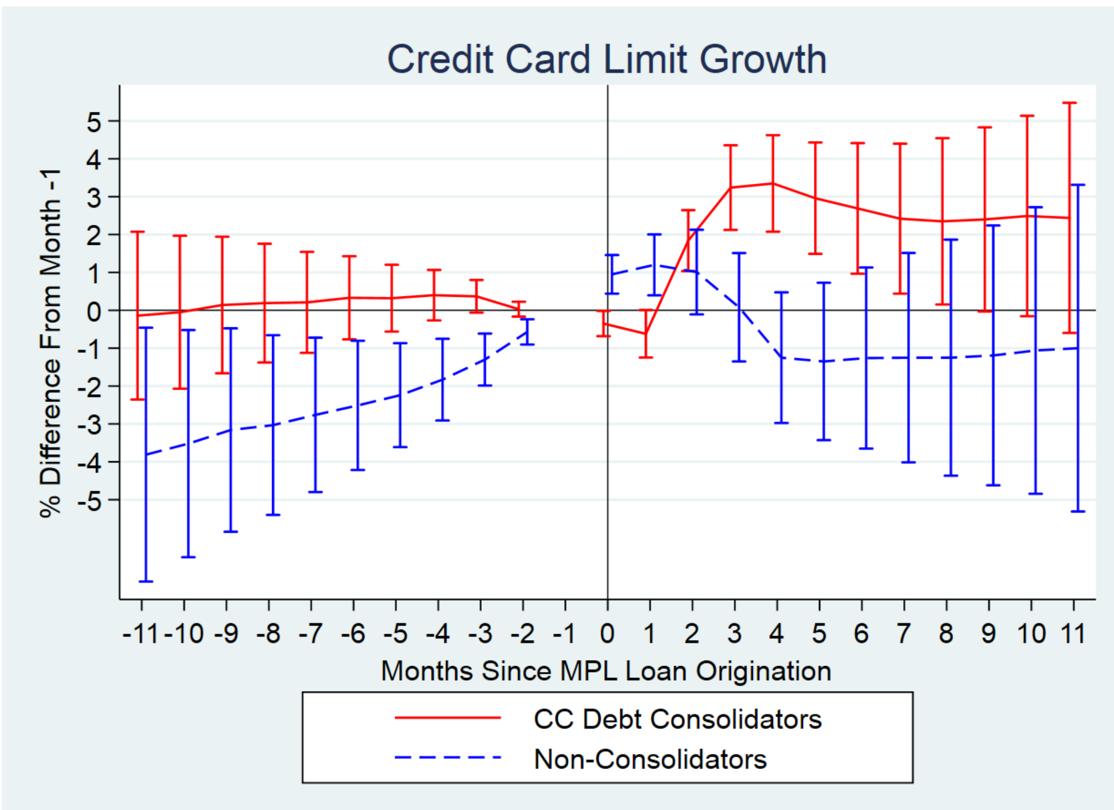


Figure A.III: Do Credit Score Improvements Or Increased Credit Availability Explain Credit Card Limit Growth?
In this figure, we study the relationship between credit scores and credit card limit growth. The x-axis displays the months since loan inception, where $Month_0$ refers to the month in which the MPL trade is opened. $Month_{-1}$ and $Month_{+1}$ refer to the month before and the month immediately following the month of origination, respectively. All other monthly indicators are defined in an analogous manner. The y-axis displays differences relative to $Month_{-1}$, 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. In Panel A (Panel B), we study credit scores (credit card limit growth). The solid, red line displays the evolution of credit scores and credit card limit growth of MPL borrowers who use MPL funds to consolidate credit card debt, while the dashed, blue line displays the same for non-consolidators. Both 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 the Online Appendix.



