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Abstract

Fintech has been playing an increasing role in shaping financial and banking landscapes. In this paper, we use account-level data from LendingClub and Y-14M data reported by U.S. banks with assets over $50 billion to examine whether the fintech lending platform could expand credit access to consumers. We find that LendingClub's consumer lending activities have penetrated areas that may be underserved by traditional banks, such as in highly concentrated markets and in areas that have fewer bank branches per capita. We also find that the portion of LendingClub loans increases in areas where the local economy is not performing well.

Keywords: fintech, LendingClub, marketplace lending, banking competition, shadow banking, peer-to-peer lending
JEL Classification: G21, G28, G18, L21

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I. Introduction and Background on the Market for Unsecured Consumer Lending

We have seen the explosive growth of online alternative lending since 2010. Advances in fintech lending and the use of big data have started to change the way consumers and small businesses secure financing. While the number of these nonbank lenders has been growing rapidly, the volume of their lending is still far from approaching the volume of traditional bank lending. There have been a few setbacks in these markets recently, but the growth has started to pick up.[1] It is unclear what the long-term growth trend will be for this industry and how it will impact the financial landscape.

As with any shadow banking entity, there are concerns about the potentially uneven regulatory playing field. While the growth of nonbank lending may raise some regulatory concerns, these nonbank lenders' fintech platforms and their ability to use nontraditional alternative information sources to collect soft information about creditworthiness may provide significant value to consumers and small business owners, especially those who have little or no credit history. In addition, as more are added to the pool of small business owners and the consumer population, millenniials are more comfortable with technology and therefore may be more comfortable dealing with an online lender than dealing with a traditional bank.[2]

TransUnion (2017) reported that, as of 2017:Q3, the personal unsecured loan market had reached nearly $112 billion. Fintech lenders that represented only 3 percent of this market in 2010 are now estimated to have a 30 percent market share. Other participants in the market are traditional banks, credit unions, and traditional finance companies. Despite the increases in consumer credit over the last several years, the 2016 Survey of Consumer Finance (Bricker et al., 2017) found that 20.8 percent of the families felt credit constrained, and this result has been fairly consistent in recent years.

Credit cards are the most comparable bank product to fintech consumer loans because they are the bank product consumers turn to most often when they need unsecured credit. In addition, in this study, we focus on fintech consumer loans that are used by the borrowers to pay off their credit card balances or for debt consolidation. Credit cards account for the lion's share of unsecured

[1] Athwal (2016) reports that, despite the market volatility and concerns around recent issues at LendingClub, "most alternative lending startups continue to experience phenomenal growth."

[2] See Jagtiani and Lemieux (2016) for more on the roles of technology in small business lending and partnership models between banks and fintech lending platforms.

consumer debt ($731 billion in 2017:Q3).[3] Interestingly, there is evidence that credit card lending is related to geographic location. Carbo-Valverde and Perez-Saiz (2016) find that the probability of obtaining a credit card or line of credit from a bank increases 60 percent when the bank has a branch within 10 km of the household.

As with other technology startups, there are a plethora of firms, and the landscape is changing constantly. Generally, fintech lenders operate in the consumer, small business, or real estate market. The first fintech lending platforms appeared in 2005. LendingClub and Prosper, which were started in 2006 and 2007, respectively, are currently the biggest players in the consumer personal lending space. Galland (2018) estimated that LendingClub will obtain a 45 percent market share, with Avant and SoFi being two other prominent firms in the fintech consumer lending market. This paper uses LendingClub data to investigate whether banking concentration impacts the presence of LendingClub and its quantity of fintech lending in a region.

We explore whether fintech firms expand the availability of credit in areas that may be underserved by traditional banks. We examine the relationship between the various measures of credit gaps (such as banking market concentration, declining bank branches, bank branches per capita) and the expansion of fintech lending for consumer unsecured loans, focusing on loans in which the borrower has stated the purpose of the loan to be refinancing credit cards and/or other debt consolidation. We compare the results to similar credit card lending (through the traditional lending channel) made by banks with over $50 billion in total assets that report Y-14M credit card (account-level) data monthly.

The rest of the paper is organized as follows. Section II presents the literature review. In Section III, we describe our data from the various sources. Section IV explores the geography of fintech loans that are made for consumers to pay off credit card balances and for other debt consolidation purposes versus credit card loans made by large banks (with assets greater than $50 billion). In Section V, we explore the impact of market concentration and local credit gaps on fintech consumer lending. Section VI presents regression analysis to confirm the stories based on heat maps and charts. Section VII concludes and provides a discussion of policy implications.

[3] This credit card volume dwarfs the personal unsecured loan market, which also accounts for the approximately 57 percent of families with credit cards who only used them for convenience and did not carry a balance (2016 Survey of Consumer Finance, as reported in Bricker et al. (2017)). Our data exclude credit cards that are used for convenience; only cards that carry a balance are included in our analysis in this paper.

II. The Literature

Information asymmetries have been an important issue in the banking literature. Jaffee and Russell (1976) and Stiglitz and Weiss (1981) explained how information asymmetries between borrowers and lenders can lead to a market equilibrium in which credit is rationed. Frame, Srinivasan, and Woosley (2001) and Einav, Jenkins, and Levin (2013) found that technologies such as credit scoring reduce information asymmetries between borrowers and lenders and expand credit availability in the small business and auto loan markets, respectively. Morse (2015) reviewed the existing literature on the topic of fintech lending, focusing on whether the type of technologies employed by fintech firms can mitigate information frictions in lending. She posits that access to or price of credit could be improved by better capturing soft information contained in proximity information and better profiling of loan applicants.

Many papers have found that relationships and soft information can provide advantages in borrower screening and reduce information asymmetries in banking — see, for example, Petersen and Rajan (1994); Boot and Thakor (2000); Berger and Udell (2002); Liberti and Petersen (2017); Berger, Miller, Petersen, Rajan, and Stein (2005); Stein (2002); Karlan (2007); Iyer and Puri (2012); and Schoar (2014). Researchers are beginning to look at this issue for fintech lending. Freedman and Jin (2011); Everett (2015); Lin, Prabhala, and Viswanathan (2013); and Lu, Gu, Ye, and Sheng (2012) all look at using various types of soft information related to a borrower's social network to infer creditworthiness. However, inferring credit risk from one's social network does present issues related to consumer regulations around fair and equal access to credit that need to be addressed in the use of such data.

Another issue with the use of this type of information is that if funding is limited to connections with friends, there is a limited ability to improve credit conditions in the aggregate. Researchers have investigated identifying other soft information that could be leveraged in an online loan application. Michels (2012) finds that voluntary disclosure of hard information, such as income, income source, education, and other debt, yields lower interest rates. Herzenstein, Sonenshein, and Dholakia (2011) use text analysis of borrower narratives and find limited usefulness. Gao and Lin (2013) use text mining and find that more complex narratives correlate with higher default rates. Ravinia (2013); Pope and Sydnor (2011); and Duarte, Siegel, and Young (2012) analyze photo-based discrimination. The results are mixed, with some findings of bias toward attractive or trustworthy faces and against racial minorities. A central issue to the value of this line of research is that once borrowers understand how lenders use this information, borrowers have the option to alter the way they submit text or photo information.

