Fintech Lending: Financial Inclusion, Risk Pricing, and Alternative Information

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Abstract

Fintech has been playing an increasing role in shaping financial and banking landscapes. Banks have been concerned about the uneven playing field because fintech lenders are not subject to the same rigorous oversight. There have also been concerns about the use of alternative data sources by fintech lenders and the impact on financial inclusion. In this paper, we explore the advantages/disadvantages of loans made by a large fintech lender and similar loans that were originated through traditional banking channels. Specifically, we use account-level data from the LendingClub and Y-14M bank stress test data. We find that LendingClub's consumer lending activities have penetrated areas that lose bank branches and in those in highly concentrated banking markets. LendingClub borrowers are, on average, more risky than traditional borrowers given the same FICO scores. We also find a high correlation between interest rate spreads, LendingClub rating grades, and loan performance. However, the correlations between the rating grades and FICO scores (at origination) have declined from about 80 percent (for loans that were originated in 2007) to only about 35 percent for recent vintages (originated in 2014-2015) -- indicating that alternative data has been increasingly used. The use of alternative information sources has allowed some borrowers who would be classified as subprime by traditional criteria to be slotted into "better" loan grades and therefore get lower priced credit. Also, for the same risk of default, consumers pay smaller spreads on loans from the LendingClub than from credit card borrowing.

Keywords: fintech, LendingClub, marketplace lending, banking Competition, shadow Banking, credit spreads, credit performance, P2P lending, peer-to-peer lending
JEL Classification: G21, G28, G18, L21

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Fintech Lending: Market Penetration, Risk Pricing, and Alternative Information

I. Introduction

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 nonbank lenders has been growing rapidly, their total 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 again.[1] It is still 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 potential uneven regulatory playing field. Depository institutions are subject to a number of consumer protection and transparency regulations that attempt to ensure that customers are treated fairly, have equal access to credit, and receive offers that can be easily compared and understood. Even when shadow banking entities are subject to consumer protection and transparency laws, the supervision of their compliance is the responsibility of the Consumer Financial Protection Bureau (CFPB) which is risk-focused based on consumer complaints, the seriousness of the issues, and the availability of staff.[2] These entities are increasingly affiliating themselves with traditional banks. Banking regulators have been responding to this change in the lending landscape. For example, the Federal Deposit Insurance Corporation (FDIC) has cautioned banking institutions not to abrogate their responsibility for maintaining lending standards by relying on marketplace partners. The Office of Comptroller of the Currency (OCC) has proposed a national fintech charter to move its associated shadow banking activities under the regulatory umbrella.

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

[2] The CFPB has authority to regulate certain markets in the nonbank space, such as mortgages and credit cards. Although the CFPB could declare a particular market being significant and go through a formal process to start supervising that market, the agency is not currently doing that for online alternative lenders but it has started accepting complaints related to these online marketplace lenders (MPLs).

And, as mentioned in a speech by Lael Brainard (2016), member of the Board of Governors of the Federal Reserve System, the Federal Reserve has also established a multidisciplinary working group that is engaged in a 360-degree analysis of fintech innovation.

While the growth of nonbank lending may raise some regulatory concerns, the firms' technology 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 for those with little or no credit history. In addition, as more millennials make up the pool of small business owners and the consumer population, they are more comfortable with technology and therefore, may be more comfortable dealing with an online lender than in dealing with a traditional bank.

Over the past decade, online alternative lenders have evolved from platforms connecting individual borrowers with individual lenders,[3] to sophisticated networks featuring institutional investors, direct lending (on their balance sheet), and securitization transactions. There have also been indications that these alternative lenders may find it advantageous to partner with banking institutions to originate loans through traditional banks. As an example, the LendingClub originates some of its loans through WebBank.

While the alternative data sources and the algorithms used by online alternative lenders have allowed for faster and lower cost credit assessments, these innovations could potentially carry a risk of disparate treatment and fair lending violations. We explore some of the potential consumer benefits that could come from these new algorithms. Several questions have been raised by regulators and policymakers around these issues.

Credit Access -- Do fintech firms expand the availability of credit so that previously underserved consumers now have access to credit? Can the use of alternative data (e.g., to build internal credit rating

[3] Frequently referred to in prior research as peer-to-peer (P2P).

systems such as the one designed by LendingClub) increase access to credit for consumers -- by allowing lenders to better assess their creditworthiness?

