MARKETPLACE LENDING

A STUDY OF THE RELATIONSHIP BETWEEN ALTERNATIVE LENDERS AND COMMERCIAL BANKS

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Marketplace Lending: An analysis of the relationship between online lenders and traditional banks

Abstract:

Using a conceptual framework developed by Tang (2019), this paper examines whether Marketplace lending platforms operate as substitutes or complements to bank lending in terms of borrower credit quality and loan size. Employing data on 85,660 loans funded by LendingClub from 2009-2012, we investigate the relative difference in U.S. areas affected by the regulation of FAS 166/167. We use a difference-in-difference method where areas affected by the regulation constitute a treatment group and unaffected areas a control group. When allowing for geographical heterogeneity we find that Marketplace lenders serve borrowers of lower credit quality than banks and simultaneously attract a fraction of borrowers with access to bank credit. In terms of loan size, however, Marketplace leneders operate as a substitute, i.e. originates loans of the same sizes as banks. When adding year fixed effects to our model, it provides no evidence on what relationship is taking place on the loan size dimension.

Keywords: Marketplace Lending, FinTech, Consumer Credit, FAS 166/167, P2P lending

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1 Introduction

Recent years' development of financial technology, more commonly known as FinTech, has changed the financial landscape dramatically. With competitive advantages in the form of technological processes and fewer regulatory constraints, FinTech-actors have caused a powerful upheaval for the old-fashioned incumbents within the banking sector (Bloomberg, 2018)(Buchak et al, 2017). Within the FinTech-field, alternative lending is the third largest segment with a transaction value amounting to $220.9 billion globally in 2018. Looking at this measure, the U.S. accounts for the second biggest market with a transaction value of $31.5 billion. Despite constituting the second biggest market globally, the alternative lending platforms only account for a small share of the general financial sector within the U.S. With its looming growth potential, it is still unclear to what extent these actors are posing a threat to commercial banks (Statista, 2019). To assess this question, this paper aims to investigate whether Marketplace lending platforms (MPLPs) operate as substitutes or complements to traditional bank lending.

Marketplace lending is a form of alternative lending and refers to online venues where individuals can request loans from investors at an appropriate interest rate (Statista, 2019). MPLPs have a reputation of serving high-risk borrowers and originate smaller loans to a greater extent than banks (Komos, 2018). Banks usually reject smaller loans as their manual processes require time and work, resulting in unprofitability. By contrast, online lenders' automatized interest-setting processes result in scalability (P. Jeffery, D. Arnold, 2014). Empirical analyses have tried to answer what relationship exists between MPLPs and banks. Huan Tang (2019) concludes in her paper *Peer to Peer lenders vs banks: Substitutes or complements?* that the Marketplace lending platform LendingClub operates as a substitute to banks in the U.S. in terms of borrower credit quality, by serving borrowers already catered for by banks. Tang (2019) further finds that in terms of loan size, the platform operates as a complement to banks by originating loans of smaller sizes. By replicating the work of Tang (2019), we aim to establish if these results are valid and thus if Marketplace lending platforms do not take on riskier borrowers, but rather serve as a complement to banks on the loan size dimension. To contribute further, we first perform an identical analysis on a subsample consisting of four U.S. states and then highlight the impact of time-fixed effects in a third analysis, by excluding these in our model. We use data on funded MPL-loans from the U.S. market leader LendingClub. LendingClub was one of the first operators within Marketplace lending and has since its launch in 2006 issued $56.8 million worth of loans, corresponding to 72 % of all MPL-loans issued in the U.S. (P2Pmarketdata, 2020).

To examine the relationship between MPLPs and traditional bank lending, we employ a conceptual framework developed by Tang (2019). In the applied framework, MPLPs either operate as substitutes or complements to traditional banks. If the two creditors operate as complements, MPLPs and banks serve separate customer segments in terms of borrower credit quality and loan size. In this scenario, MPLPs are assumed to cater for low credit quality-borrowers looking for smaller loans. If a substitutional relationship prevails, MPLPs and banks serve the same segment of borrowers and loans in terms of size. Since it is not possible to observe if a customer served by a MPLP qualifies for a bank loan, the framework uses an exogenous shock to bank credit supply. Post shock, the framework assumes that primarily low credit quality-borrowers are rejected by banks and that these, subsequently, turn to MPLPs. The shock to banks' credit supply aims to distinguish and measure the quality and characteristics of rejected borrowers. In case the two creditors are complements, the rejected applicants will be high credit quality-borrowers in the eyes of MPLPs. If the creditors instead operate as substitutes, borrowers of low quality will represent low quality-borrowers also from the perspective of MPLPs. The same reasoning holds when considering loan size, where primarily small loans are rejected due to banks' credit supply constraints.

Using the regulation of FAS 166/167 as an exogenous shock to commercial banks’ credit supply, effective in the first quarter of 2011, we investigate how LendingClub loans are re-characterized after the potential migration of former bank customers. FAS 166 *Accounting for Transfers of Financial Assets* and 167 *Amendments to FASB Interpretation No. 46(R)* was implemented by the Financial Accounting Standards Board (FASB) as a consequence of the financial crisis in 2008. The regulations initiated by investors and the Securities and Exchange Commission (SEC), required banks to consolidate securitized assets formerly held off-balance sheet. The purpose of the regulations was to improve existing financial accounting standards and hence protect investors. Instead of stretching the use of off-balance sheet entities, banks now had to include their securitized off-balance sheet assets into their risk-weighted assets (FASB 2009). Looking into the Call Reports of 2011, we find that 33 banks consolidated their securitized assets due to the implementation of FAS 166/167.

We employ FAS 166/167 to distinguish loan applicants affected by banks' credit supply constraints from those not affected. The LendingClub-data set provides us with a 3-digit zip code of every loan applicant. Since this 3-digit zip code is the most precise geographical information of every loan origination, we categorize our data set into areas based on these. An area is considered affected (treatment group) if a bank branch of an affected bank is present in the area. Correspondingly, an area is considered unaffected (control group) if no affected bank is located within it. In this manner, we use a difference-in-difference method in which we use the control group as a counterfactual scenario, i.e where a tightening of credit supply never took place. We further control for potential underlying differences between the areas to eliminate the risk of omitted variable bias, by the use of control variables and fixed effects.

Our empirical investigation is divided into three analyses. First, we examine our research question with year fixed and area fixed effects included in our model on the full sample and a subsample. Following studies empathizing the thorough consideration required when adopting fixed effects models, we also exclude year fixed effects and perform re-estimates on the full sample (Hill, 2019). To capture the relative change in borrower and loan characteristics originated in affected areas after the implementation of FAS 166/167, we perform frequency distribution tests. In these tests, the number of borrowers within 10 different intervals of borrower credit quality and loan size is set to dependent variables. As a measure of borrower credit quality, we use the FICO-score, which is an applicant's individual credit score based on his/her credit report. We find that MPLPs operate as substitutes *and* complements to banks in terms of borrower credit quality, by supplying credit to a population of lower credit quality and simultaneously attracting borrowers qualifying for bank loans. Tests on the full sample, including year fixed effects in our model, present a disproportionate increase in the number of funded borrowers within the 6th range by 24.8 % in comparison to pre-shock levels (over the control group). Our test on the subsample exhibits a similar tendency, where we find a relative increase by 55.3 % in the same interval. These findings are supported when adopting a model that excludes year fixed effects. Performing this model on the full sample presents an increase in the 6th range, but also in the adjacent ranges, summing up to a relative increase by 35.4 %. Applying the conceptual framework to these findings, it can be concluded that what constitutes low credit borrowers from the banks' perspective, is considered average credit quality-borrowers from MPLPs point of view. In terms of loan size, however, we find that MPLPs operate as substitutes to banks by originating loans of the same size as banks. We perform the same frequency distribution test and find that the number of loans in the lower ranges increases relative to the control group and pre-shock levels. In aggregate, the number of loans within the ranges 1-4 increases by 38.2 % in the treatment group post shock.

Despite having a reputation of processing loans at a higher speed more cost-efficiently, we find that MPLPs do not originate small loans to a greater extent than banks. Thus, the platforms and banks compete for loans of the same sizes. MPLPs does, however, expand the credit pool in the U.S. by supplying credit to borrowers not catered for by banks and at the same time attract borrowers with access to bank loans. By this, we conclude that the expansion of MPLPs most likely will come at the cost of commercial banks.