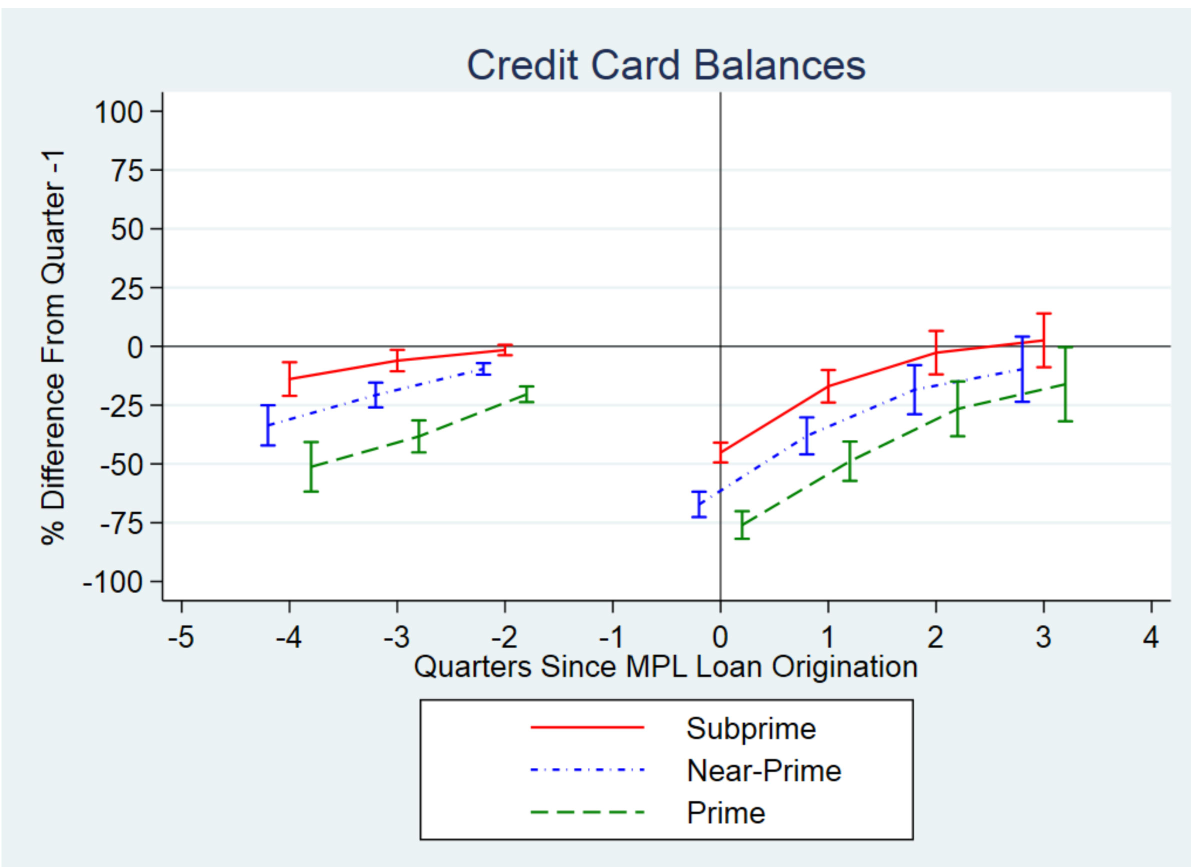
(a) *Credit Scores*



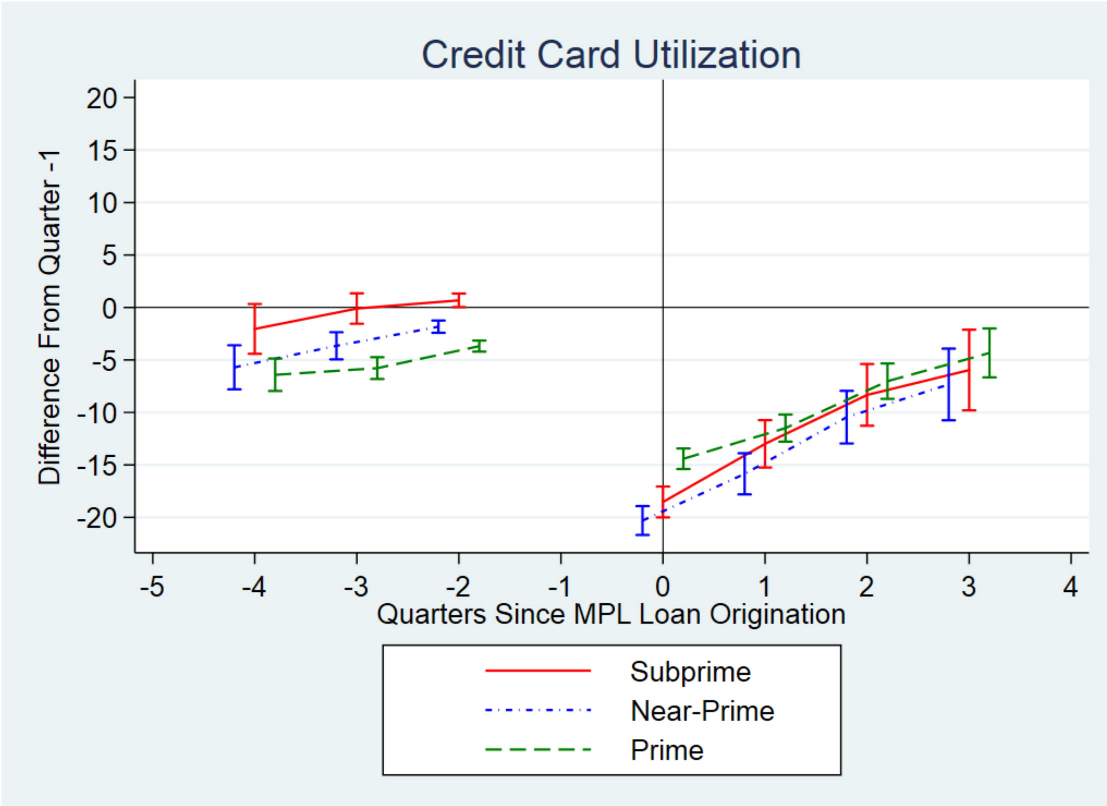
(b) *Credit Card Limit Growth*

Figure A.IV: Impact of Ex Ante Credit Quality of MPL Borrowers

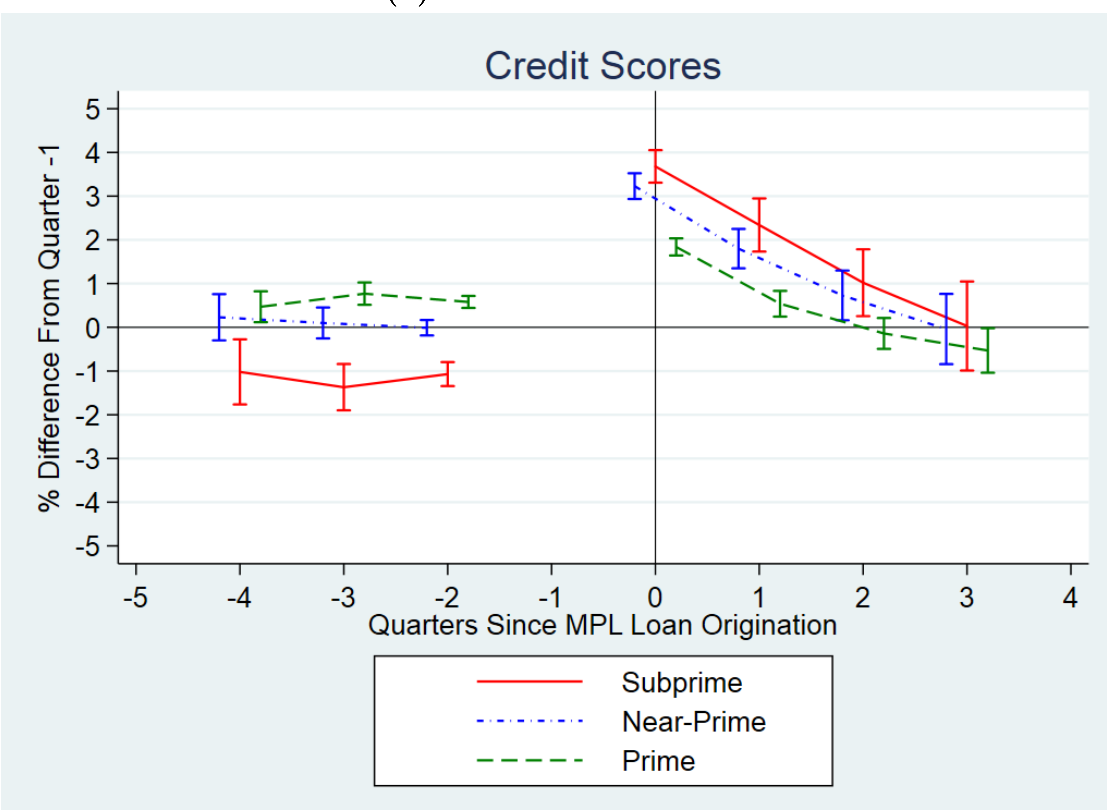
In this set of figures, we present event study plots that highlight differences in the evolution of credit profiles of marketplace lending (MPL) platform borrowers, differentiated by the credit quality of the borrower. We focus on one-time MPL borrowers. An MPL borrower is classified as *subprime*, *near-prime*, or *prime* if their credit score is below 620, between 620 and 680, and greater than equal to 680, respectively, in the month immediately before MPL loan origination. Panels A, B, C, D, and E show our analysis of credit card balances, credit card utilization, credit scores credit card limit growth, credit card default occurrences, respectively. The x-axis displays the quarters since loan inception, where $Quarter_0$ refers to the quarter in which the MPL trade is opened. $Quarter_{-1}$ and $Quarter_{+1}$ refer to the quarter before (months [-3,-1]) and the quarter immediately following (months [+4,+6]) the quarter of origination, respectively. All other quarters are defined in an analogous manner. The y-axis displays 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 the Online Appendix.