Another way to leverage proximity is to use local economic information as a proxy for personal knowledge. Ramcharan and Crowe (2013) find that crowd investors consider relevant local house price data in the loan approval process and the interest rate to charge on the loan. Bertsch, Hull, and Zhang (2016) study the impact of macroeconomic factors on perceived default probabilities and therefore individual loan rates. Using Prosper and LendingClub data, the authors find that borrowers in states with higher unemployment rates receive higher interest rates, even after controlling for borrower and loan characteristics, including employment status. They also examine how expected future improvements in the economy, as measured by changes in the real yield curve, induce decreases in interest rates in the peer-to-peer market. Buchak, Matvos, Piskorski, and Seru (2017) study the rise of shadow banks and fintech firms in the residential lending market. They find that fintech penetration is positively associated with more minority residents, lower unemployment, higher bank regulatory burden, and a more concentrated market. Havrylchyk, Mariotto, Rahim, and Verdier (2017) find that fintech lenders expanded in areas where there was a lower density branch network. Chen, Hanson, and Stein (2017) find that nonbank finance companies that provide credit to small businesses grew most rapidly after the financial crisis in counties where the largest four bank holding companies had the largest presence, responding to a legitimate shortfall in the supply of small business credit.

Overall, research studies indicate that fintech firms have the potential to address information asymmetries. Research has shown that fintech lenders can leverage information on a borrower's social network, appearance, and ability to disclose. Some work has shown that variables on local conditions can serve as a proxy for some of the alternative information discussed. Additionally, newer research has found that banking market concentration is also a factor in fintech growth. In this paper, we examine how both local economic information and banking market concentration impact the quantity of fintech lending in a specific geography.

III. The Data

Consumer Loans from a Fintech Platform: We use data from LendingClub's consumer platform as representative of fintech consumer lending for two reasons. First, LendingClub is one of the few lenders that have made their data publicly available. Second, it is one of the larger, more established alternative lenders in this space; therefore, the results here are likely to apply more broadly. We use loan-level data (with detailed information about the loan and the borrower) and 5-digit zip code segment-level data (with distribution of loans by zip codes and years) from

LendingClub's consumer loans that were originated from 2010 to 2016.[4] The loan-level database contains loan-specific information (i.e., loan rate, maturity, and origination date), risk characteristics of the borrowers (i.e., FICO scores, employment, debt-to-income (DTI) ratio, age, and homeownership), and other risk characteristics. We focus on loans that were specified for two purposes: credit cards and debt consolidation. As shown in Figure 1, these loans account for almost 90 percent of all LendingClub consumer loans as of 2014–2015 origination vintages.

Since the location of loans in the public version of the LendingClub data is presented at the 3-digit zip code level, we also use proprietary segment-level data at the 5-digit zip code segment level from LendingClub as a supplement to more precisely identify the location of the loans. We observe the differences between fintech and traditional lending channels in terms of lending to fill potential credit gaps in underserved areas.

Traditional Lending Channel (Credit Card Loans): To explore comparable loans made by traditional banks, we use loan-level (account-level) credit card data from the Federal Reserve's Y-14M reports, reported monthly by large banks with at least $50 billion in assets. From this data set, we focus on the reporting period 2014–2016 and include only those accounts that were originated in 2015 or earlier to examine 12 months of performance.[5] We do not include accounts that were originated prior to 2014 to avoid the sample selection bias in our analysis. Accounts that were originated earlier and were closed (due to default or other reasons) would have been dropped from the Y-14M reports in 2014–2016. We do not include charge cards in the analysis because there is no associated credit limit for these cards. In addition, for credit cards, we only include consumer cards that were issued for general purposes and private label cards (business cards and corporate cards are not included). Since consumers report that they borrow from LendingClub to pay off credit cards, we compare LendingClub loans for credit card (and debt consolidation) purposes with Y-14M consumer cards that carry balances (where consumers actually borrow), so-called revolvers. Y-14M data contain similar information that is available in the LendingClub data set (i.e., borrowers' risk characteristics, origination date, origination amount, location of the borrowers, and borrowers' credit scores). A few variables are reported by LendingClub, but not in Y-14M reports,

[4] The data are much cleaner after 2009. Between April and October 2007, LendingClub suspended sales of notes to lenders owing to the requirement to register these as borrower-dependent note securities with the U.S. Securities and Exchange Commission. For a period prior to April 2008, LendingClub also suspended lending when it entered into an arrangement with WebBank that allowed it to avoid individual state usury laws. In addition, some economic variables are not consistently available at the 5-digit zip code level before 2010.

[5] We note that the stress testing data in the Y-14M reports are constrained by the limited number of very large systemically important banking institutions and thus may not fully represent the entire population of U.S. banking firms.

such as homeownership and DTI ratio at origination. We estimate market concentration measures using the amount of credit card lending activities reported by these banks. The Herfindahl-Hirschman Index (HHI), a commonly accepted measure of market concentration, is calculated in this paper at different granularities (at the 5-digit zip code, 3-digit zip code, and county levels) based on the market share of credit card lending and the number of reporting banks that make credit card loans in the market.[6] The calculated HHI approximates the degree of market concentration (or degree of competition) in the credit card lending market.[7] The U.S. Department of Justice defines a concentrated market as one that has an HHI above 2,500.[8] The HHI measure is useful in exploring the role of LendingClub in highly concentrated lending markets.

Characteristics of Overall Consumers with Credit History: We compare LendingClub data with the overall consumer population with credit records in the consumer credit panel data set. The Federal Reserve Bank of New York/Equifax Consumer Credit Panel (FRBNY Equifax CCP) data set contains consolidated financial information about consumers who have a credit record and account-specific information about each of the credit accounts associated with those consumers.[9] Our FRBNY Equifax CCP sample includes only the primary consumers (with assigned consumer identification) that have at least three continuous years of credit records (avoiding the possibility of fake accounts) and have been assigned some type of credit score.

We compare the trends for LendingClub borrowers with those from the overall U.S. consumer population. The summary of these differences for homeownership[10] and DTI are presented in Figures 2A and 2B, respectively. Figure 2A shows that LendingClub borrowers are less likely to be homeowners compared with the general U.S. consumer population in the FRBNY

[6] A market definition in terms of 5-digit zip codes corresponds to roughly the size of a town. There are about 43,000 5-digit zip codes in the U.S. At a less granular level, we estimate the HHI measures at the 3-digit zip code and county levels. There are 929 3-digit zip codes and about 3,000 counties in the U.S.

[7] For the HHI calculation, only credit cards that carry a balance (revolvers) are included in the analysis. Transactors are excluded from all the analyses in this paper because the rate and behavior of transactors are not comparable with LendingClub loans.

[8] An HHI less than 1,500 indicates an unconcentrated (or competitive) banking market, an HHI between 1,500 and 2,500 indicates moderate concentration, and an HHI above 2,500 indicates a highly concentrated banking market.