Previous literature. Our paper relates to previous literature addressing the implications of the growth of alternative lending. Wolfe and Yoo (2017) present evidence in line with Marketplace lending platforms being substitutes to banks as small (rural) commercial banks lose lending volume in response to the rise of Marketplace lending. Further, the authors find that as the MPL-market grows, rural banks take on riskier borrowers. However, the empirics show no sign that larger urban banks follow the same trend. On the borrower credit quality dimension, our results go in line with that of Wolfe and Yoo. Since MPLPs attract a fraction of borrowers who qualify for a bank loan, it is likely that banks need to lower their threshold level of borrower credit quality in order to deliver at capacity. The study does however not take loan and borrower characteristics of borrowers served by MPLPs into consideration, which is the focus in our study. De Roure et al. (2016) state that loans channeled via Marketplace lending platforms bear higher interest rates and serve riskier borrowers, who are not eligible for loans supplied by traditional banks. The authors further find that MPLPs operate as complements, serving a market segment unserved by banks. Using data from the largest Marketplace lending platform in Germany (Auxmoney) and the national bank Deutsche Bundesbank, the De Roure et al. present that MPLPs are lending relatively more in areas where banks are lending less, serving customers not considered as "bankable" by banks. A similar research has been conducted on the Chinese market where Jiang et al. (2018) find that MPLPs serve borrowers not catered for by banks. These results align partly with our findings. However, MPLPs' business models might vary across borders since regulations applicable to these vary widely between countries. Meanwhile, the structure of the banking industry in a specific country/area influences the playfield in which MPLPs operate (GAO, 2011). The studies made by De Roure et al. and Jiang et al. provide valuable insight on the phenomena of MPLPs, however we can not draw any firm conclusions based on research made on markets different from the one in our study. Studies conducted on adjacent research fields include the paper by Buchak, G. et al. (2017), investigating the rise of shadow banks. Shadow banks refers to financial intermediaries that perform activities similar to those of banks, but are not regulated as one, and thus include MPLPs (The Economist, 2016). Using data on U.S. banks and household credit, complementarity is documented in the residential lending market between traditional bank lending and shadow bank lending with shadow banks operating within the high risk borrower field. It is further demonstrated how shadow banks expand their market share in geographical areas where traditional banks are affected by regulatory burden and capital tightening constraints. Since the term shadow banks refers to a broader spectrum of actors, this study does not reveal the nature of MPLPs.

2 Conceptual Framework

The framework used in our analysis is developed by Tang (2019) and provides the foundation for our research method. It describes the possible relationships between traditional bank lending and MPLPs depending on two different dimensions: borrower credit quality and loan size. The framework allows for three different cases:

1. Banks and MPLPs operate as perfect substitutes
2. Banks and MPLPs operate as perfect complements
3. Banks and MPLPs operate as both substitutes and complements, depending on the borrower and loan characteristics

In case (1), MPLPs and banks serve the same customer segment, meaning that all loans originated from one could be catered for by the other. In case (2), Tang (2019) assumes that MPLPs are serving customers of lower credit quality and that they are originating loans of smaller sizes than banks. The framework does not allow for the opposite to prevail. In case (3), MPLPs and banks are serving different customer clienteles to some extent, but also cater for an overlapping customer clientele. Also in this case, the framework is built upon the principle that MPLPs are originating smaller loans and serving borrowers with lower credit quality.

In order to investigate our research question, an exogenous shock to bank credit supply is required. It is assumed that this constraint in credit supply will primarily affect borrowers of lower credit quality applying for smaller loan amounts. This assumption is strengthened by evidence on the fixed costs banks experience when originating loans, suggesting a higher priority for larger loans (BAI, 2015). By introducing this shock, we are allowed to measure the migration of rejected borrowers turning to MPLPs and the following effect on loans originated by the platform.

Considering first the case for borrower quality (1). Borrowers each maintain a hypothetical quality γ. The framework is based on the assumption that banks and MPLPs only serve borrowers with quality above a certain threshold $\underline{\gamma}^{i}$, for i $\in \{bank, MPL\}$. In case MPLPs and banks operate as perfect substitutes, this threshold level of borrower quality is equivalent,

$\underline{\gamma}^{bank} = \underline{\gamma}^{MPL}$. MPLPs and banks then compete for the same customers at every level of quality above the threshold; the unbanked population is not served by MPLPs. When banks tighten their lending criteria, this leads to an increase in $\underline{\gamma}^{bank}$, implying that primarily low quality borrowers are rejected. Rejected borrowers will turn to MPLPs, since the framework assumes that all customers served by banks are above the threshold level of borrower credit quality of MPLPs. Our frequency test will in this case present an increase in the number of originated loans by borrowers in the lower end of the credit quality range, indicating that low credit quality borrowers from the bank's perspective is also considered low credit quality borrowers from MPLPs' perspective.

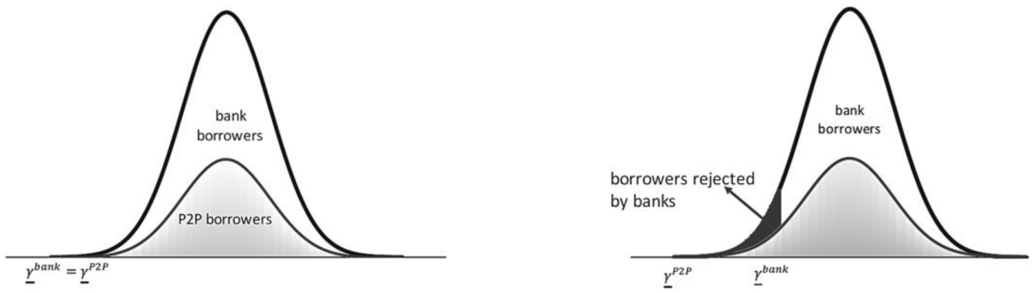

Figure 1: Borrower Credit Quality Distribution: Perfect Substitutes[1]

This figure displays the distribution of MPL borrower credit quality before and after banks tighten their lending criteria. The thick line on the top illustrates the aggregate distribution of borrower credit quality of both banks and MPLPs. The white area on top portrays the borrowers served by banks, while the shadowed area under portrays the borrower pool served by MPLPs. The left figure represents the distribution of MPL borrowers in case of perfect substitutability (i.e., MPLPs and banks serve the same clientele) and refers to the state before the credit supply shock. The right-hand figure represents the distribution of MPL borrowers post shock. The borrowers in the dark area migrate from banks to MPLPs. Note: P2P = MPL.

If instead the two creditors operate as perfect complements (2), MPLPs are serving an unbanked population of lower credit quality, $\gamma^{MPL} < \gamma^{bank}$. In this case, no borrowers served by MPLPs would be catered for by banks. When banks experience a constraint to their credit supply, indicating an increase in γ^{bank}, the rejected population will constitute high quality borrowers from the perspective of MPLPs. If banks and MPLPs are operating as complements, our frequency test will present an increased number of originated loans by borrowers in the higher end of the credit quality range.

[1] Figure 1, illustrations made by Tang, H., 2019, *P2P Lenders versus Banks – Substitutes or Complements?*, p.7

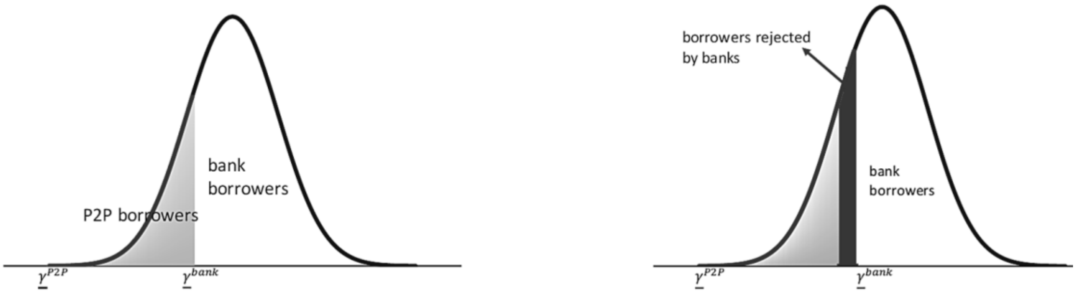

Figure 2: Borrower Credit Quality Distribution: Perfect Complements[2]

See notes for Figure 1.

Considering case (3), in which neither of the above relationships holds; MPLPs and banks operate both as substitutes and complements. In this case, MPLPs cater for an unbanked population and simultaneously attract consumers qualifying for a bank loan. MPLPs threshold level for minimum borrower quality is then still lower than that of banks, $\gamma^{MPL} < \gamma^{bank}$. Borrowers of low credit quality from a bank-perspective then constitute average credit quality in the eyes of MPLPs. If this intermediate relationship prevails, our frequency test will present an increase in the number of originated loans in the middle of the credit quality range.

The same concept applies when considering loan size instead of borrower credit quality. The framework then assumes that smaller loan amounts are offered by MPLPs to a greater extent.