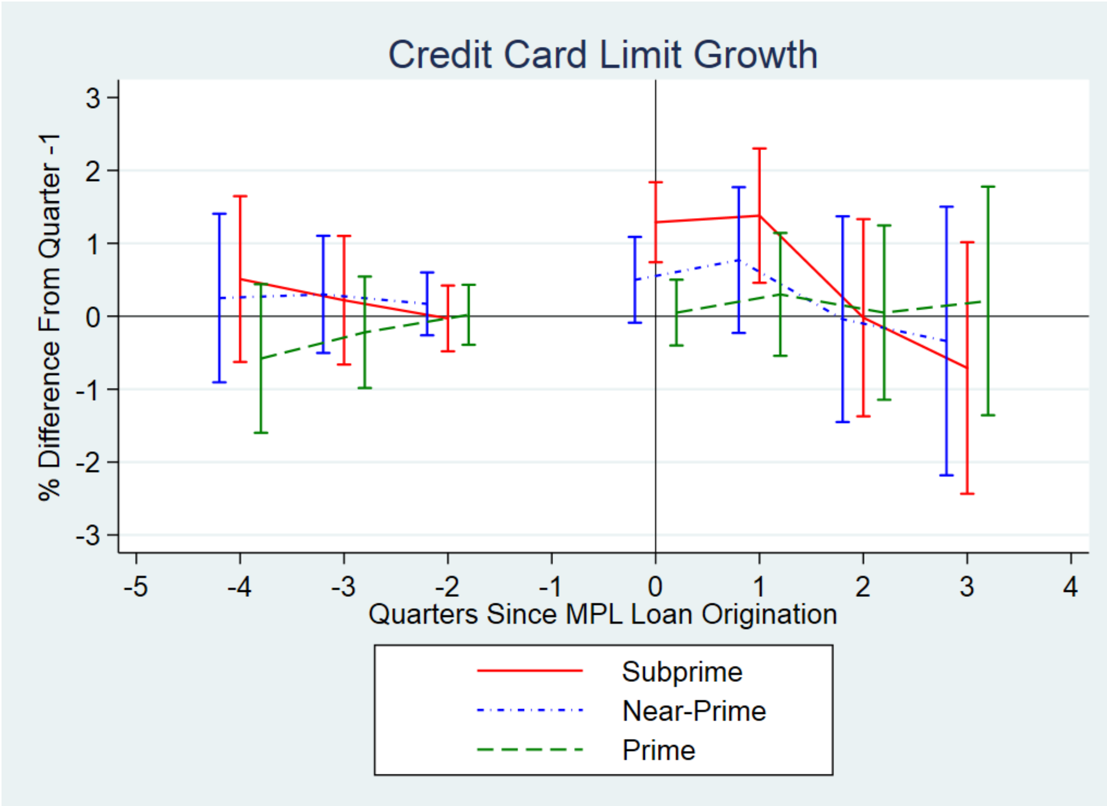
(a) *Raw Credit Card Balance*



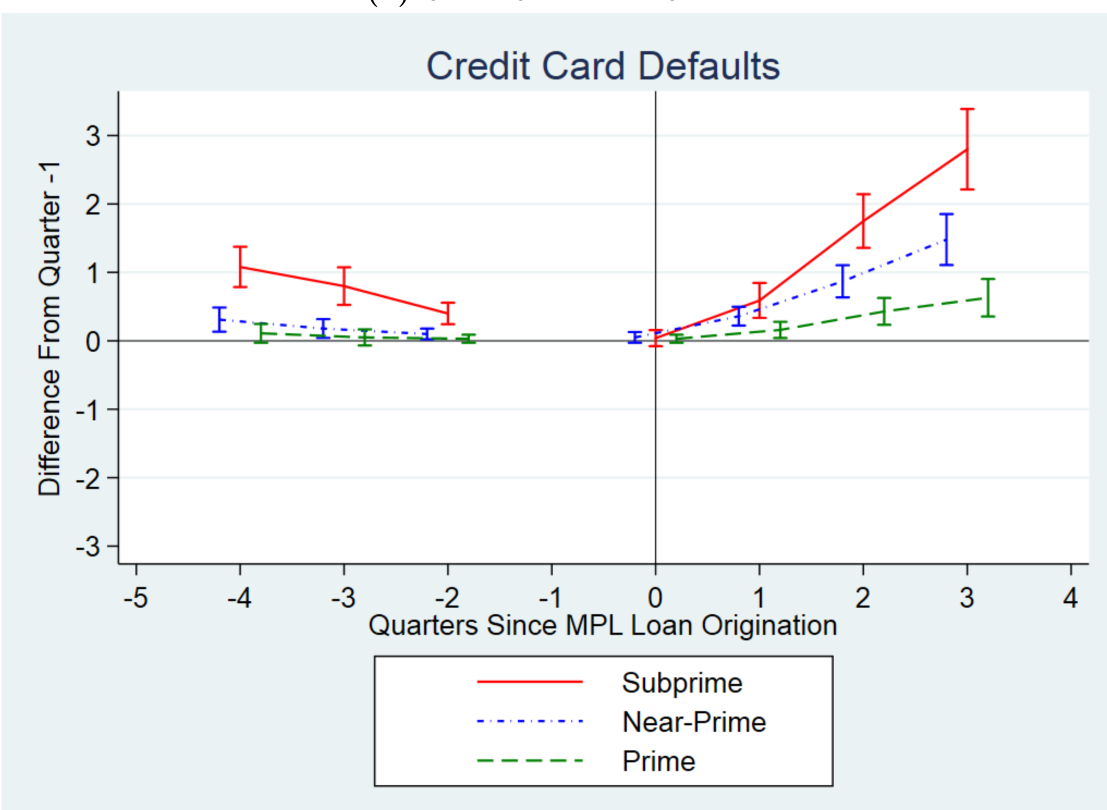
(b) *Credit Card Utilization*



(c) *Credit Scores*



(d) *Credit Card Limit Growth*



(e) *Probability of Default on Credit Cards*

Online Appendix (For Online Publication Only)

A. *Institutional Background Of Marketplace Lending and Loan Application Process*

Marketplace lenders promote themselves as cutting out the "middle man" (intermediary banking institutions) and directly connecting individual borrowers and lenders. 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.[20] Moreover, MPLs function completely online; thus, unlike banks, they do not incur the fixed investment costs of setting up and maintaining brick-and-mortar branches. Phillippon (2015) shows that the cost of traditional financial intermediaries in the United States has remained between 1.5–2% of intermediated assets over the last 30 years. However, a recent Lending Club (one of the largest MPL platforms in the United States) report shows that Lending Club carries a 60% lower operational cost than banks due to its electronic services.[21]