[9] Primary consumers are followed through time on the FRBNY Equifax CCP, allowing us to examine their behavior over the years. Those who are part of the primary consumer's household would also be included in the database as long as they continue to belong to a primary consumer's household; otherwise, they are dropped from the database.

[10] From the FRBNY Equifax CCP, we define homeownership as having at least one mortgage with at least a $100 balance.

Equifax CCP sample (people with credit records).[11] Our data indicate that as of 2012–2016, about 40 percent of LendingClub borrowers did not own a home. Figure 2B shows that LendingClub borrowers are more leveraged than general U.S. consumers from the FRBNY Equifax CCP population.[12] The DTI ratio calculated from the FRBNY Equifax CCP data is the median total debt (excluding mortgages) divided by median household income.[13] The DTI for the average U.S. population is significantly lower than for LendingClub borrowers.

Figures 3A and 3B show the distribution of the borrowers' FICO scores for LendingClub borrowers versus the overall U.S. consumers from FRBNY Equifax CCP. LendingClub borrowers do not have very low FICO scores. Their average FICO score is only very slightly below the average of overall Equifax consumers. This analysis suggests that on average LendingClub borrowers are less likely to own homes and are more highly leveraged but have credit scores within the normal range of the consumers represented in the FRBNY Equifax CCP. These data do not seem to indicate that LendingClub borrowers on average represent the lower end of creditworthy consumers.

Deposit Activities and Branching Data: In addition to the market concentration measure based on credit card lending activities from Y-14M data (described earlier), we use data on market concentration based on the FDIC Summary of Deposits (SOD) data, which report deposits that each banking organization accepted from each bank branch each reporting year. The calculated HHI from deposit-taking by banks would approximate the degree of market concentration in the banking market. In addition, we explore other similar variables such as number of bank branches per capita in the local areas (5-digit zip code, 3-digit zip code, and county). A smaller number of branches per capita or declining bank branches in the community could serve as a proxy for the degree of credit gap that may exist in the community. We obtain branching information from the FDIC SOD database.[14]

Economic Variables: We collect various economic factors from the Census Bureau database and from the Haver Analytics database. We use data on economic factors, such as local unemployment, local average household income, local home price index, and population density.

[11] Homeowners who have already paid off all their mortgage loans are not captured in this analysis, which may result in an underestimation of the ratio of homeowners from the general FRBNY Equifax CCP population — with no impact on the ratio of homeownership for LendingClub borrowers.

[12] LendingClub borrowers' reported DTI ratio is defined as the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LendingClub loan, divided by the borrower's self-reported monthly income.

[13] For total debt calculation, we exclude severely delinquent balances (at least 120 days past due).

[14] When there is no bank branch in the zip code, we convert 0 branch to 0.1 to avoid the indefinite amount of change when calculating the change in bank branches in terms of ratio (rather than the number of branches).

We use the most granular level of economic factors where appropriate and possible — at the 5-digit zip code, county, or 3-digit zip code level.

IV. Heat Maps of Fintech Loans versus Traditional Loans

We investigate whether LendingClub made loans in areas where there may be an unmet demand for consumer credit. Specifically, we explore the geographic distribution of LendingClub loans, focusing on areas where: 1) the credit card lending market is highly concentrated; 2) the number of bank branches decreased significantly; 3) there are fewer bank branches per capita; and 4) the average income per capita is low (to proxy low- and middle-income neighborhoods).

Geographic Distribution of LendingClub Loans: LendingClub consumer lending was initially concentrated in the Northeast and on the West Coast. As of 2016, LendingClub developed its national footprint, with $28 billion of total loans originated. Figure 4A presents the LendingClub consumer loan portfolio distribution as of 2010 and 2016, respectively. The map is color-coded based on the portfolio concentration in the county — five brackets (colors) — where darker colors represent a larger share of LendingClub's loan portfolio.

Similarly, Figure 4B shows the geographic distribution of credit card loans made by large U.S. banks. The distribution looks similar to LendingClub's portfolio as of the same time (June 2016), where larger proportion of loans are more concentrated on the West and East Coasts. The differences lie mostly in the southeast and northeast regions. Further analysis (presented in Section VI) suggests that LendingClub seems to have more presence in counties that have fewer bank branches per capita and when the credit card loan market is more concentrated (i.e., where greater share of credit card loans in the county are originated by a fewer number of large banks).

LendingClub loans were concentrated along the West and East Coasts in 2010 (about three years after its inception). By 2016, its lending activities expanded to cover roughly the entire country, with the exception of a small pocket (in white) in the Midwest.[15] However, the concentration seems to remain on the West and East Coasts. We explore whether LendingClub's activities have had a significant relationship with the various indicators for underserved areas.

V. Potential to Provide Credit in Underserved Areas

We start by examining LendingClub's portfolio distribution in terms of banking market concentration, as measured by the deposit market HHI. We define the market in two ways in terms

[15] Iowa appears to be the exception because of its unique state law, as discussed in Wolfe and Yoo (2017).

of 3- and 5-digit zip codes. The deposit market HHI calculation is based on the deposit-taking activities that each bank branch is making in the various zip codes in a given year, based on the FDIC SOD data. The overall landscape of the U.S. banking market (5-digit zip code market) based on banking (deposit-taking) activities is presented in Figure 5A, where approximately 80 percent of the markets are considered highly concentrated (purple). Figure 5B shows that about 50 percent of all LendingClub consumer loans outstanding are in the highly concentrated markets with the HHI greater than 2,500.

Then, we explore the distribution of consumer loans made by LendingClub (in terms of the number of accounts and the total outstanding amount) across counties with varying degrees of bank branching activities. We divide the U.S. market into 929 zip code groups (3-digit zip codes) and assign them to four segments based on the percentage change in the number of bank branches in a 3-digit zip code in each year. The four segments are (1) no decline in bank branches, (2) up to a 5 percent decline, (3) a 5–10 percent decline, and (4) more than a 10 percent decline. Figure 6A shows the landscape of the banking markets during the period from 2010 to 2015 based on the percentage changes in bank branches in the 3-digit zip code group. About 10 percent of all the banking markets experience at least a 5 percent decline (green and purple) in bank branches from 2014 to 2015. Figure 6B shows that for the same period (2014–2015), about 40 percent of LendingClub consumer loans were made in the markets that experienced at least a 5 percent decline (green and purple) in bank branches. Over the years, an increasing percentage of LendingClub loans were originated in markets that had a declining number of bank branches. More than 75 percent of newly originated loans in 2014 and 2015 were in areas where bank branches declined in the local market.

Figure 7A shows the landscape of the banking markets in the period between 2010 and 2016 based on the number of bank branches per capita (100,000 people) in a county. Less than 30 percent of all the banking markets have less than 30 bank branches for each 100,000 people. Figure 7B shows that almost 70 percent of LendingClub newly originated loans in 2014 and 2015 were in these areas (blue and red) where there were fewer bank branches per capita. Again, LendingClub seems to be filling a potential credit gap.