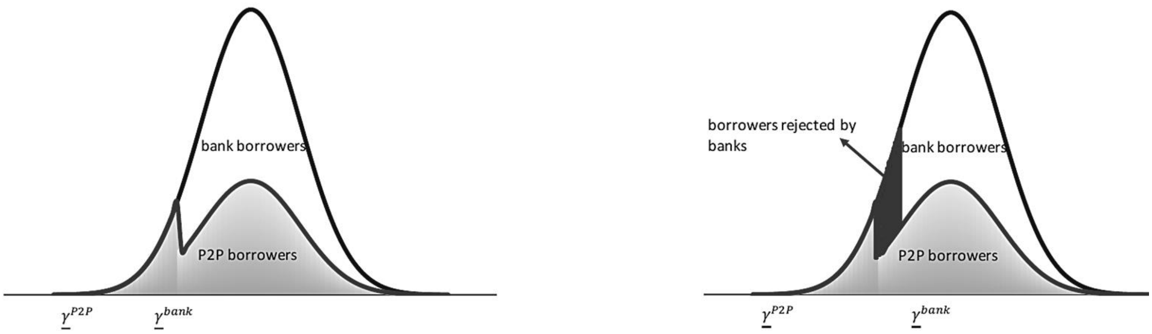

Figure 3: Borrower Credit Quality Distribution: Intermediate case[3]

See notes for Figure 1.

[2] Figure 2, illustrations made by Tang, H., 2019, *P2P Lenders versus Banks – Substitutes or Complements?*, p.8

[3] Figure 3, illustrations made by Tang, H., 2019, *P2P Lenders versus Banks – Substitutes or Complements?*, p.10

Exogenous shock. The conceptual framework requires a shock to banks' credit supply in order to investigate the following effects on MPLPs' borrower and loan characteristics. Dou et al. (2017) present evidence that the implementation of FAS 166/167 impacted small business lending negatively, a finding that is replicated and strengthened by Tang (2019). Due to the unavailability of data, we can not conduct the same experiment on a consumer credit level. However, Ryan et al. (2018) present that, out of their sample banks, 5.6 % of all banks' assets were consolidated due to FAS 166/167. Out of these assets, 80 % consisted of credit such as credit card master trusts. Thus, FAS 166/167 constitutes an adequate empirical bank credit supply shock to our framework.

3 Background

Zopa was the first operator in the field of Marketplace lending, and launched in the UK in 2005. The U.S. soon followed, with LendingClub and Prosper launching in 2006. The idea behind these platforms was to provide an online venue that matched individual investors with retail borrowers. The early success and rapid growth of these operators partially owes to the financial crisis in 2008, when banks suffered from capital constraints and heightened regulations, forcing a contraction in credit supply. Alternative lending platforms offered a flexible alternative that not only filled the gaps after banks retraction, but also contributed to a change in consumers' attitude towards the credit market (Statista, 2020). In contrast to banks' tedious and manual processes, Marketplace lending platforms' applications were completely online-based, and required substantially lower amounts of time and effort to retrieve funding. These flexible processes were partially enabled by technology advancements and the use of in house-algorithms that assessed creditworthiness in a revolutionizing way. By taking soft information such as social media usage into account, MPLPs assess creditworthiness more efficiently than banks (Lo, B., 2016).

In addition to soft information, LendingClub filters out ineligible applicants based on two crucial measurements: the FICO-score and the debt-to-income (DTI) ratio. The FICO-score, named after the founding company Fair Isaac Corporation is based on consumers' credit reports, payment history and amounts owed. The credit score measure ranges from 300 to 850, where a score above 650 is generally indicating a good credit history. The FICO-score is widely used by financial intermediaries to establish creditworthiness and thus represents borrower credit quality throughout our empirical analysis (FICO, 2020).

Today, the main difference between the credit operations of U.S.s' MPLPs and banks', is that banks carry risk in the form of outstanding loans on their balance sheets. MPLPs do not lend themselves and are thus not required to hold capital to absorb potential losses, reflecting the notary model based on which MPLPs operate. The notary model means that all accepted loan applications are originated by partner banks, where the platform then purchases the loans from partner banks and issues a promissory note to lenders, rather than a contract. After the financial crisis 2008, the Securities and Exchange Commission (SEC) cited the need for compliance with the Securities Act of 1933, which in practice resulted in promissory notes issued by MPLPs being regarded as debt-backed securities (P2Pmarketdata, 2020). Although the initial business model of the MPLP was to offer individual investors opportunities to invest on a micro-level, institutions make up most of the investor-base today. More recently, the sector in general has attracted more institutional investors, prompting the operators within the sector to be referred to Marketplace lenders rather than Peer-to-Peer lenders. (Lendingclub, 2020)(Deloitte, 2016).

4 Hypotheses

Since we investigate whether the results of Tang (2019) are replicable, her results form the foundation of our hypotheses.

Our first hypothesis addresses the loan volume and the number of loans in the period after the credit supply shock. Following the results presented by Tang (2019), we expect affected areas to experience a relative increase in loan volume.

Hypothesis 1. *Funded amount and the number of funded loans will increase relatively more in areas affected by FAS 166/167 post-shock, regardless if MPLPs serve as substitutes or complements to traditional bank lending.*

The second hypothesis covers borrower credit quality. Since Tang (2019) finds that MPLPs operate as substitutes to banks in terms of borrower credit quality, we expect to see the same tendency.

Hypothesis 2. *There will be a relative increase in the number of loans within the lower FICO-score ranges (1-5) and no relative increase in the higher ranges of borrower quality.*

The third hypothesis regards loan size. Following Tang (2019), we expect to find that MPLPs operate as complements to banks on the loan size dimension.

Hypothesis 3. *There will be a relative increase in the number of loans within the higher ranges (6-10) of the loan size distribution and no relative increase in the lower ranges.*

5 Data

Data on funded loans is retrieved from LendingClub's website. To investigate the effects of FAS 166/167 on MPLPs, we collect data between the years 2009-2012, constituting two years before and two years after the implementation of the regulation. The data set contains information about borrower and loan characteristics. Borrower characteristics include FICO-score, debt-to-income ratio, employment length and location (zip code and state) of the applicants. The first three digits of an applicant's zip code is specified, which is the most precise geographical information LendingClub provides. We categorize our data set into groups based on this 3-digit number, which results in 820 groups; throughout the analysis referred to as "areas". Funded loans are originated from 48 U.S. states and the District of Columbia.

Loan characteristics include information such as funded amount, origination date, loan term (36 or 60 months) and interest rate. The final regression sample is constructed using 85 660 unique loans.

To construct treatment and control groups, we control for banks affected by FAS 166/167 and thereafter the location of these. Data is retrieved from the Call Reports of 2011, available at Federal Financial Institutions Examination Council (FFIEC). Banks that consolidated their securitized assets under FAS 166/167 reported the size of their consolidated Variable Interest Entities (VIEs) in the Call Reports under Schedule RC-V. A bank is considered affected if it reports consolidation under this section. By looking into the Call Reports from the first quarter after FAS 166/167 came into use, we find that 33 banks consolidated assets under the regulation of FAS 166/167.[4] In order to determine what areas were affected by the regulation, data on the geographical presence of branches of the 33 banks is retrieved from the Summary of Deposits in 2011. The Summary of Deposits are available at the Federal Deposit Insurance Corporation's website. In the reports, the respective zip code is retrieved in which we use the first three digits to merge the geographical bank branch

[4] We would like to thank Yiwei Dou, Stephen G.Ryan and Biqin Xie for their valuable input regarding banks affected by FAS 166/167.

information with our LendingClub-data set. In total, we establish that 721 areas were affected (treatment group) and 99 areas unaffected (control group) by the regulation. From this data, three new variables are created. The variable *Treated,* takes the value of 1 if the funded loan is reported from an area with at least one bank affected by FAS 166/167, otherwise 0. Correspondingly, a dummy variable named *Post* takes the value 1 if the funded loan originated after 2010. As a difference-in-difference estimator, the interaction-variable *Treated*Post* takes the value of 1 if the loan originates from a treated area and is applied for after the shock.

To control for differences in areas over time, we collect data on state specific demographics that may influence the number of loans originated in an area at a certain point in time. The three first digits in a zip code that we use as an identifier of area, represents a Sectional Center Facility (SCF), which is not used for economic analysis purposes and thus demographical data within this area is not retrievable. For this reason we use state level data. We collect statistics on population, aggregate personal income and unemployment rate from the Bureau of Economic Analysis and the U.S. Bureau of Labor Statistics. The control variable *Income per Capita* is calculated by dividing aggregate income by population for every corresponding year, and represents average income per capita in the state of the observation. *Unemployment* similarly represents the average unemployment rate. Data on population is used to normalize funded amount and number of loans when these are set as dependent variables in our regressions.