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

MPLs provide unsecured loans for successful loan applications. Prospective borrowers are required to provide the intended purpose of the borrowed funds and the reasons provided range from debt consolidation to medical bills to financing various kinds of consumption. However, MPLs do not have any mechanism in place to ensure that borrowed funds are used for the purpose stated in the loan application. Thus, it is unclear whether borrowers actually use loan funds for their stated purpose or they simply "game the system" to increase the probability of loan origination.[22]

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

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

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

B. 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.

C. The k-Nearest Neighbors Matching Process

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

Cohort I: Matching Bank-Unsatisfied MPL Borrowers to Bank-Unsatisfied Non-MPL Borrowing Neighbors Within Same 5-Digit ZIP

- Step 01: From the entire sample of MPL borrowers, we identify the subsample of individuals who unsuccessfully apply for bank credit prior to MPL loan origination. We refer to unsuccessful bank loan applicants as "bank-unsatisfied" for purposes of brevity.

  Bank applications are tracked through hard credit checks performed by banks against the applicant. 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.

  Thus, in our analysis, we only include MPL borrowers who have hard credit checks performed against them by banks prior to MPL loan origination. Moreover, we only consider individuals who fail to obtain traditional bank credit. Thus, this subsample of MPL borrowers uses MPL funds to make up for restricted access to bank credit.

- Step 02: For each MPL borrower identified in the previous step, we identify all neighbors living in the same 5-digit ZIP code as the MPL borrower in the month of MPL loan origination. The neighbors are identified such that they belong to a household distinct from the household of the MPL borrower. Within this set, we identify the subset of neighbors who have never opened a MPL trade over the period 2010–2017.

  Our baseline analysis is conducted at the 5-digit ZIP code level, since the average 5-digit ZIP code population in the United States is approximately 7,500 people.[23] This disaggregated geographic level allows for the optimal trade-off between identifying geographically proximate non-MPL borrowers, while still allowing for a sizeable matched sample of borrowers to neighbors.

- Step 03: From the subset of neighbors identified at the end of the preceding step, we further subset our non-MPL borrowing neighbors sample to include only those neighbors who have had a non-utilities, bank hard credit check performed against them in the same calendar month in which the MPL borrower originates her MPL loan.

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

- Step 04: From the subset of neighbors identified in the above step, we make use of our cohort-level, calendar-time approach to next identify neighbors who have displayed credit profile trends that are similar to ones shown by the MPL borrower in their cohort in the quarter leading up to MPL loan origination. We require that certain credit profile characteristics display identical trends for both the non-borrowing neighbor and the MPL borrower. These characteristics are credit card balances, credit card utilization ratios, and credit scores.

- Step 05: 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.

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

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

<u>Cohort II</u>: *Matching All MPL Borrowers to Bank-Unsatisfied Non-MPL Borrowing Neighbors Within Same 5-Digit ZIP*

- In this cohort, we do not require MPL borrowers to be unsuccessful bank applicants prior to MPL loan origination. Thus, we use the entire sample of MPL borrowers, and match each borrower to her closest bank-unsatisfied neighbor within the same 5-digit ZIP code. The remaining matching steps are identical to the approach described above.

<u>Cohort III</u>: *Matching All MPL Borrowers to Bank-Unsatisfied Non-MPL Borrowing Neighbors Within Same 9-Digit ZIP*

- In this cohort, we do not require MPL borrowers to be unsuccessful bank applicants prior to MPL loan origination. Thus, we use the entire sample of MPL borrowers, and match each borrower to her closest bank-unsatisfied neighbor within the same 5-digit ZIP code. The remaining matching steps are identical to the approach described above.

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

<u>Cohort IV</u>: *Matching All MPL Borrowers to Neighbors Within Same 5-Digit ZIP Originating Unsecured Installment Loans from Traditional Banking Intermediaries*

- Identical to the baseline matching approach, except that MPL borrowers are now matched to neighbors who originate unsecured installment loans from traditional banking intermediaries in the same month. These bank installment loans are verified to be non-auto, non-mortgage, and non-student loan related.

D. Supplementary Tables

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

A brief summary of the additional tests is presented below:

- In Appendix Table OA.I, we show that MPL borrowers do not use MPL funds to consolidate auto loans, mortgages, or student loans.

- In Appendix Table OA.II, we study the evolution of credit card utilization ratios of MPL borrowers.
- In Appendix Table OA.III, we present our baseline results across different groups of MPL borrowers on the basis of pre-MPL loan origination credit card utilization. Borrowers are grouped into 'low', 'high', and 'very high' utilization groups if their pre-origination utilization is under 50%, between 50% and 90%, and over 90%, respectively.
- In Appendix Table OA.IV, we present our baseline results across different groups of MPL borrowers on the basis of pre-MPL loan origination income quintiles.
- In Appendix Table OA.V, we present our baseline results for two subsets of MPL borrowers – those with at least one medical-related account in collections prior to the origination of the MPL loan, and those with no medical-related accounts in collection prior to the origination of the loan.

Table OA.I: Do MPL Borrowers Consolidate Other Debt?