In addition, we explore market concentration in the credit card lending market. The HHI is calculated for each 3-digit zip code, based on the credit card balance (loans) issued by each of the reporting banks. The landscape of the credit card lending market is presented in Figure 8A for the period 2013–2016.[16] By design, the credit card lending market is more concentrated than the deposit market because there are not as many banks issuing credit card loans. About 80 percent of all the 3-digit zip code markets had an HHI greater than 2,500 (purple and green color) in 2014 and 2015. About 90 percent of LendingClub loans (for credit cards and debt consolidation purposes) as of 2014 and 2015 were made in these highly concentrated card markets, with HHI greater than 2,500 as shown in Figure 8B. This analysis points to the possibility that fintech lenders can provide credit in areas that may be underserved by traditional banks.

VI. Regression Analysis

We further explore this (whether fintech lending activities penetrate areas that need additional credit) with regression analysis, using loan-level data from LendingClub, in conjunction with Y-14M loan-level data, and other data sources. It is important to note that the borrower's address reported on the LendingClub website is limited to the 3-digit zip code (there are about 900 3-digit zip codes in the U.S.), which imposes a limit on the level of granularity in this study. We calculate all the economic and other related variables to match the 3-digit zip code areas accordingly.

The dependent variables are defined for LendingClub loans for credit cards and debt consolidation as:

1) Number of accounts originated in a specific 3-digit zip code in a specific year;
2) Log of amounts originated in a specific 3-digit zip code in a specific year;
3) Log of outstanding amounts in a specific 3-digit zip code as of year-end; and
4) Ratio of the amount of LendingClub loans outstanding to the amount of combined LendingClub loans and Y-14M credit card loans outstanding in a specific 3-digit zip code as of year-end.

The analysis focuses on key factors such as the credit card loan market concentration index at the 3-digit zip code level, the percent change in number of bank branches in the 3-digit zip code in the year, and the number of bank branches per capita in the community (3-digit zip code) in the year, etc. In the regression, we attempt to control for other factors that would influence the demand for credit in the local market, such as average personal income, local economic environment such as

[16] We are unable to go back to 2010 for an analysis that involves data from Y-14M stress test data because of the unavailability of Y-14M data prior to 2013. The data collection started in 2012 but was less reliable when banks first started reporting these new data items.

local house price index, local unemployment rate, and year dummies.[17] The results are reported in Tables 1 and 2.

Regression results, overall, suggest that the LendingClub penetrated areas that are likely to benefit from additional credit supply (so-called underserved areas). Table 1 explores the relationship between LendingClub loan origination activities and key measures of underserved areas, such as the existing banking and other financial services that are available to residents in the local community. Table 2 focuses on LendingClub's outstanding loan balance (rather than origination activities) and the relative share of LendingClub loans to all loans made in the local community.

The key variables that proxy these local activities include the number of bank branches per capita (100,000 people) in the local market (defined by the 3-digit zip code), the percent changes in bank branches in the local community (again in the 3-digit zip code), and the degree of concentration in the local credit card loan market (as measured by HHI calculated from credit card loans outstanding in zip codes that were issued by each of the reporting banks). We expect there would be more of a need for credit and other financial services in areas that have fewer bank branches per capita. Therefore, the change in bank branches would also impact consumers. Ideally, we would observe that LendingClub penetrated areas that lost bank branches more than other areas. In addition, we would expect to see more credit provided in areas that have a higher HHI (e.g., HHI > 2,500).

The results from Table 1 indicate that based on loan origination activities, measured in terms of loan accounts and loan amount, the amount of lending LendingClub committed to specific 3-digit zip code areas in a year seems to be larger in areas that have a lower number of bank branches per capita and in highly concentrated lending market areas (with HHI > 2,500). The activities both in terms of loan accounts and loan amounts are negatively (and positively) related to the number of branches per capita (and to the market concentration indicators), respectively. The coefficient on the *Number of Branches/100,000 (3-Digit Zip)* variable are significantly negative, and the coefficient on the *D_HHI>2500 for Credit Card Market (3-Digit Zip)* variable are significantly positive, after controlling for all other relevant factors that impact the lending activities. These results are consistent with what we presented earlier in Figures 6A, 6B, 7A, and 7B. LendingClub seems to have increased credit availability, making credit more accessible to people in highly concentrated credit markets.

[17] Local economic factors, population, and bank branching and deposit variables are measured at the 3-digit zip code level in response to the fact that LendingClub reports location by 3-digit zip code.

The deposit market concentration measures (when HHI is measured based on deposit activities, from SOD data versus the calculated HHI based on credit card market concentration) are not significant in any of the regressions (not shown). The plots in Figures 5A and 5B show that about 50 percent of LendingClub's portfolio are loans in highly concentrated deposit markets with HHI greater than 2,500, but actually about 80 percent of all the 5-digit zip codes have an HHI greater than 2,500. Unlike deposit market concentration, the positive relationship between market concentration (in the credit card loan market) and LendingClub activities remains significant in the regressions, even after controlling for other risk and economic factors. Fintech lending could benefit consumers in these highly concentrated market areas.

In exploring fintech activities in areas where traditional banks are pulling out, our plots in Figures 6A and 6B show a rising trend of LendingClub loans in locales where bank branches are declining. But the regression results do not show a significant relationship between changes in bank branching and LendingClub activities after controlling for all other relevant risk and economic factors associated with the areas, such as the local unemployment rate. Changes in bank branches in the local area, *Percent Change in Bank Branch (3-Digit Zip),* are not significant after controlling for other relevant factors in the regressions. It is not the percent decline in bank branches that is important, but the ultimate number of bank branches per capita that is relevant in determining the deficiency in the local credit market. The results are consistent with an argument that fintech lending platforms could potentially increase the availability of credit in underserved areas.[18]

The importance of the number of bank branches per capita in determining LendingClub activities in the local market remains significantly negative in Table 2 when we explore different measures of LendingClub activities. In Table 2, LendingClub activities are measured in terms of outstanding balance (rather than originations during the year), loan balance outstanding at the end of each year (in columns 1 and 2), and share of LendingClub loans in which the denominator is the total of credit card loans made by Y-14M reporters plus total LendingClub loans in the 3-digit zip code. Again, the fintech lending platform seems to have penetrated underserved areas. Interestingly, in columns 3 and 4 of Table 2, the share of LendingClub loans in a local area is positively related to unemployment and negatively related to the home price index and per capita

[18] Our approach differs from that used by Ahmed, Beck, McDaniel, and Schropp (2016), which uses PayPal data. The authors find a positive relationship between the decline in the number of bank branches and the number of PayPal loans in the county. We use the ratio (rather than the number) of the reduction in bank branches to total number of bank branches in the beginning of the year to control for highly populated locations (e.g., New York City or San Francisco) where more branches could be closed (e.g., through mergers) without being noticed, because they are a small fraction of the population and could lead to different findings.

income, indicating LendingClub may gain market share in areas where economic variables indicate a more challenging environment.