Since our LendingClub data set is a form of panel data, we consolidate all relevant variables on area and quarter basis resulting in 9098 observations – one observation for each combination of area and quarter. The data set is unbalanced in the sense that not all areas contain observations for all time periods. However, we choose to proceed with this unbalanced data set since we want to avoid the phenomena of survival bias in our sample.[5]

Descriptive statistics. Table (1) presents a summary of the statistics of the entire sample and the subsample. Panel A describes the average borrower with a FICO-score of 711, a DTI-ratio of 15.3 %, and an employment length of 5 years. The average loan size is $12,447 with an interest rate of 13 %. The dummy-variables provide insights on the distribution of loans. 89.1 % of the loans belong to the treatment group, 82.5 % belong to the years 2011 and 2012 and the interaction-dummy (difference-in-difference estimator) makes up 73.5 % of the total sample. Panel B describes statistics on the subsample group. This summary reports an

[5] Survival bias refers to the error that arises when data points that do not make it through a certain test is excluded. We could, by removing observations not including Length of Employment, unintentionally eliminate borrowers of a lower credit class.

average borrower with a FICO-score of 708, loan size of $11,784, a DTI-ratio of 15.3 % and an employment length of 5 years. The treatment group comprises 51.6 % of the loans in the subsample, leaving 48.4 % in the control group. Moreover, 83.8 % of the loans originate from 2011 and 2012 and the difference-in-difference estimator captures 43.3 % of the loans.

Table 1: Summary of Statistics: LendingClub loans

Variable	Min	Mean	Median	Max	Std, Dev	Nr of Obs
	Panel A, All funded applications					
FICO Score	664	711	704	850	34	85660
Funded Amount	1000	12447	10200	35000	7833	85660
Treated	0	0.891	1	1	0.311	85660
Post	0	0.825	1	1	0.380	85660
Treated*Post	0	0.735	1	1	0.441	85660
Nr of Loans per Area	1	38	1	241	44	85660
Maturity	0	0.223	0	1	0.416	85660
DTI	0	0.153	0.152	0.350	0.074	85660
Interest Rate	0.054	0.130	0.131	0.249	0.042	85660
Employment length	1	6	5	10	3	82849
Mortgage	0	0.459	0	1	0.498	85660
Home Owner	0	0.079	0	1	0.269	85660
Annual Income	4000	69450	60000	7141778	61648	85660
	Panel B, Subsample 4 states					
FICO Score	664	708	699	829	33	6207
Funded Amount	1000	11784	10000	35000	7526	6207
Treated	0	0.516	1	1	0.500	6207
Post	0	0.838	1	1	0.368	6207
Treated*Post	0	0.433	0	1	0.496	6207
Nr of Loans per Area	1	38	27	162	36	6207
Maturity	0	0.211	0	1	0.408	6207
DTI	0	0.153	0.152	0.349	0.073	6207
Interest Rate	0.054	0.131	0.131	0.249	4.184	6207
Employment length	1	5	5	10	3	6207
Mortgage	0	0.496	0	1	0.500	6207
Home Owner	0	0.050	0	1	0.219	6207
Annual Income	4800	65011	56000	780000	41720	6207

This table reports the summary of statistics of LendingClub's borrower and loan charactheristics for all funded loans 2009-2012. Panel A reports all funded applications within the period in all U.S. areas. Panel B reports statistics solely for the states of Washington, Oregon, Nevada and Arizona. Variable definition is found in Table (A1).

6 Empirical Strategy & Results

In this section, we outline our empirical strategy, introduce our regressions, and present our results. Three analyses are conducted. First, we examine the entire data set, containing all applicable U.S. areas. To test for validity, a second analysis is made on a subsample. In a third step we conduct tests on the full sample, but exclude year fixed effects in our model.

Since our research question contains three branches, our analysis is divided into three corresponding tests. To test our first hypothesis, we start by examining if affected areas post shock experience a significant increase in the number of loans and total funded amount relative to the control group. To test our second and third hypotheses, we perform tests on the frequency distribution of FICO-score and loan size. These tests are conducted to gain insight on the characteristics of borrowers and loans originated by MPLPs as a consequence of credit constraints at traditional banks. Based on the results of the frequency tests, the relation between banks and MPLPs will be outlined.

Hausman test. To investigate if the use of fixed effects in our model is supportable, we perform the Hausman (1978) specification test. The null hypothesis is that area-specific effects are uncorrelated with any of the regressors in our model, and thus that a random effect model should be applied (Clark et al, 2012). Results on the Hausman test are presented in Table (A9). Our results do not present support for the use of random effects, leading us to reject the null hypothesis and include fixed effects in our model.

Heteroscedasticity. Our model should exhibit homoscedasticity which implies that the variance of the error term is constant along the line of fitted values. Therefore, the mean should equal to 0. If heteroscedasticity prevails, we may obtain distorted p-values and thus reduced legitimacy of the regression model results (Newbold, Carlson, Thorne, 2013). To control for heteroscedasticity, we include robust standard errors in all regressions.

Autocorrelation. Autocorrelation is common in panel data structures, indicating that error terms are correlated (Newbold et al., 2013). We expect there to be a correlation within areas' standard error, so to avoid autocorrelation, we cluster standard errors at area level in all regressions.

6.1 Time fixed effects

In this section, when our empirical analysis is conducted on the full sample as well as a subsample, we run regressions based on the following model:

$$y_{a,t} = \beta Treated_a * Post_t + Controls_{a,t} + \gamma_a + \sigma_t + \varepsilon_{a,t} \quad (1)$$

In regression (1), *a* denotes areas assembled in groups by the first 3 digits in the zip code and *t* denotes years. *Treated* is a dummy variable that takes value 1 for areas with at least one bank consolidating their securitized assets due to FAS 166/167. *Post* is a dummy variable set equal to 1 for time periods post shock; Q1 2011 and forward. Since the local demographic environment will influence the number of loans sought for in an area, we follow Tang (2019) by including market level controls. Control variables are denoted $Controls_{a,t}$. γ_a is an area fixed effect that we include in our model to adjust for geographical heterogeneity. Area fixed effects are unobservable time-invariant effects that differ between areas and thus could impact our findings. By also including year fixed effects σ_t, we control for nationwide effects that apply to a certain time period and by that is time-variant. Fixed effects minimize the risk for omitted variable bias, and allows us to focus on variation within areas rather than across (Hill 2019).

Method. To determine whether there has been a flow of rejected borrowers to MPLPs we set the dependent variable to MPLP lending volume in equation (1). Two measures are used to estimate this: funded amount and number of loans respectively. To limit variation between funded amounts in different states and to simplify our analysis and interpretation of results, we normalize the funded amount and number of loans by thousand inhabitants in each associated state. By dividing our dependent variables by inhabitants in state/1000, we furthermore capture the potential bias of more densely populated areas impacting our results to a greater extent. However, since population growth on a state-level might not reflect population growth in every area within the state, we also run regressions with the total funded amount and number of loans. This initial analysis is necessary for validating the implementation of the regulation as a sufficient negative shock, and to identify that rejected borrowers are the drivers behind potential changes in FICO-score and loan size in further analyses.

After this first step, we investigate the relative change experienced by treated areas in the number of borrowers within certain FICO and loan size intervals respectively. This is done by frequency distribution tests. When performing our frequency test on borrower credit quality, we divide possible FICO-scores ranging from 650-850 into ten equal intervals, each interval being 20 points wide. In regression (1), the number of loans within each of the ten ranges constitute the dependent variable. We can thus observe the implication of the interaction-variable *Treated*Post* in each interval. A negative coefficient implies that the treatment group is experiencing a relatively lower amount of borrowers within that specific range (over the control group), and vice versa.

As a third step of our analysis, we repeat the frequency test on the loan size dimension and divide the loan amount within the minimum to the maximum range to ten equal intervals of $3,400 each, ranging from $1,000-$35,000. We then calculate the number of loans within each interval for every area. The dependent variables are set to be the number of funded loans within each loan size range.

Results & Analysis 1. To examine the full sample, we start by estimating regression (1). First, we set the dependent variable to the funded amount within an area and secondly to the number of loans within the same area. The results of these regressions are presented in Table (A5). Our results do not provide sufficient information to draw any conclusions regarding the effect of the implementation of FAS 166/167. This holds for both funded amount and number of loans; both when these are normalized by population and when measured in absolute values. A possible explanation to our findings is that affected areas pre shock in aggregate held a lower loan volume than unaffected areas. We perform a two-sided difference in means-test (t-test), as an alternative approach, and find that there is a relative increase in the average funded amount in an affected area, but no relative increase in the number of loans. The section with p-values in Table (A2) presents our findings. Our findings suggest a potential increase in loan size in the treatment group (over the control group) but not a migration of borrowers rejected by banks turning to MPLPs. However, we allow for a potential displacement of borrowers formerly served by banks, although unobserved in our tests on the relative change in the number of loans.

Next, we perform tests on the FICO-frequency distribution. The results of the regressions are presented in Table (2). We observe a relative increase in the number of borrowers within the FICO-score range of 751-770 (range 6) by 0.340 in treated areas, corresponding to a 24.8 % increase in regards to pre shock levels. This result indicates that there is a strong relationship between areas affected by FAS 166/167 and the number of loans received by borrowers with a FICO-score within the 6th range, after the implementation of the regulation. The conceptual framework explains this to be an intermediate case, where MPLPs serve both an unbanked population with low credit quality, and borrowers already catered for by banks. However, due to being unable to distinguish between our treatment group and control group in terms of demand for MPLP-loans post shock, it can not be established that this relative increase is driven by borrowers formerly served by banks.