Price of Credit -- Do fintech firms make credit available to consumers at a lower cost than traditional bank loans? The use of alternative data sources, big data and machine learning technology, and other new artificial intelligence (AI) models could reduce the cost of making credit decisions and/or credit monitoring and lower operating costs for lenders. Fintech lenders could pass on the benefits of lower lending costs to their borrowers.

Alternative Data Sources – Do alternative sources of information used by fintech firms to evaluate credit applications contain additional information not embedded in the obvious risk factors used by traditional lenders? We note that certain alternative data sources are more prone to errors and thus could potentially create unfair disadvantages to vulnerable consumers. There may also be a risk of violating consumer privacy from the use of big data. Several alternative data sources have been used by fintech lenders -- examples include information drawn from utility payments, electronic records of deposit and withdrawal transactions, insurance claims, bank account transfers, use of mobile phones or the Internet, and other personal data such as consumer's occupation or detail about their education. These data sources were not normally used by traditional lenders.

There have been policy questions around the use of big data and the appropriate policies that would regulate fintech firms to protect consumers but without harming the innovation process. Richard Cordray, director of the Consumer Financial Protection Bureau, March 2017, pointed out potential benefits to consumers through the use of these alternative data sources.

> "*By filling in more details of people's financial lives, this information may paint a fuller and more accurate picture of their creditworthiness. So adding alternative data into the mix may make it possible to open up more affordable credit for millions of additional consumers*….."

In this paper, we address many of these questions. Specifically, we explore lending activities, pricing, the role of alternative data sources, and credit performance of similar loans originated through traditional banking channels versus online alternative lenders. The rest of the paper is organized as follows. The literature review is presented in Section II. We describe our data from the various sources in Section III. Sections IV explores the impact of fintech on credit access. Section V describes the roles of alternative information sources used by fintech lenders. Price of credit and credit performance are discussed and compared (with traditional loans) in Sections VI and VII, respectively. Section VIII concludes and discusses policy implications.

II. The Literature

Fintech is a new area of research. There are a limited number of studies, partly due to the lack of data. Fintech is a broad subject area that could touch on many different aspects of financial technology, including payments related innovations such as blockchain and other distributed ledger technology, technology to facilitate payments to individuals and businesses such as Venmo, Apple Pay and Square, as well as alternative online lenders. This paper focuses on the aspect of how fintech lenders could impact consumers and the overall banking landscape. Specifically, we explore the impact on consumers' ability to access credit, the role of alternative information sources used by fintech lenders, and the impact on the price of credit.

II.1 Impact of Fintech on Access to Credit

Mills and McCarthy (2014 and 2016) explore whether there is a credit gap in small business lending and find a significant gap especially for very small loans (less than $50,000). Some hope that fintech lenders will play an important role in closing this gap. Several articles have discussed and explored the role of fintech lenders in expanding the availability of credit and allowing borrowers who were rejected by traditional banks to access the funding they need, but the results have been mixed. Many of these articles rely on survey data, and, therefore, are subject to biases in the sample selection and inconsistent standards of responses. In addition, only a couple of fintech lenders have made their loan level data publicly available, thus providing challenges to researchers in their ability to draw broad conclusions about the industry.

The Joint Small Business Credit Survey Report (2015) conducted by the Federal Reserve has shown that credit access has been an important obstacle for smaller, younger, less profitable, and minority-owned businesses. Specifically, the report finds that only 29 percent of credit applications from very small businesses (that rely on contractors, no employees) received the full requested loan amount that they were seeking, and 30 percent received partial funding. Those that were not fully funded through the traditional channel have increasingly turned to online alternative lenders.[4]

Schweitzer and Barkley (2017) examine characteristics of businesses that borrow from online lenders, based on the 2015 survey.[5] The authors find that these borrowers have similar characteristics to those businesses that were denied credit from a bank and conclude that the findings are consistent with the argument that businesses denied funding by banks turned to fintech lenders to arrange credit for their businesses that would not qualify for traditional bank financing.

In addition, there have been several surveys conducted by the various online alternative fintech lenders that suggest the value added by their lending platforms. In the survey conducted by Funding Circle, one fifth of borrowers believed they would have been unable to secure external finance without the platform, despite being creditworthy – see Desai and Meekings (2016).[6]

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[4] With their perceived chance of being funded as the main factor in determining where they applied, small firms (with revenues less than $25,000) were nearly twice as likely to apply with an online lender as nonemployers with $100,000 in annual revenue.