VII. Conclusion and Policy Implications

Fintech has been playing an increasing role in shaping the financial and banking landscape. Technology can allow both banks and fintech lenders to serve small businesses and consumers without brick and mortar investments. In this paper, we explored the impact of fintech lending on the availability of unsecured consumer credit.[19] We would note that the Y-14M data that we use in this paper (to compare with LendingClub loans) are constrained by the limited number of reporters.[20]

In terms of credit access, we investigated whether LendingClub loans penetrated potentially underserved areas, where there is less competition in banking services, lower-income borrowers, and areas where bank branches have decreased proportionately more than others and areas with fewer bank branches per capita. We find LendingClub's consumer lending activities have penetrated areas that could benefit from additional credit supply, especially highly concentrated banking markets and other areas that have fewer bank branches per capita (i.e., smaller number of bank branches to serve a larger number of local potential borrowers). Finally, we presented some evidence that LendingClub had a higher market share in areas where economic variables indicated a more challenging environment.

We presented evidence that fintech lenders can fill credit gaps in areas where bank offices may be less available and the local economy may be more challenging. As the number of banks and banking offices continues to decline, the presence of fintech lenders may be important to supplement the availability of unsecured consumer credit. While this paper does not examine potential negatives related to online lending and consumer welfare, it does find that there are some potential positives to their presence in the market. As always, policymakers will need to consider both the pros and cons of lending by these new entrants in the financial landscape as they consider what potential regulations are needed for financial stability and consumer protection.

Jagtiani and Lemieux (2018) further explore the key roles of additional information that expand credit access to creditworthy borrowers that banks may not be serving and demonstrate

[19] Our results are derived based on loans originated on the LendingClub consumer lending platform. One should be cautious in extrapolating our findings to loans originated through other online alternative platforms.

[20] The data are submitted monthly by approximately 30 of the largest U.S. banks that are subject to stress testing. These large banking firms cover the majority of credit card loan origination.

that this credit seems to be “appropriately” risk priced.[21] These factors represent a further look at potential advantages that financial technology can provide consumers.

[21] Banks are responding to these innovations by partnering with fintech firms. More remains to be done to fully answer the question about risks to borrowers presented by these new innovations.

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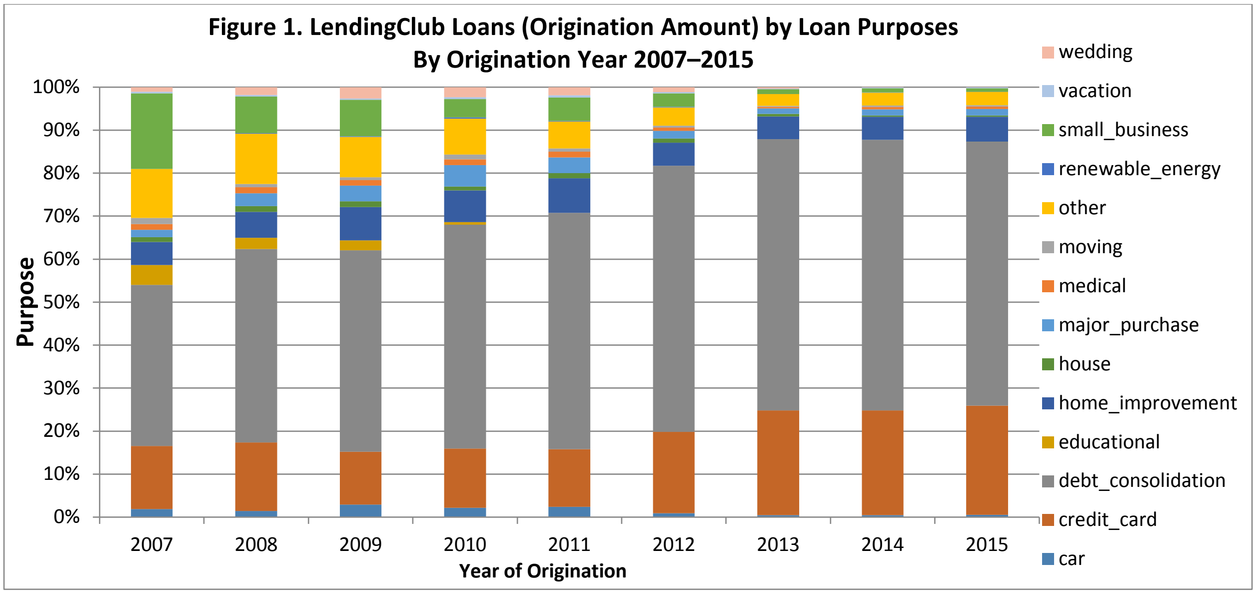
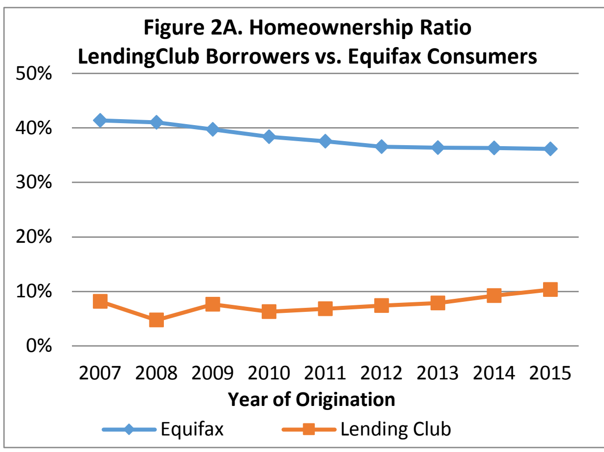
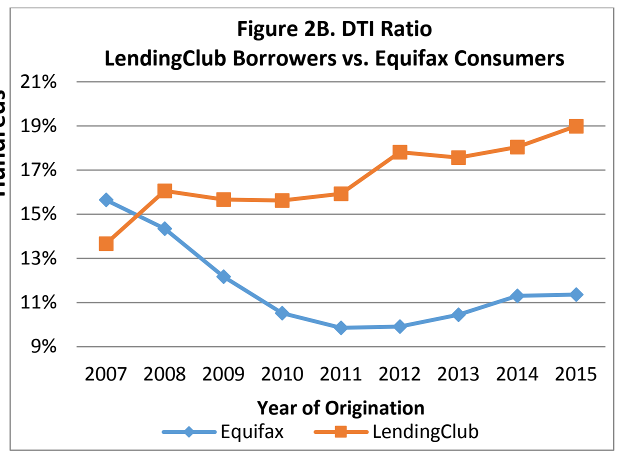
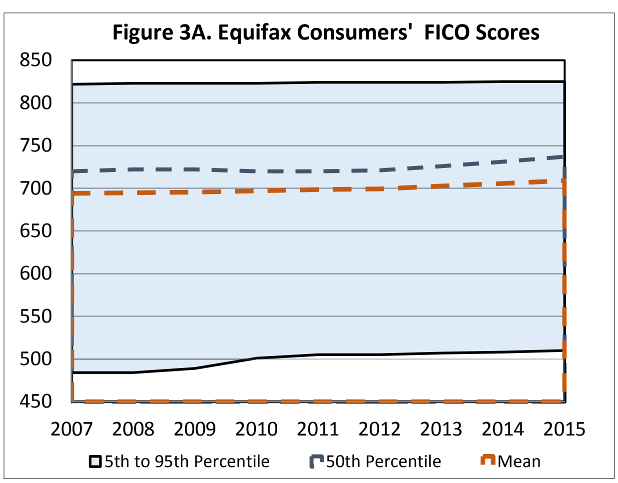