Table (A6) presents our results on the number of loans within every loan size-range. We find no evidence that treated areas experience a significant change in any of the ranges compared to the control group.

Table 2: Impact of FAS 166/167 on the distribution of MPLP borrower credit quality

	650-670	671-690	691-710	711-730	731-750	751-770	771-790	791-810	811-830	831-850
	1	2	3	4	5	6	7	8	9	10
Treated*Post	0.131	0.168	0.524	0.221	0.260	0.340**	0.096	0.135	-0.040	.
	(0.272)	(0.470)	(0.391)	(0.272)	(0.174)	(0.106)	(0.089)	(0.076)	(0.164)	.
Income per Capita	0.000	0.000*	0.000	0.000	0.000	0.000	0.000	0.000	-0.000	.
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	.
Unemployment	0.160	-0.231	-0.227	-0.136	0.028	0.056	0.026	-0.002	-0.057	.
	(0.217)	(0.351)	(0.284)	(0.169)	(0.086)	(0.052)	(0.040)	(0.039)	(0.108)	.
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3461	5382	5470	5090	4423	3471	2454	1492	377	48
R^2	0.252	0.283	0.288	0.273	0.175	0.123	0.059	0.044	0.127	.
Ad R^2	0.251	0.282	0.288	0.272	0.174	0.122	0.057	0.040	0.113	.

This table reports the bank credit supply shock's impact on the frequency distribution of MPL borrower credit quality, estimated from regression equation (1). The dependent variable is the number of MPL borrowers in each of the 20-point FICO score intervals between 650 and 850. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured on a state level. Treated is a variable indicating whether there are affected banks in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Year and area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Results & Analysis 2. The classification of an affected area potentially influences our findings. For instance, there is a risk that borrowers in the outskirts of an affected area diminish the effect of the borrowers rejected by banks' increased tendency to apply for MPL-loans. By scaling down our analysis to examine only four states, solely composed by either affected or unaffected areas, we are minimizing the risk for this potential error source. Also, the number of loans originated in the treatment group and the control group in this subsample is proportionate in the period before the implementation of FAS 166/167, in contrast to the two groups in the full sample. The control group consists of areas located in Oregon and Washington, whereas treated areas are located in Nevada and Arizona.

In the same manner, as with the tests on the entire data set, we estimate equation (1) on the subsample. We first estimate the coefficient for treated areas by setting the dependent variable to funded amount and number of loans (both normalized and non-normalized) in the states. The results are presented in Table (A7). We find no evidence that affected states experienced a relative increase in funded loan volume after the shock. As in the analysis of the full sample, we perform t-tests on means. Our findings are presented in Table (A3) under the column presenting p-values. We do not find an increase in the average funded amount nor number of loans in an affected area in relation to unaffected areas. However, as in the analysis of the subsample, we allow for an unobservable migration of borrowers rejected by banks and perform the next steps in our analysis.

Next, we perform frequency tests on FICO-score by setting the dependent variable to the number of borrowers within every respective range. The regressions, presented in Table (3), reveals that treated areas saw a relative increase in the number of borrowers within the FICO-score range 751-770 (range 6) by 0.729, corresponding to a 55.3 % increase. These findings are in line with those on the entire sample, empathizing that affected areas saw relatively more borrowers within the 6th range receiving funding post shock.

Lastly, we perform the frequency test on loan size, presented in Table (A7). As with the tests on loan size made on the entire sample, the data present insufficient information for us to draw any conclusions.

Table 3: Impact of FAS 166/167 on the distribution of MPLP borrower credit quality in the subsample group

	650-670	671-690	691-710	711-730	731-750	751-770	771-790	791-810	811-830	831-850
	1	2	3	4	5	6	7	8	9	10
Treated*Post	0.809	2.915	3.193	0.872	0.939	0.729**	0.160	0.219	-0.262	
	(1.016)	(2.119)	(1.732)	(0.793)	(0.541)	(0.230)	(0.206)	(0.228)	(0.204)	
Income per Capita	-2.627	13.000	7.179	-9.709**	0.660	-5.260**	-5.029***	149.900*	36.830	
	(4.546)	(11.960)	(9.371)	(3.477)	(3.838)	(1.666)	(0.931)	(60.700)	(104.100)	
Unemployment	-0.789***	-1.880***	-1.577***	-0.903***	-0.075	0.077	-0.030	0.010	-0.064	
	(0.216)	(0.296)	(0.396)	(0.154)	(0.199)	(0.124)	(0.161)	(0.097)	(0.076)	
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	237	346	358	323	279	222	154	96	24	
R^2	0.369	0.428	0.385	0.421	0.234	0.187	0.035	0.155	0.135	
Ad R^2	0.353	0.418	0.375	0.410	0.218	0.165	-0.005	0.098	-0.048	

This table reports the bank credit supply shock's impact on the frequency distribution of MPL borrower credit quality in the subsample group, estimated from regression equation (1). The dependent variable is the number of MPL borrowers in each of the 20-point FICO score intervals between 650 and 850. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured on a state level. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Year and area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. * p<0.05, ** p<0.01, *** p<0.001

6.2 Excluding Time Fixed effects

Recent studies made on the phenomena of fixed effects empathize that the adjustment for fixed effect in models requires sufficient variability over time independent variables (Hill 2019). In the third part of our analysis, we thus perform tests that exclude time-fixed effects. The regression equation is specified as follows:

$$y_{a,t} = \beta Treated_a * Post_t + Controls_{a,t} + \gamma_a + \varepsilon_{a,t} \qquad (2)$$

We estimate the regression equation (2) in the same manner as regression (1). The dependent variable is set to funded amount, number of loans, and number of borrowers within the ten various ranges, measuring FICO-score and loan size.

Results & Analysis 3. Table (4) presents what we find when setting the independent variable to funded amount and number of loans. Post shock, funded amount increases with an additional $58,988 per area affected by FAS 166/167, and additional loans funded increased by, on average, 4.369. This corresponds to an increase of 29.6 % and 109.5 %, respectively; both coefficients significant at the 0.1 % significance level.

Table 4: Impact of FAS 166/167 on MPLP loan volume

	Amount/1000* ($)	Amount ($)	Number/1000* (#)	Number (#)
	1	2	3	4
Treated*Post	7,266***	58989***	0,001**	4.369***
	(1.666)	(11641)	(0.000)	(0.828)
Income per Capita	0,002***	13.08***	0,000***	0.001***
	(0.000)	(2.471)	(0.000)	(0.000)
Unemployment	-7,829***	-53745.8***	-0,001***	-3.656***
	(0.926)	(6249)	(0.007)	(0.445)
Area Fixed Effects	Yes	Yes	Yes	Yes
Observations	9098	9098	9098	9098
R^2	0.126	0.113	0.124	0.227
Ad R^2	0.125	0.113	0.124	0.226

This table reports the bank credit supply shock's (FAS 166/167) impact on MPL loan volumes, estimated from regression equation (2). The dependent variable is MPL origination volume divided into either the funded amount or the number of loans per area. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured on a state level. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. The asterisk* implies a variable divided per 1000 inhabitants in a state. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Next, we perform frequency tests on FICO-score by estimating Equation (2), setting the dependent variable to the number of loans within each FICO-score interval. As presented in Table (5), coefficients are positive and significant within the range 691-790 (range 3-7). The relative increase within this interval sums up to 35.4 % compared to pre shock levels. More importantly, within the range 751-770 (range 6) there is an additional increase (over the control group) of funded borrowers by 0.539 correspondings to an increase of 33.9 %. This coefficient is significant at the 0.1 % significance level and aligns with our previous findings. The conceptual framework presents these results as an intermediate case, implying that MPLPs serve a low credit quality-segment as well as a fraction of the population served by banks.

Lastly, we test the predictions on frequency on the loan size dimension. The dependent variable is set to the number of loans within each loan size range. The results are presented in Table (6). In contrast to our previous findings, our results indicate a substitutional relationship between MPLPs and banks when allowing for time-invariant effects. We find that the increase in MPL-volume was partly driven by smaller loan originations within the range of $1,000-14,600 (range 1-4). The results are significant at the 1 % significance level for loan sizes between $1,000-4,400 and $7,800-14,600 whereas the interval $4,400-7,800 is significant at 0,1%. To summarize, there was a relative increase by 2.917 borrowers within the loan size-range 1-4 in affected areas post-shock; that is an increase of 38.2 %.