[5] Note that the survey groups the data by the type of institutions -- bank (small and large), credit union, online lender and other. It is not clear whether online lenders include online applications submitted to traditional banks or fintech lenders.

[6] OnDeck Analysis Group (2015) found that its borrowers did not have viable financing options outside of OnDeck and estimated that its first $3 billion in small business loans generated $11 billion in business activity. In addition, PayPal Working Capital (PPWC), based on its own data, also found that nearly 35 percent of its loans went to low-and-moderate-income (LMI) businesses, compared with 21 percent of retail bank loans – see Ahmed, Beck, McDaniel, and Schroop (2016). They also report that nearly 25 percent of PPWC loans were disbursed to the 3 percent of counties that have lost more than 10 banks since 2008.

Yet, there are studies that find contrary results. Freedman and Jin (2011) use data from Prosper to demonstrate how peer-to-peer (P2P) lenders have evolved toward serving consumers who would traditionally obtain financing from banks because the platform excludes more and more subprime borrowers. In this paper, we use loan-level data (rather than the survey data) to explore the relationship between the amount of loans made by a fintech lender and the characteristics of the banking environment – such as the degree of banking competition, the decline in bank branches in that zip code, and whether it is a LMI neighborhood – to determine whether fintech loans increased access to credit in those areas where traditional banks are pulling back.

Following the financial crisis, there have been concerns about the availability of credit for small business. Jagtiani and Lemieux (2016) pointed out that while credit for small businesses has rebounded, community banks (with less than $1 billion in total assets), which have been the traditional go-to source of small business credit lost ground in this market.[7] Large banks maintained their presence in the market even while the asset size of many banks grew. A big part of this change has been technology. Today the largest banks are not relying on physical offices to grow their small business lending. Technology plays an important role in allowing banks to reach a wider group of borrowers. Jagtiani and Lemieux find that between 1997 and 2014 larger banks doubled the number of counties where they had a significant presence in small business lending but did not have bank branches. Literature so far has focused on the roles of Fintech lender in enhancing credit access to small business owners. We explore similar impacts on individual consumers in this paper.

II.2 The Roles of Alternative Information Sources

Online fintech lenders often rely on their own algorithms for credit underwriting. We suspect that some of the information used in their algorithms may include nontraditional information (not used by traditional banks in their lending decisions). Some fintech lenders have developed their own online

[7] In 1997 over 14 percent of small community bank assets were in small business loans. By 2016, that was down to around 11 percent.

lending platforms that use “big data” in their own proprietary algorithms that they developed to evaluate the credit risk of the borrowers. Through this new approach to credit risk evaluation, some consumers could potentially enhance their credit access. For example, consumers with short credit history may not satisfy a bank’s traditional lending requirements, but these same consumers could potentially get a loan from an online alternative lender that uses alternative data sources.[8] There have been concerns that consumer privacy may be compromised in the process if information such as insurance claims, utility bills, transactions in bank accounts, and social network, are used by lenders without the borrower’s consent.

There has been no serious research that explores these specific questions related to fintech lenders. An older study by Fame, Srinivasan and Woosley (2001) examines the effect of the newly developed small business credit scores on lending activities, using data collected via a phone survey of the 200 largest U.S. banking institutions. The authors find that the small business credit scoring lowered information costs and information asymmetries between borrowers and lenders -- leading to increases in small business lending (SBL).[9] Similarly, it is reasonable to expect the new algorithms used by fintech lenders to expand lending activities to previously underserved consumers.

There have been reports by online lenders about the additional information sources that they use. Online fintech lenders are relying more on alternative sources of information, such as sales data from Amazon, eBay and other marketplaces, shipping data from postal services, cash flow analysis from business checking accounts and payment processors; and, aspects of social media to analyze and project businesses' profitability. Crosman reports in the American Banker (June 14, 2016) that SoFi no longer uses FICO scores when determining loan qualifications. In addition, Kabbage claims that FICO scores are not part of their creditworthiness determination (although FICO scores are used for benchmarking and

[8] See more discussion in Demyanyk and Kolliner (2014).
[9] Specifically, the authors find small business credit scoring by banks is associated with an 8.4 percent increase in the portfolio share of small business loans, or $4 billion per institution.

investor reporting). A quote in this article by Ron Suber, president of Prosper Marketplace, states that "Prosper gets 500 pieces of data on each borrower; the FICO score is just one data point." While the company uses FICO scores to screen borrower candidates – a score of at least 640 is needed to be considered for a loan. Prosper analyzes additional data to determine the ultimate credit decision.