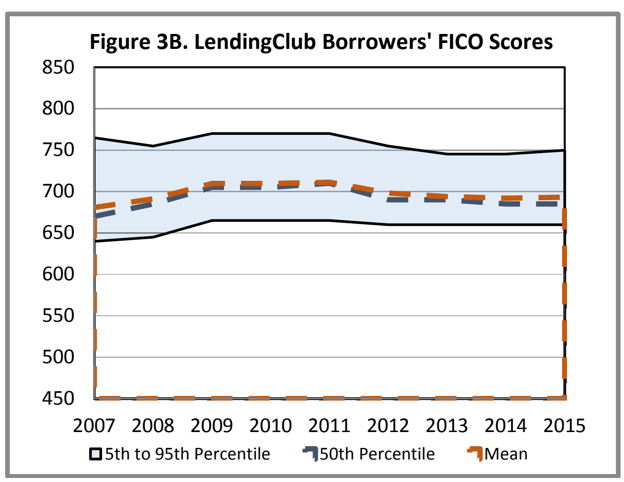
Source: LendingClub (loan-level data from the LendingClub website)





Sources: LendingClub (loan-level data from the LendingClub website) and the FRBNY Equifax CCP

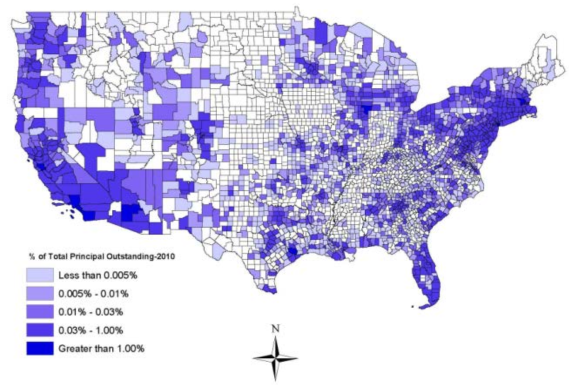




Sources: LendingClub (loan-level data from the LendingClub website) and the FRBNY Equifax CCP

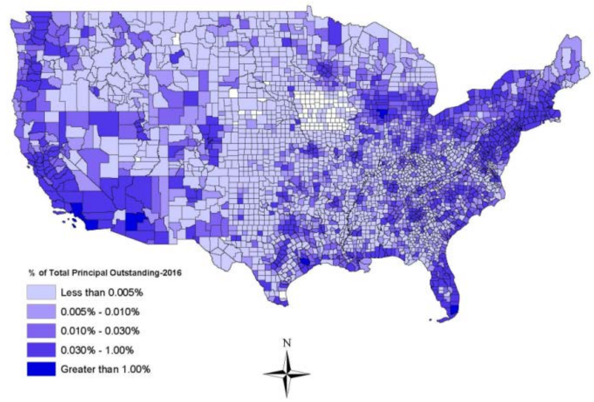
Figure 4A. Geographic Distribution of the LendingClub Consumer Loan Portfolio (Percent of Total Principal Outstanding in Each County)

As of December 31, 2010



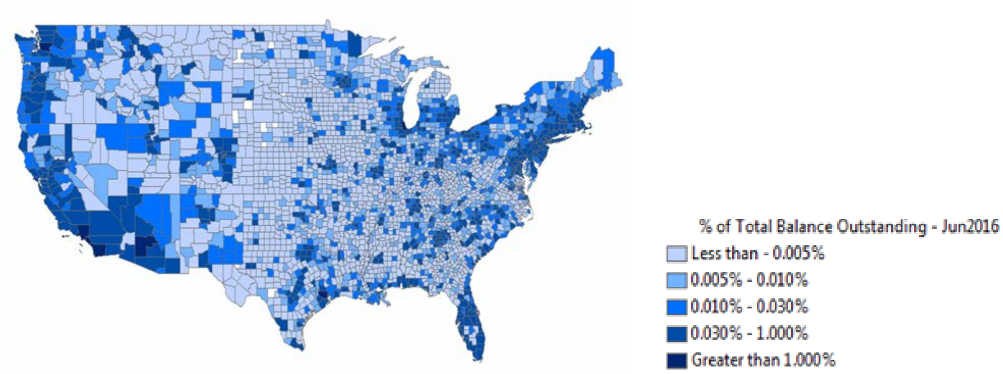
Source: LendingClub data

As of June 30, 2016



Source: LendingClub data

Figure 4B. Geographic Distribution of Credit Card Loan Market (Credit Card Loans Originated by CCAR Banks) — Percent of Credit Card Balance in Each County Relative to the Total Credit Card Balance in the U.S.) — as of June 30, 2016



Source: Y-14M CCAR Stress Test data (credit cards, revolvers only)

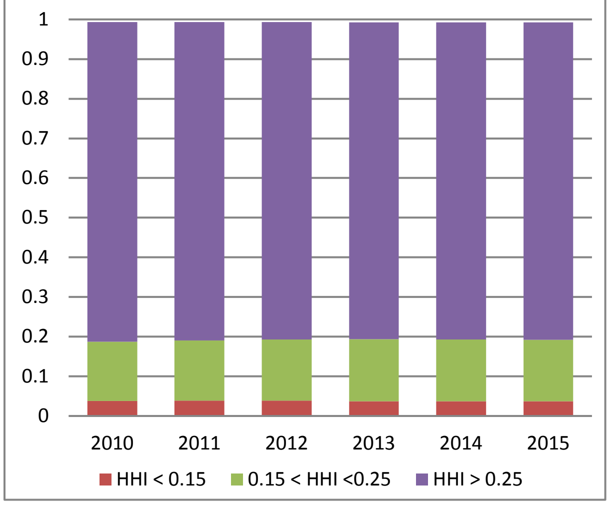


Figure 5A. Landscapes of U.S. Banking Market by 5-Digit Zip Code HHI (2010–2015)

Sources: FDIC Summary of Deposits Database

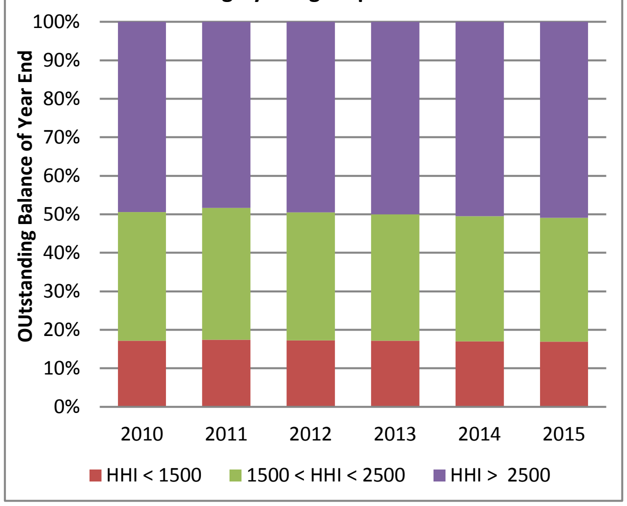


Figure 5B. LendingClub Consumer Loans Outstanding by 5-Digit Zip Code HHI Markets