In this table, we report regression results that document the fluctuation of debt balances along broad trade lines in the period of time 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 differences in balances relative to levels in $Quarter_{-1}$, which serves as the absorbed period for our event study. Columns (I), (II), and (III) report event study estimates for auto, mortgage, and student debt, 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 the Online Appendix. I and Y-Q refer to individual and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Auto Balance	Mortgage Balance	Student Debt Balance
	(I)	(II)	(III)
Pre-MPL Loan Origination Trends			
$Quarter_{-4}$	4.50***	0.34*	-0.75
	(0.54)	(0.19)	(0.60)
$Quarter_{-3}$	3.82***	0.24**	-0.15
	(0.43)	(0.12)	(0.40)
$Quarter_{-2}$	2.43***	0.13**	0.03
	(0.20)	(0.06)	(0.23)
Post-MPL Loan Origination Trends			
$Quarter_0$	-3.33***	-1.45***	-0.71***
	(0.22)	(0.10)	(0.23)
$Quarter_{+1}$	-4.16***	-2.77***	-1.21***
	(0.43)	(0.19)	(0.47)
$Quarter_{+2}$	-4.79***	-2.81***	-1.54**
	(0.46)	(0.26)	(0.66)
$Quarter_{+3}$	-6.33***	-2.86***	-2.06**
	(0.56)	(0.31)	(0.82)
Observations	8,800,583	5,415,718	4,871,286
Adjusted R^2	0.81	0.96	0.97
Controls	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q

Table OA.II: Impact Of MPL Funds On Credit Card Utilization Ratios

This table reports results documenting the evolution of credit card utilization ratios in the period of time 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. In columns (I)–(IV), we report event study estimates for the cohort-level analysis. In column (I), bank-unsatisfied MPL borrowers are compared to socioeconomically identical bank-unsatisfied neighbors within the same 5-digit ZIP. In column (II) (column (III)), the entire sample of MPL borrowers is compared to socioeconomically similar bank-unsatisfied neighbors within the same 5-digit ZIP (9-digit ZIP). In column (IV), all MPL borrowers are compared to neighbors within the same 5-digit ZIP who originate unsecured installment loans from traditional banks. In columns (V) and (VI), we report estimates for event study specifications that capture within-borrower and time-varying regional trends, respectively. Standard errors are clustered at the cohort and year-quarter levels (columns (I)–(IV)), at the individual- and year-quarter levels (column (V)), and at the 5-digit ZIP and year-quarter levels (column (VI)). The cohort-creation process is described in the Online Appendix. All control variables included in the analysis are defined in the Online Appendix. *I*, *C*, *Z*, and *Y-Q* refer to individual, cohort, 5-digit ZIP code, and year-quarter, respectively. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable: Credit Card Utilization					
	Cohort-Level Analysis				Within-MPL Analysis	
	Bank-Unsatisfied MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 5-Digit ZIP	All MPL Borrowers vs. Bank-Unsatisfied Neighbors 9-Digit ZIP	All MPL Borrowers vs. Unsec. Install. Bank Borrowers 5-Digit ZIP	Individual Trends	Regional Trends
	(I)	(II)	(III)	(IV)	(V)	(VI)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-1.71	-1.93*	-1.91*	-1.85*	-4.99***	-4.87***
	(1.19)	(1.10)	(1.08)	(1.01)	(1.00)	(0.78)
$Quarter_{-3}$	-1.52**	-1.75**	-1.71**	-1.59**	-3.35***	-3.56***
	(0.75)	(0.75)	(0.68)	(0.66)	(0.63)	(0.56)
$Quarter_{-2}$	-1.07***	-1.20***	-1.27***	-1.10***	-1.72***	-1.49***
	(0.33)	(0.35)	(0.33)	(0.31)	(0.30)	(0.15)
Post-MPL Loan Origination Trends						
$Quarter_{0}$	2.22***	2.29***	1.67***	-7.48***	-18.33***	-16.99***
	(0.33)	(0.38)	(0.36)	(0.24)	(0.64)	(0.59)
$Quarter_{+1}$	0.57	0.57	0.13	-6.38***	-14.01***	-13.32***
	(0.66)	(0.69)	(0.66)	(0.51)	(0.94)	(0.74)
$Quarter_{+2}$	-1.48	-1.47	-1.88*	-6.20***	-9.02***	-7.99***
	(1.02)	(1.05)	(1.01)	(0.74)	(1.21)	(1.05)
$Quarter_{+3}$	-2.70**	-2.71**	-2.78**	-5.99***	-6.18***	-5.34***
	(1.27)	(1.28)	(1.25)	(0.95)	(1.62)	(1.24)
$Quarter_{+4}$	-3.51**	-3.57**	-3.55**	-5.73***		
	(1.46)	(1.50)	(1.48)	(1.14)		
$Quarter_{+5}$	-4.24**	-4.29**	-4.34**	-5.75***		
	(1.75)	(1.76)	(1.72)	(1.33)		
$Quarter_{+6}$	-4.87**	-4.88**	-4.87**	-5.98***		
	(1.97)	(1.98)	(1.98)	(1.56)		
$Quarter_{+7}$	-5.33**	-5.32**	-5.11**	-6.02***		
	(2.14)	(2.14)	(2.06)	(1.70)		
Differential Post-Trends of MPL Borrowers						
$Quarter_{0} \times$ MPL	-17.25***	-18.49***	-17.33***	-6.95***		
	(0.44)	(0.45)	(0.48)	(0.52)		
$Quarter_{1} \times$ MPL	-11.32***	-12.39***	-11.98***	-3.91***		
	(0.59)	(0.51)	(0.54)	(0.53)		
$Quarter_{2} \times$ MPL	-5.99***	-6.87***	-6.79***	-1.42***		
	(0.54)	(0.43)	(0.51)	(0.41)		
$Quarter_{3} \times$ MPL	-2.89***	-3.66***	-4.32***	-0.08		
	(0.45)	(0.36)	(0.49)	(0.35)		
$Quarter_{4} \times$ MPL	-0.96**	-1.56***	-2.39***	0.70**		
	(0.41)	(0.33)	(0.44)	(0.35)		
$Quarter_{5} \times$ MPL	0.32	-0.34	-1.05**	1.03***		
	(0.41)	(0.35)	(0.46)	(0.36)		
$Quarter_{6} \times$ MPL	1.24***	0.53	-0.34	1.21***		
	(0.43)	(0.40)	(0.48)	(0.38)		
$Quarter_{7} \times$ MPL	1.82***	1.18***	0.11	1.20***		
	(0.48)	(0.40)	(0.55)	(0.41)		
Observations	5,922,504	44,485,974	1,363,021	14,759,776	15,710,940	15,710,940
Adjusted R^2	0.75	0.75	0.80	0.76	0.60	0.62
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ C\times Y\text{-}Q$	$I,\ Y\text{-}Q$	$I,\ Z\times Y\text{-}Q$