Moldow (2015) of Foundation Capital writes that alternative data sources, such as business sales volume from credit cards or accounting programs, the rating of a store on Yelp, the length of time a prospective borrower has used the same e-mail address, and even the amount of time a prospective borrower spends on the lending website to decide how much money to request, offer insights in determining the creditworthiness of borrowers. Mills and McCarthy (2016) report that online lenders Fundbox and Bluevine evaluate borrowers' QuickBooks, Xero, or FreshBooks data when underwriting loans. This evaluation is in addition to employing the application program interface (API), which allows a borrower to authorize direct access to various financial records in seconds. Recently, PayPal and Square have started to offer credit to their existing business merchants based on access to sales data, which is useful during the underwriting process, and the ability to directly deduct loan repayments from the merchants' revenue, as reported by Wack in the American Banker (2015).

Previous studies that examine characteristics of borrowers find that soft information, such as applicants' looks (based on photographs) and stronger and more verifiable relational network, is related to the borrowers' success in getting funding and/or receiving a better price – see Duarte, Siegel and Young (2012) using marketplace lending data from Prosper; Lin, Prabhala and Viswanathan (2009) also using data from Prosper; and Gonzalez and Loureiro (2014) using survey data. Furthermore, Iyer, Khwaja, Luttmer, and Shue (2014) use Prosper data and find that lenders in P2P markets infer borrowers' creditworthiness by using soft information that can predict default with 45 percent greater accuracy than by using credit scores. Soft information seems to be particularly useful when screening borrowers with lower credit ratings.

The Consumer Financial Protection Bureau (2017) released a request for information to explore the impact of alternative data sources, including data from mobile phones, rent payment histories, electronic transactions such as deposits, withdrawals and transfers, building credit histories and increasing credit access. There have been concerns about the potential risks posed by these data sources because they may be biased and could potentially have an adverse impact on credit access to low-income and underserved communities.[10] In this paper, we shed more light on the role of alternative information sources and their relationship with traditional credit scores. Many believe that the role of big data and alternative information will increase exponentially in the future. Issues around consumer privacy and disparate treatment of protected classes still need to be explored.

II.3 The Impact of Fintech on the Price of Credit

In addition to being convenient and faster for consumers, online alternative lending technology has provided enhanced efficiency to lenders through lower operating costs. It is important to investigate whether fintech lenders pass the savings on to consumers with lower credit costs and whether the pricing is appropriate for the risk taken.[11] A few studies have attempted to compare lending rates from online alternative platform with traditional sources, but those studies have been subject to significant data limitation and the results have been mixed.

Mach, Carter, and Slattery (2014) explored the rates on small business loans, using LendingClub consumer loan data that were specified as being used for small business purposes. They find that rates vary by loan purposes and that business loans (i.e., consumer loans with small business purposes) are subject to a higher rate even after controlling for the quality of loan applications. In addition, when comparing the interest rates on LendingClub loans with interest rates on business loans reported by

[10] There may also be risk that online fintech lenders could use these new data sources and data mining techniques to identify consumers who are less sophisticated and vulnerable to exploitation.

[11] Morse (2015) explores a number of issues related to fintech disruption and financial disintermediation. The paper concludes that at least some cost savings seem to accrue to investors (since 80 percent of P2P funds come from institutional investors), and that the borrowers' social circles and local economic indicators are useful in predicting credit risk.

National Federation of Independent Business members, the authors conclude that P2P small business borrowers paid a rate that was approximately twice as high as small business loans obtained from traditional sources. However, it should be noted that the small business purpose loans from the LendingClub consumer loan data are not likely to represent the typical small business loans because they have very small origination amounts, are unsecured and are underwritten to an individual consumer on the consumer loan platform.[12]

Demyanyk and Kolliner (2014) explore the difference in credit card rates, using data from bankrate.com, and interest rates charged on LendingClub's consumer loans. The authors find that more creditworthy consumers receive preferred rates using a P2P lender over a credit card. However, the data are not directly comparable at the loan level.

In contrast, in Germany, De Roure, Pelizzon and Tasca (2016) use data from Auxmoney, a German P2P lending site, and bank lending and interest rates data from Deutsche Bundesbank. The authors find that, after controlling for risk characteristics of the borrowers, interest rates are comparable for loans made by P2P alternative lenders and those made by traditional banks. Furthermore, Buchak, Matvos, Piskorski and Seru (2017) study the rise of fintech and non-fintech shadow-banking activities in the residential lending market.[13] Evidence in their paper suggests that fintech customers are among the borrowers who value fast and convenient services and that fintech lenders command an interest rate premium for their services.