Table 5: Impact of FAS 166/167 on the distribution of MPLP borrower credit quality

	650-670	671-690	691-710	711-730	731-750	751-770	771-790	791-810	811-830	831-850
	1	2	3	4	5	6	7	8	9	10
Treated*Post	0.187	0.857	1.120**	0.647*	0.733***	0.539***	0.224**	0.095	-0.013	.
	(0.315)	(0.456)	(0.349)	(0.263)	(0.140)	(0.103)	(0.072)	(0.057)	(0.163)	.
Income per Capita	0.000**	0.000***	0.000***	0.000***	0.000***	0.000**	0.000*	0.000*	0.000	.
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	.
Unemployment	-0.798***	-2.077***	-1.674***	-0.764***	-0.151*	0.003	0.001	-0.054*	-0.093	.
	(0.145)	(0.245)	(0.191)	(0.121)	(0.061)	(0.043)	(0.030)	(0.026)	(0.095)	.
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3461	5382	5470	5090	4423	3471	2454	1492	377	48
R^2	0.185	0.212	0.220	0.220	0.146	0.109	0.050	0.038	0.091	.
Ad R^2	0.184	0.212	0.220	0.219	0.146	0.108	0.049	0.036	0.084	.

This table reports the bank credit supply shock's impact on the frequency distribution of MPL borrower quality, estimated from regression equation (2). The dependent variable is the number of MPL borrowers in each of the 20-point FICO score intervals between 650 and 850. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured on a state level. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Table 6: Impact of FAS 166/167 on the frequency of MPLP loan size

	1000-4400 1	4400-7800 2	7800-11200 3	11200-14600 4	14600-18000 5	18000-21400 6	21400-24800 7	24800-28200 8	28200-31600 9	31600-35000 10
Treated*Post	0.448**	0.898***	0.827**	0.744**	-0.0379	0.316	-0.178	-0.485***	.	.
	(0.163)	(0.208)	(0.293)	(0.232)	(0.374)	(0.304)	(0.170)	(0.129)	.	.
Income per Capita	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.234***	-0.776***	-1.133***	-0.852***	-0.564***	-1.053***	-0.243**	-0.099	-0.082	0.285**
	(0.070)	(0.110)	(0.153)	(0.129)	(0.120)	(0.148)	(0.087)	(0.090)	(0.127)	(0.087)
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4764	5673	5477	4400	3869	3529	1927	2093	1087	456
R^2	0.133	0.193	0.207	0.199	0.219	0.219	0.139	0.162	0.116	0.047
Ad R^2	0.132	0.193	0.207	0.198	0.218	0.218	0.138	0.160	0.114	0.042

This table reports the bank credit supply shock's impact on the frequency distribution of MPL loan size, estimated from regression equation (2). The dependent variable is set to the number of MPL borrowers in each of the $3400 loan size intervals ranging from $1000- $35000. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured per state belonging to each area. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. * p<0.05, ** p<0.01, *** p<0.001

7 Discussion

Comparing the analysis made on the full sample with the one made on the subsample (both including time fixed effects), one finds similar tendencies. The number of borrowers within the 6th FICO-range increases in both cases, where affected areas in the subsample experienced a higher increase per area. This relative difference in loans is reasonable since the subsample covers areas in states either fully affected or unaffected by banks' credit supply constraints. In this case, an applicant suffers from geographical limitations since she is less likely to receive funding in a neighboring area.

Although these findings suggest a relative increase in loans within the 6th FICO-range, we are unable to apply the conceptual framework to these as the regression equation (1) does not estimate a relative increase in demand for MPLP-loans in affected areas. This concludes that our data in combination with the model adjusting for time fixed effects, fails to recognize FAS 166/167 as a sufficient shock to banks' credit supply, or MPLPs are simply not the ones to serve borrowers formerly served by banks. However, it can be concluded that a positive relationship prevails between affected areas post shock and borrowers within the 6th FICO-score range. The model excluding time fixed effects presents similar tendencies as the model adjusting for them, however more prominent. There is not only a relative increase in the number of borrowers within the 6th range but also in near ranges, in relation to the control group. In contrast to our hypothesis, following Tang (2019), this is presented as an intermediate case in the conceptual framework. Our results suggest that MPLPs' expansion is leading to intensified competition within the consumer credit industry and that they pose a threat to commercial banks, in line with previous literature (Wolfe et al., 2017). Our findings further suggest that MPLPs are expanding the credit pool in the U.S. by taking on riskier borrowers than banks, which is furthermore demonstrated in previous literature (De Roure et al., 2016) (Jiang et al., 2018) (Buchak, G. et al., 2017). An important note is that this study does not consider creditworthiness in objective terms, as the evaluations of borrower credit quality differ between banks and MPLPs. A borrower denoted "high risk" in this study, is viewed from banks' perspectives. Further research taking measures such as default rates of borrowers into account, is therefore encouraged, to reveal the true characteristics of the two creditors' customer segments.

When using the model excluding year fixed effects, we further conclude that MPLPs gain market share when banks experience credit supply constraints. This conclusion is supported by previous studies made (Buchak, G. et al., 2017). Our results suggest that there was an additional increase in loan volume in affected areas over the control group, after the implementation of FAS 166/167. These findings highlight the fact that a critical determinant in our results is the inclusion/exclusion of time fixed effects.

Our findings on the loan size dimension deliver unexpected results. In contrast to Tang (2019), who demonstrate complementarity between banks and MPLPs in terms of loan size, we find the opposite to prevail. From our regression estimates, it is established that the number of borrowers in affected areas applied for smaller loans than those in unaffected areas, after the implementation of FAS 166/167. The conceptual framework explains this as substitutability between banks and MPLPs in regards to loan size. Despite MPLPs' technological advantages and cost-minimizing processes, they do not demonstrate scalability by originating smaller loans than traditional banks. Our findings thus imply that the growth of MPLPs comes at the cost of commercial banks. It must be noted, however, that LendingClub does not provide loans larger than $35,000 indicating that the two creditors operate as substitutes only in the small loan market.

Limitations. Comparing our results with the findings of Tang (2019), it is evident that further research is required to establish what relationship prevails between commercial banks and MPLPs. Other methods should be used to avoid relying on assumptions that are required in the use of the conceptual framework. In case the method of Tang (2019) is followed, several fundamental parts should be acknowledged, that we were unable to empathize, which potentially contributed to our findings. Our definition of an affected area (where at least one affected bank is present) is a critical determinant. By not taking the magnitude of asset consolidation into account, banks were considered equally affected in our empirical analysis. Even though all the affected banks were subject to the regulation to some extent, they may have tightened their credit supply variously, depending on how much was consolidated. Thus, certain affected areas were presumably more exposed to the shock than other affected areas. The geographical definition of our areas is another critical determinant in our empirical analysis. In contrast to Tang (2019), we did not obtain precise geographical information on LendingClub-applicants. The fact that an area was considered affected when an affected bank is located within it, in combination with our areas being of larger sizes than those of Tang (2019), resulted in an uneven ratio between the control and treatment group. The same complex of problems holds for areas' underlying differences. Our use of Sectional Center Facilities (SCF) as a separator of markets precluded collection of precise geographical data. Explanatory variables measuring the banking market structure would heighten the level of accuracy in our model and allow estimates to be precise. To further investigate what relationship prevails between MPLPs and banks, more precise measures are encouraged. Furthermore, as important as it is to investigate different markets due to diverse regulatory environments, as critical is the examination of various MPLPs on every market. These might differ in strategies and thus pose a threat to commercial banks to different extents.

8 Conclusion

Marketplace lending has changed the consumer credit market dramatically since its first emergence in 2005. With the reputation of processing loan applications more cost-efficiently at a higher speed, enabled by the use of advanced technology tools and algorithms, it is widely assumed that they are supplying loans not served by commercial banks. By the use of a conceptual framework developed by Tang (2019), we establish that Marketplace lenders serve borrowers that banks consider too risky and simultaneously attract a fraction of borrowers qualifying for a bank loan.

We also investigate the relationship between banks and MPLPs in terms of loan size. Banks face high fixed costs when originating loans which lead them to reject smaller loans to a great extent. On the contrary, the technological advantages of MPLPs are often portrayed as an advantage in scalability. However, we find that Marketplace lending platforms do not originate smaller loans than banks but rather operate as a substitute to commercial bank lending on the loan size dimension.

The expansion of MPLPs within the U.S. financial markets has raised concerns among incumbents. We establish that this concern is justified. Although the emergence of Marketplace lenders entails an expansion of the credit pool in the U.S., this consequence is not as apparent as the increase in competition that comes along with it. However, due to the dynamic nature of the regulatory and technological environment, MPLPs operate within, further research is encouraged.