Table OA.III: Cross-Sectional Cuts – Utilization

This table reports results documenting the evolution of credit profile characteristics in the period of time surrounding the origination of MPL loans, where MPL borrowers differ in their pre-origination credit card utilization ratios. 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A and B focus on credit card balances and credit card defaults, respectively. In either panel, column (I), column (II), and column (III) report results for MPL borrowers with pre-origination utilization ratios in the [0%–50%], [50%–90%), and 90%+ ranges. All specifications 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 the Online Appendix. *I* and *Y-Q* refer to individual and year-quarter, respectively. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Credit Card Balance			Panel B: Credit Card Defaults		
	0–50%	50–90%	90%+	0–50%	50–90%	90%+
	(I)	(II)	(III)	(I)	(II)	(III)
Pre-MPL Loan Origination Trends						
$Quarter_{-4}$	-15.46***	-44.44***	-28.39***	0.32***	0.47***	0.63***
	(5.90)	(4.40)	(3.38)	(0.08)	(0.10)	(0.10)
$Quarter_{-3}$	-10.02**	-29.75***	-17.25***	0.21***	0.31***	0.45***
	(4.03)	(2.65)	(2.09)	(0.07)	(0.08)	(0.09)
$Quarter_{-2}$	-6.73***	-14.54***	-6.31***	0.11***	0.16***	0.24***
	(1.93)	(1.26)	(1.04)	(0.04)	(0.05)	(0.06)
Post-MPL Loan Origination Trends						
$Quarter_0$	-44.52***	-71.36***	-68.07***	-0.02	-0.01	0.01
	(3.35)	(2.82)	(2.31)	(0.03)	(0.04)	(0.05)
$Quarter_{+1}$	-13.70***	-44.48***	-38.45**	0.17**	0.31***	0.45***
	(4.92)	(4.14)	(3.05)	(0.07)	(0.08)	(0.09)
$Quarter_{+2}$	5.60	-24.50***	-21.28***	0.54***	0.88***	1.30***
	(6.48)	(5.60)	(4.28)	(0.10)	(0.13)	(0.14)
$Quarter_{+3}$	14.35	-15.07**	-14.75***	0.91***	1.45***	2.12***
	(9.07)	(7.25)	(5.27)	(0.14)	(0.20)	(0.21)
Observations	3,614,405	7,762,805	4,333,346	3,683,329	7,902,291	4,556,959
Adjusted R^2	0.54	0.55	0.60	0.12	0.13	0.14
Controls	✓	✓	✓	✓	✓	✓
Fixed Effects	*I, Y-Q*	*I, Y-Q*	*I, Y-Q*	*I, Y-Q*	*I, Y-Q*	*I, Y-Q*