Source: LendingClub data

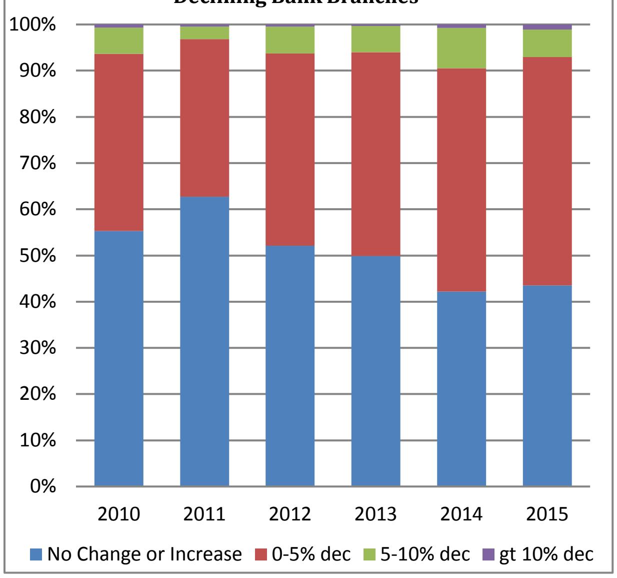


Figure 6A. Bank Branch Landscapes Share of 3-Digit Zip Codes with Declining Bank Branches

Sources: FDIC Summary of Deposits (for branch data)

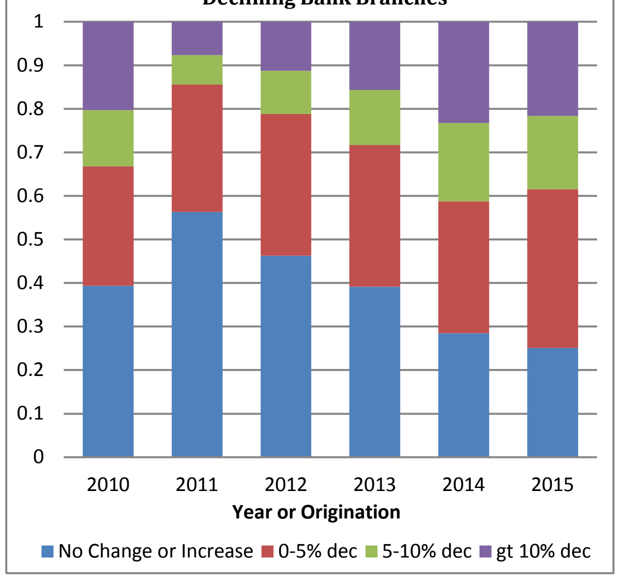
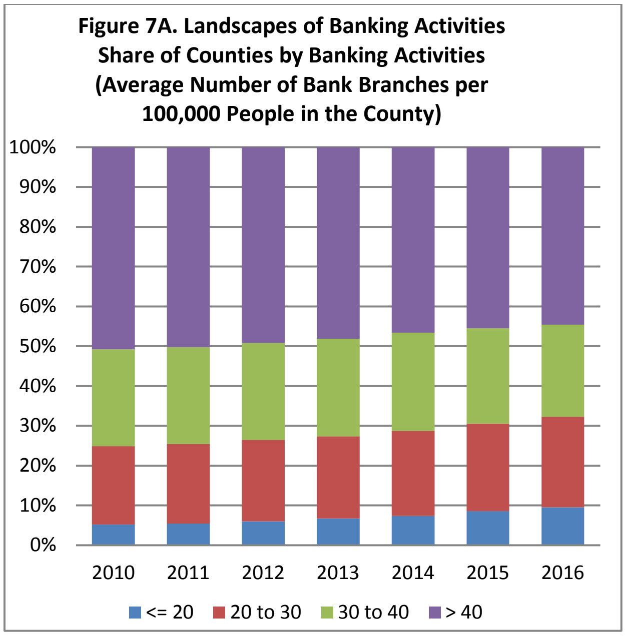
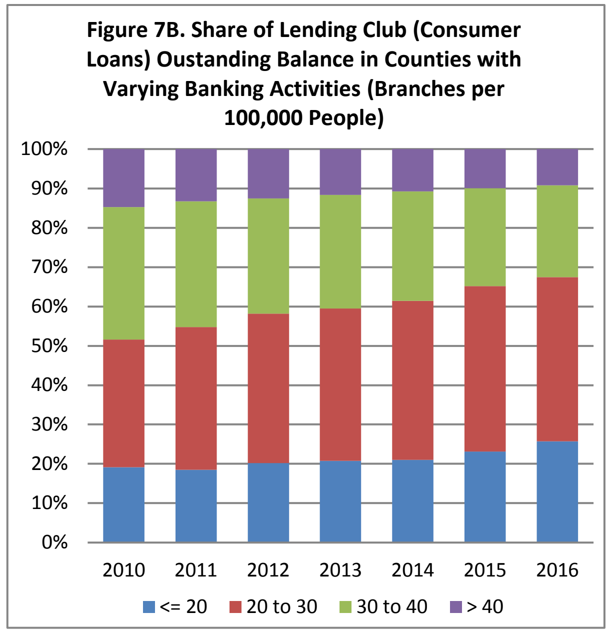


Figure 6B. Distribution of LendingClub Portfolio Amount of Loans in 3-Digit Zip Codes with Declining Bank Branches

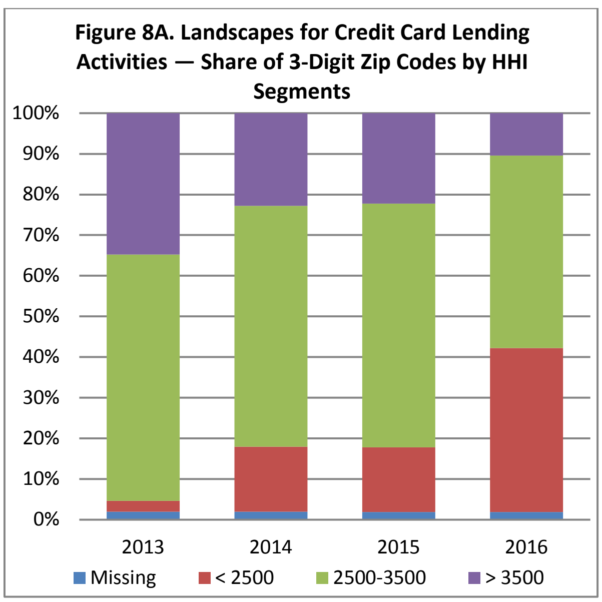
Sources: LendingClub Data



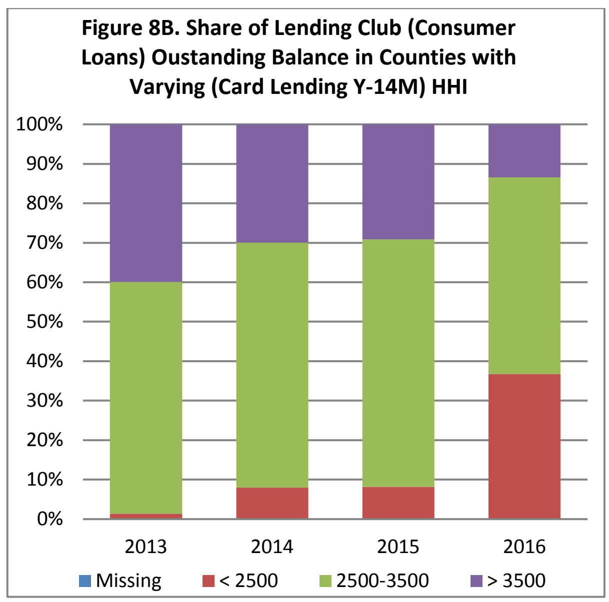
Source: FDIC Summary of Deposits (for branch data) and Census Bureau (for population data)[22]