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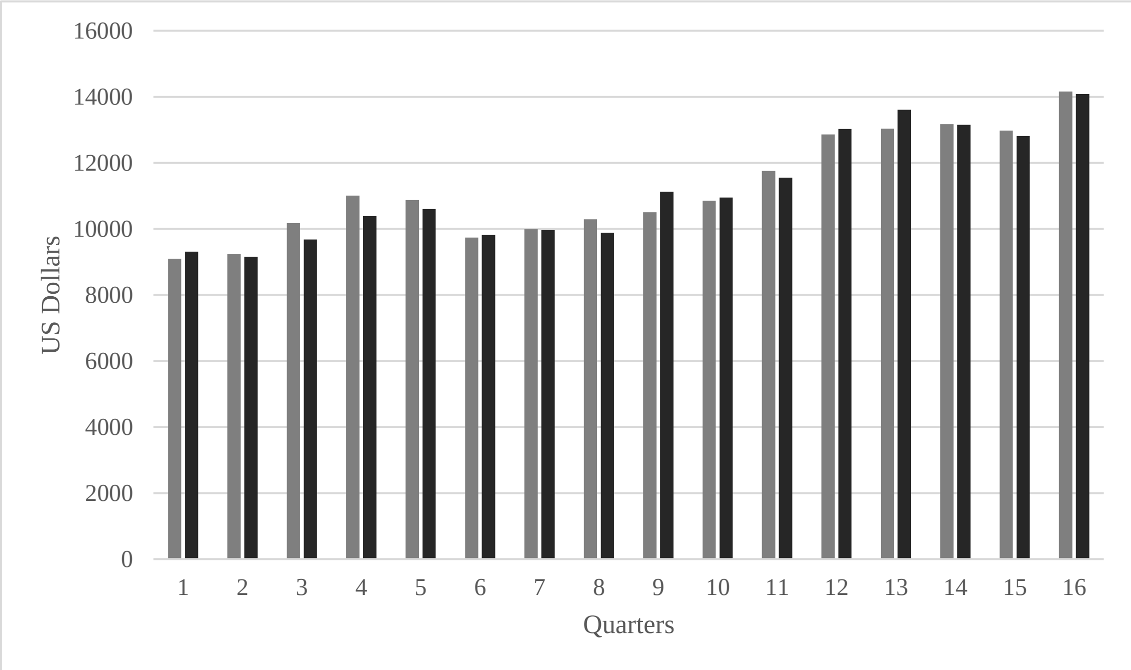
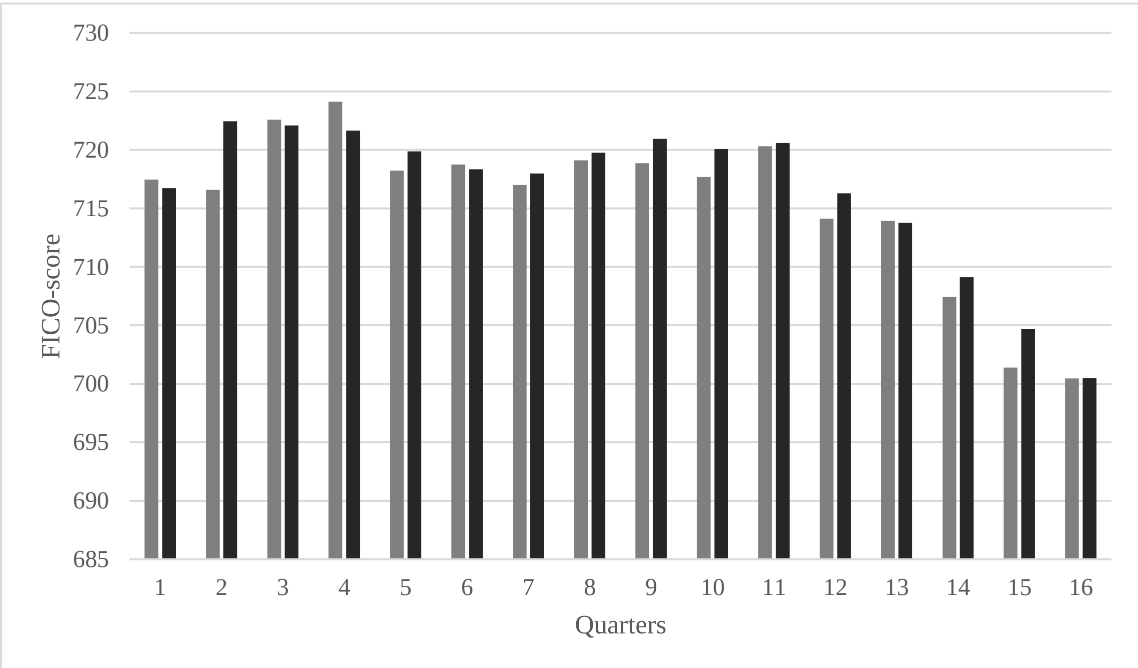
Appendix

Graph 1: Average Funded amount for control vs treatment group, LendingClub. Quarter 1 = Q1 2009.



Graph 2: Average FICO-score for control vs treatment group, LendingClub. Quarter 1 = Q1 2009.



These two graphs illustrates LendingClub’s average funded amount and FICO-score 2009-2012 where light grey line depicts the control group and the darker line the treatment group.

Table A1: Definitions of Variables

Variable	Definition	Source
Credit Supply Shock		
Post	Time dummy variable that takes value 1 after 2010 (post shock)	
Treated	Takes value 1 if at least one bank is affected by FAS 166/167 in a given area	Call Report, Schedule RC-V
Treated*Post	Interaction variable (diff-in-diff estimator) that takes value 1 if the loan originates from an affected area post shock	Call Report, Schedule RC-V
County demographics		
Personal Income per capita	Personal income per capita in a given area 2009-2012	Bureau of Economic Analysis
Population	Total population in a given state 2009-2012	Bureau of Economic Analysis
Unemployment rate	Unemployment rate in a given state 2009-2012	U.S. Bureau of Labor Statistics
Loan & Borrower characteristics		
FICO Score	FICO score indicating the credit worhtiness of a borrower. Starting from 650 ranging to 850.	LendingClub
Funded Amount	The dollar amount requested by the borrower and funded by LendingClub.	LendingClub
Maturity	Maturity of the loan, takes value 0 if maturity is 36 months and 1 if maturity is 60 months.	LendingClub
DTI	Debt-to-income ratio of a borrower	LendingClub
Interest Rate	The interest rate set by LendingClub, accepted by both borrower and lender.	LendingClub
Employment length	Self-reported employment length of the borrower	LendingClub
Mortgage	Status of home ownership reported by borrower at registration. Takes value 1 if the borrower owns his/her home under mortgage.	LendingClub
Home Owner	Status of homeownership reported by borrower at registration. Takes value 1 if the borrower owns his/her home completely.	LendingClub
Annual Income	The annual income of the borrower. Self-reported to LendingClub under registration.	LendingClub

Table A2: Summary of Statistics – Treatment and Control group

Panel A: Pre-shock

Variable	*Control group*						*Treatment group*						p-value
	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	
Funded Amount	1000	10172	9000	25000	6181	1580	1000	9940	9000	25000	6071	13402	0.152
FICO	664	719	714	814	37	1580	664	720	714	824	36	13402	0.662
Nr of loans/Area	1	12	9	45	11	1580	1	11	7	64	11	13402	0.000
Debt-to-income	0	0.123	0.123	0.250	0.064	1580	0	0.128	0.130	0.250	0.066	13402	0.003
Employment length	1	4.724	4	10	3	1544	1	4.799	4	10	3	13145	0.410

Panel B: Post-shock

Variable	*Control group*						*Treatment group*						p-value
	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	
Funded Amount	1000	12983	11200	35000	8014	7726	1000	12972	11100	35000	8063	62952	0.910
FICO	664	708	699	850	33	7726	664	709	704	850	34	62952	0.000
Nr of loans/Area	1	50	34	241	50	7726	1	43	27	233	45	62952	0.000
Debt-to-income	0	0.152	0.150	0.350	0.074	7726	0	0.159	0.158	0.350	0.075	62952	0.000
Employment length	1	5.562	5	10	3	7430	1	5.750	5	10	3	60730	0.000

The table reports the summary of statistics of the main sample divided into four corresponding groups. Panel A reports statistics of the treatment group and the control group two years before FAS 166/167, i.e. 2009-2010. Panel B reports statistics of the treatment group and the control group two years after FAS 166/167, i.e. 2011-2012. The p-values in the last column are for a two-sided difference-in-means test.