Table OA.IV: Cross-Sectional Cuts – Income

This table reports results documenting the evolution of credit profile characteristics in the period of time surrounding the origination of MPL loans, where MPL borrowers differ in their pre-origination monthly incomes. 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A and B focus on credit card balances and credit card defaults, respectively. In either panel, column (I) (column(V)) reports results for the borrowers with pre-origination monthly incomes falling in the bottom (top) quintile. Columns (II)–(IV) document results for MPL borrowers with pre-origination monthly incomes falling in the middle three quintiles, in ascending order of financial well-being. All specifications 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 the Online Appendix. I and Y-Q refer to individual and year-quarter, respectively. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Credit Card Balance					Panel B: Credit Card Defaults				
	Low	Quintile 2	Quintile 3	Quintile 4	High	Low	Quintile 2	Quintile 3	Quintile 4	High
	(I)	(II)	(III)	(IV)	(V)	(I)	(II)	(III)	(IV)	(V)
Pre-MPL Loan Origination Trends										
$Quarter_{-4}$	-27.32***	-33.29***	-34.20***	-35.73***	-33.99***	0.95***	0.62***	0.46***	0.40***	0.23***
	(5.13)	(5.00)	(4.36)	(4.13)	(3.65)	(0.15)	(0.10)	(0.09)	(0.08)	(0.05)
$Quarter_{-3}$	-16.24***	-21.58***	-22.67***	-23.72***	-23.06***	0.64***	0.43***	0.32***	0.27***	0.15***
	(3.23)	(3.16)	(2.70)	(2.63)	(2.34)	(0.13)	(0.08)	(0.08)	(0.08)	(0.05)
$Quarter_{-2}$	-7.27***	-10.29***	-11.18***	-11.52***	-11.39***	0.34***	0.23***	0.16***	0.14***	0.08***
	(1.59)	(1.45)	(1.34)	(1.28)	(1.13)	(0.07)	(0.05)	(0.05)	(0.04)	(0.03)
Post-MPL Loan Origination Trends										
$Quarter_0$	-58.64***	-65.25***	-68.26***	-69.59***	-58.93***	0.14**	0.07	0.05	0.04	-0.02
	(2.67)	(3.05)	(2.88)	(2.90)	(2.38)	(0.07)	(0.05)	(0.04)	(0.04)	(0.02)
$Quarter_{+1}$	-22.57***	-32.78***	-38.14***	-43.56***	-40.88***	0.55***	0.40***	0.38***	0.36***	0.25***
	(4.52)	(4.55)	(4.01)	(3.94)	(3.44)	(0.14)	(0.09)	(0.08)	(0.06)	(0.04)
$Quarter_{+2}$	-3.34	-12.73**	-17.63***	-22.79***	-24.95***	1.63***	1.13***	0.96***	0.82***	0.53***
	(6.38)	(6.21)	(5.54)	(4.96)	(4.33)	(0.22)	(0.14)	(0.12)	(0.11)	(0.07)
$Quarter_{+3}$	4.60	-3.35	-8.28	-13.43* *	-17.35***	2.80***	1.89***	1.60***	1.20***	0.75***
	(7.93)	(8.01)	(7.16)	(6.78)	(5.80)	(0.35)	(0.23)	(0.20)	(0.16)	(0.09)
Observations	3,166,968	3,290,559	2,951,173	3,157,916	3,144,015	3,161,139	3,229,891	3,243,129	3,252,637	3,255,397
Adjusted R^2	0.53	0.52	0.53	0.55	0.59	0.14	0.13	0.13	0.13	0.12
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed Effects	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q	I, Y-Q

Table OA.V: Health Shocks

This table reports results documenting the evolution of credit profile characteristics in the period of time surrounding the origination of MPL loans, where MPL borrowers differ in terms of medical collections in the pre-MPL origination period. 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 differences relative to $Quarter_{-1}$, which serves as the absorbed period for our event study. Panels A and B focus on credit card balances and credit card defaults, respectively. In either panel, column (I) reports results for individuals with at least one medical-related account in collections prior to the origination of the MPL loan. Column (II) reports results for individuals with no medical-related account in collections prior to the origination of the MPL loan. All specifications 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 the Online Appendix. *I* and *Y-Q* refer to individual and year-quarter, respectively. *,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Credit Card Balance		Panel B: Credit Card Defaults	
	Prior Medical Collections	No Prior Medical Collections	Prior Medical Collections	No Prior Medical Collections
	(I)	(II)	(I)	(II)
Pre-MPL Loan Origination Trends				
$Quarter_{-4}$	-28.98***	-34.54***	0.38***	0.31***
	(5.19)	(4.11)	(0.09)	(0.07)
$Quarter_{-3}$	-18.64***	-22.77***	0.28***	0.21***
	(3.28)	(2.57)	(0.08)	(0.06)
$Quarter_{-2}$	-8.89***	-11.06***	0.15***	0.12***
	(1.60)	(1.22)	(0.05)	(0.04)
Post-MPL Loan Origination Trends				
$Quarter_0$	-55.29***	-68.48***	-0.03	0.02
	(2.83)	(2.51)	(0.04)	(0.03)
$Quarter_{+1}$	-22.44***	-41.85***	0.17**	0.20***
	(4.58)	(3.55)	(0.09)	(0.06)
$Quarter_{+2}$	-4.48	-21.91***	0.77***	0.50***
	(6.36)	(4.76)	(0.12)	(0.10)
$Quarter_{+3}$	2.51	-12.40*	1.67***	0.94***
	(8.05)	(6.47)	(0.23)	(0.15)
Observations	4,894,629	10,817,170	4,754,906	10,622,052
Adjusted R^2	0.54	0.57	0.12	0.12
Controls	✓	✓	✓	✓
Fixed Effects	*I, Y-Q*	*I, Y-Q*	*I, Y-Q*	*I, Y-Q*