Sources: LendingClub Data



Sources: Y-14M stress test data (for credit card loan balance and issuing banks) in each zip code



Sources: LendingClub Data

[22] We collect population data at the census tract level and sum them up to the county level. We then use the Census Tract Crosswalks to convert the statistics to the 3-digit zip code level (to match the way in which LendingClub data are reported).

Table 1. Regression Results: Relationship Between LendingClub Loan (Cards and Debt Consolidation) Origination and Local Credit Market (Market Defined as 3-Digit Zip Code)

Dependent variables measure LendingClub's loan origination activities in the specific 3-digit zip code in a specific year. The dependent variable for the regression in columns 1 and 2 is the number of loans (for credit card payoff and debt consolidation) originated by LendingClub in a specific 3-digit zip code each year. The dependent variable in columns 3 and 4 is the log of dollar amount of loans (for credit card payoff and debt consolidation) that were originated by LendingClub in a specific 3-digit zip code in each year. The sample period is from 2013 to 2016 (based on availability of Y-14M data, which are used to calculate the HHI market concentration for credit card lending). The sample includes only LendingClub loans specified for "Credit Cards" or "Debt Consolidation" purposes. The *** and ** represent statistical significance at the 1% and 5%, respectively. The P-values are reported in the parentheses.

	Dependent Variable = Number of LendingClub Loan Accounts Originated in 3-Digit Zip Code Year		***Dependent Variable = Log of LendingClub $ Loans Originated in 3-Digit Zip Code Year***	
Independent Variables	(1)	(2)	(3)	(4)
Intercept	–1,022.2394*** (0.0001)	–1,159.0607*** (0.0001)	8.5682*** (0.0001)	6.6865*** (0.0001)
Unemployment rate (3-digit zip code)	–4.6406** (0.0235)	–2.3536 (0.2277)	–0.1271*** (0.0001)	–0.0956*** (0.0001)
Home price index (3-digit zip code)	0.0640*** (0.0001)	0.6121*** (0.0001)	–0.0044*** (0.0001)	–0.0048*** (0.0001)
Log of income per capital (3-digit zip code)	88.8129*** (0.0001)	95.5220*** (0.0001)	0.5190*** (0.0001)	0.6112*** (0.0001)
Number of branches/ 100,000 (3-digit zip code)	–1.2670*** (0.0003)	—	–0.0174*** (0.0001)	—
Percent change in bank branch (3-digit zip code)	—	–8.8310 (0.5564)	—	–0.0816 (0.1983)
D_HHI>2500 for credit card market (3-digit zip code)	89.0689*** (0.0001)	90.9655*** (0.0001)	1.0839*** (0.0001)	1.1102*** (0.0001)
D_2014	126.2777*** (0.0001)	131.3847*** (0.0001)	1.2630*** (0.0001)	1.3337*** (0.0001)
D_2015	287.4517*** (0.0001)	294.5384*** (0.0001)	1.7019*** (0.0001)	1.7998*** (0.0001)
D_2016	299.3796*** (0.0001)	303.6597*** (0.0001)	2.2153*** (0.0001)	2.2745*** (0.0001)
Adjusted R^2 observation number	39.09% 5,539	38.95% 5,538	65.36% 5,539	64.53% 5,538

Table 2. Regression Results: Relation Between LendingClub Loan (Cards and Debt Consolidation) Outstanding and Local Credit Market (Market Defined as 3-Digit Zip Code)

The dependent variable for the regression in columns 1 and 2 is the log of the dollar amount of LendingClub loans (for credit card payoff and debt consolidation) outstanding in a specific 3-digit zip code as of year-end. The dependent variable in columns 3 and 4 is the ratio of the dollar amount of LendingClub loans (for credit card payoff and debt consolidation) to the combined dollar amount of LendingClub loans (for credit card payoff and debt consolidation) and Y-14M credit card loans that were outstanding in a specific 3-digit zip code as of year-end. The sample period is from 2013 to 2016 (based on the availability of Y-14M data, which are used to calculate the HHI market concentration for credit card lending). The *** and ** represent statistical significance at the 1% and 5%, respectively. The P-values are reported in the parentheses.

	Dependent Variable = Log of LendingClub Loan Outstanding in 3-Digit Zip Code as of Year-End		***Dependent Variable = Ratio of Lending Club Loan Outstanding to Combined LendingClub and Y-14M Loan Outstanding in 3-Digit Zip Code as of Year-End***	
Independent Variables	(1)	(2)	(3)	(4)
Intercept	8.6726*** (0.0001)	6.7462*** (0.0001)	0.0995*** (0.0001)	0.0755*** (0.0001)
Unemployment rate (3-digit zip code)	–0.1268*** (0.0001)	–0.0943*** (0.0001)	0.0010*** (0.0002)	0.0015*** (0.0001)
Home price index (3-digit zip code)	–0.0046*** (0.0001)	–0.0050*** (0.0001)	–0.0001*** (0.0001)	–0.0001*** (0.0001)
Log of income per capital (3-digit zip code)	0.5129*** (0.0001)	0.6069*** (0.0001)	–0.0037*** (0.0001)	–0.0024*** (0.0001)
Number of branches/ 100,000 (3-digit zip code)	–0.0179*** (0.0001)	—	–0.0002*** (0.0001)	—
Percent change in bank branch (3-digit zip code)	—	–0.0717 (0.2551)	—	0.0174 (0.2940)
D_HHI>2500 for credit card market (3-digit zip code)	1.0774*** (0.0001)	1.1038*** (0.0001)	–0.0004 (0.7076)	–0.0006 (0.5900)
D_2014	1.4450*** (0.0001)	1.5181*** (0.0001)	0.0296*** (0.0001)	0.0304*** (0.0001)
D_2015	1.8241*** (0.0001)	1.9248*** (0.0001)	0.0581*** (0.0001)	0.0593*** (0.0001)
D_2016	2.6194*** (0.0001)	2.6798*** (0.0001)	0.0536*** (0.0001)	0.0539*** (0.0001)
Adjusted R^2 observation number	67.97% 5,501	67.10% 5,500	46.55% 3,376	46.09% 3,376