Table A3: Summary of Statistics Subsample – Treatment & Control group

Panel A: Pre-shock

	Control group						*Treatment group*						
Variable	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	p-value
Funded Amount	1000	9265	8000	24974	5681	491	1000	9463	8375	25000	5915	513	0.588
FICO	664	716	714	809	35	491	664	720	714	819	37	513	0.082
Nr of loans/Area	1	7	6	19	5	491	1	11	9	29	7	513	0.000
Debt-to-income	0	0.126	0.126	0.249	0.064	491	0	0.122	0.121	0.250	0.064	513	0.239
Employment length	1	4.722	4	10	3	491	1	4.630	4	10	3	500	0.669

Panel B: Post-shock

	Control group						*Treatment group*						
Variable	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	Min	Mean	Median	Max	Std. Dev.	Nr of Obs	p-value
Funded Amount	1000	12358	10575	35000	7777	2516	1000	12150	10000	35000	7684	2687	0.332
FICO	664	706	699	824	32	2516	664	707	699	829	33	2687	0.296
Nr of loans/Area	1	32	26	97	23	2516	1	55	45	162	43	2687	0.000
Debt-to-income	0	0.158	0.157	0.349	0.073	2516	0	0.160	0.158	0.349	0.074	2687	0.419
Employment length	1	5.536	5	10	3	2409	1	5.546	5	10	3	2542	0.919

The table reports the summary of statistics of the subsample divided into four corresponding groups. Panel A reports statistics of the treatment group and the control group two years before FAS 166/167, i.e. 2009-2010. Panel B reports statistics of the treatment group and the control group two years after FAS 166/167, i.e. 2011-2012. The p-values in the last column are for a two-sided difference-in-means test.

Table A4: Control variables - demographics

Variable	Min	Mean	Median	Max	Std, Dev	Nr of Obs
	Control variables - demographics					
Population	559851	16100000	11500000	8760000	12100000	85660
Income per Capita	5014.937	45037	44641.47	68397.01	6743	85660
Unemployment Rate	3.9	8.781	8.6	14.9	1.712	85660

This table reports the demgeographical control variables. All variables are defined at state level

Table A5: Impact of FAS 166/167 on MPLP loan volume

	Amount/* ($)	Amount ($)	Number/* (#)	Number (#)
	1	2	3	4
Treated*Post	1.532	21146	0.002	1.230
	(2.569)	(13366)	(0.010)	(0.932)
Income per Capita	0.000	2.545**	0.000	0,000*
	(0.000)	(1.073)	(0.000)	(0.000)
Unemployment	-0.193	-2106.900	0.000	-0.260
	(1.005)	(8372.3)	(0.000)	(0.602)
Year Fixed Effects	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes
Observations	9098	9098	9098	9098
R^2	0.182	0.305	0.066	0.068
Ad R^2	0.181	0.305	0.066	0.068

This table reports the bank credit supply shock's (FAS 166/167) impact on MPL loan volumes, estimated from regression equation (1). The dependent variable is MPL origination volume divided into either the funded amount or the number of loans per area. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured per state belonging to each area. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Year and area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. The asterisk* implies a variable divided per 1000 inhabitants in a state.

* p<0.05, ** p<0.01, *** p<0.001

Table A6: Impact of FAS 166/167 on the frequency distribution of MPLP loan size

	1000-4400 1	4400-7800 2	7800-11200 3	11200-14600 4	14600-18000 5	18000-21400 6	21400-24800 7	24800-28200 8	28200-31600 9	31600-35000 10
Treated*Post	0.156	0.248	0.232	0.279	0.013	0.173	0.262	-0.020	.	.
	(0.148)	(0.223)	(0.295)	(0.294)	(0.281)	(0.273)	(0.228)	(0.162)	.	.
Income per Capita	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment	-0.022	-0.144	-0.123	-0.153	0.018	-0.123	0.053	0.127	-0.059	0.356**
	(0.094)	(0.161)	(0.218)	(0.193)	(0.150)	(0.199)	(0.109)	(0.114)	(0.147)	(0.119)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4764	5673	5477	4400	3869	3529	1927	2093	1087	456
R^2	0.165	0.250	0.280	0.247	0.265	0.273	0.162	0.176	0.116	0.050
Ad R^2	0.164	0.250	0.279	0.246	0.264	0.272	0.160	0.174	0.113	0.043

This table reports the bank credit supply shock's impact on the frequency distribution of MPL loan size, estimated from regression equation (1). The dependent variable is set to the number of MPL borrowers in each of the \$3400 loan size intervals ranging from \$1000- \$35000. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured per state belonging to each area. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Year and area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A7: Impact of FAS 166/167 on MPLP loan volume in subsample group

	Amount/1000* ($)	Amount ($)	Number/1000* (#)	Number (#)
	1	2	3	4
Treated*Post	28.430	82254	0.002	6.518
	(18.810)	(59308)	(0.002)	(4.492)
Income per Capita	79.580	14019	0.005	-7.572
	(76.800)	(282607)	(0.006)	(21.960)
Unemployment	-6.954***	-38455.9***	-0.000***	-2.600***
	(1.433)	(7223.7)	(0.000)	(0.535)
Year Fixed Effects	Yes	Yes	Yes	Yes
Area Fixed Effects	Yes	Yes	Yes	Yes
Observations	535	535	535	535
R^2	0.319	0.428	0.321	0.439
Ad R^2	0.311	0.421	0.314	0.433

This table reports the bank credit supply shock's impact on MPL loan volumes in the subsample group, estimated from regression equation (1). The dependent variable is MPL origination volume divided into either the funded amount or the number of loans per area. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured per state belonging to each area. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Year and area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. The asterisk* implies a variable divided per 1000 inhabitants in a state. * p<0.05, ** p<0.01, *** p<0.001

Table A8: Impact of FAS 166/167 on the frequency distribution of MPLP loan size

	1000-4400 1	4400-7800 2	7800-11200 3	11200-14600 4	14600-18000 5	18000-21400 6	21400-24800 7	24800-28200 8	28200-31600 9	31600-35000 10
Treated*Post	1.139	1.821	1.580	1.092	1.294	0.660	0.537	-1.148	.	.
	(0.606)	(1.152)	(1.195)	(0.737)	(0.717)	(0.783)	(0.362)	(0.808)	.	.
Income per Capita	-0.769	-7.792	-14.780	3.599	-5.236	5.835	7.818***	-0.431	-441.800	-52.130
	(4.778)	(8.953)	(7.809)	(6.288)	(3.626)	(4.018)	(2.166)	(4.432)	(340.0)	(476.1)
Unemployment	-0.261	-0.251	-0.924***	-0.763**	-1.743***	-1.220**	-0.411	-1.636**	-0.925	-0.386
	(0.144)	(0.189)	(0.186)	(0.229)	(0.300)	(0.373)	(0.315)	(0.581)	(0.651)	(0.914)
Year Fixed Effects										
Area Fixed Effects										
Observations	327	376	349	289	251	206	150	110	60	53
R^2	0.302	0.359	0.409	0.341	0.427	0.432	0.209	0.257	0.190	0.017
Ad R^2	0.289	0.348	0.398	0.327	0.413	0.414	0.175	0.221	0.147	-0.043

This table reports the bank credit supply shock's impact on the frequency distribution of MPL loan size in the subsample group, estimated from regression equation (1). The dependent variable is set to the number of MPL borrowers in each of the $3400 loan size intervals ranging from $1000- $35000. The impact is measured per area (defined as the area of the first 3 digits in each U.S. zip code). The control variables are measured per state belonging to each area. Treated is a variable indicating whether there are affected banks in in the area and the Post is a dummy set to 1 for years after 2010 and set to 0 otherwise. Year and area fixed effects are included in all regressions. Standard errors are clustered at the area level and are given in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Table A9: Hausman's test for fixed/random effects

Model (dependent variable)	Chi-Sq Statistics	p-Values	Fixed/Random
Funded amount per 1000	84.85	0.000	Fixed Effects
Funded amount	313.66	0.000	Fixed Effects
Number of loans per 1000	63.98	0.000	Fixed Effects
Number of loans	357.04	0.000	Fixed Effects
FICO interval 650-670	762.73	0.000	Fixed Effects
FICO interval 671-690	413.71	0.000	Fixed Effects
FICO interval 691-710	453.67	0.000	Fixed Effects
FICO interval 711-730	-	-	
FICO interval 731-750	62.52	0.000	Fixed Effects
FICO interval 751-770	22.54	0.000	Fixed Effects
FICO interval 771-790	80.2	0.000	Fixed Effects
FICO interval 791-810	19.15	0.000	Fixed Effects
FICO interval 811-830	15.82	0.001	Fixed Effects
FICO interval 831-850	N/A	N/A	
Loan size interval 1000-4400	107.68	0.000	Fixed Effects
Loan size interval 4400-7800	306.1	0.000	Fixed Effects
Loan size interval 7800-11200	-	-	
Loan size interval 11200-14600	-	-	
Loan size interval 14600-18000	200.38	0.000	Fixed Effects
Loan size interval 18000-21400	1257.87	0.000	Fixed Effects
Loan size interval 21400-24800	198.58	0.000	Fixed Effects
Loan size interval 24800-28200	304.59	0.000	Fixed Effects
Loan size interval 28200-31600	84.1	0.000	Fixed Effects
Loan size interval 31600-3500	7.52	0.0233	Fixed Effects