Emekter, Jirasakuldech and Lu (2014) explore credit risk and loan rates using LendingClub data. As expected, the authors find that borrowers with high FICO scores and low debt-to-income (DTI) ratios are associated with low default risk. Interestingly, they also find that the higher interest rates charged for the high-risk borrowers are not large enough to compensate for a higher probability of loan default.

[12] LendingClub started its new small business lending platform in 2014, but the data from this platform have not been made publicly available.

[13] They find that fintech firms accounted for almost a third of shadow bank loan originations by 2015 and that fintech lenders possess technological advantages in in pricing.

Dietrich and Wernli (2015) use data from Cashare, the biggest player in the Swiss P2P lending market (with a market share of nearly 98 percent). Data consist of information on 665 loans for private individuals granted between April 7, 2008 and December 31, 2014. The authors find that interest rates are significantly lower for larger loans amounts or when the borrower owns a home. The rates are, however, significantly higher for female borrowers and for those with higher debt-to-income (DTI) ratios.

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 borrowers in states with higher unemployment rates receive higher interest rates, even after controlling for borrower and loan characteristics, including their own 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 P2P market.[14]

Pricing on platform lending seem to have evolved over the years. For example, Lin and Wei (2016), using data from the Prosper platform, compare Prosper's pre-December 2010 auction-based model with its current posted-price model. The authors find that the interest rates assigned by the platform's current posted-price model are about 100 basis points higher than what borrowers would have received in auctions. In addition, they find that loans originated under the posted-price model are more likely to default.

We use a unique data set that allows us to compare online alternative lending rates and traditional credit card loans. We compare account-level credit card data that large banks submitted to the Federal Reserve for stress testing with online consumer loans that were made for credit card (and debt consolidation) purposes.

[14] They find that the December 2015 Federal Open Market Committee liftoff signaled improvements in the future outlook of the economy and lower perceived default probabilities by investors leading to lower average interest rates and reduction of credit spread.

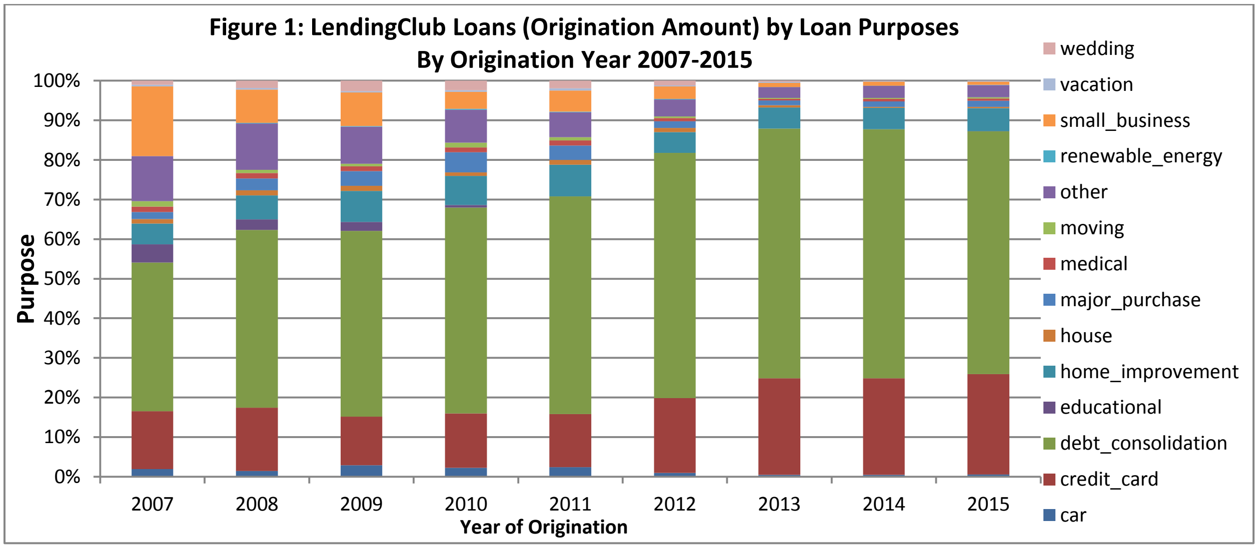
III. The Data

We use five main sources of data in this paper: data on loans that were originated through online alternative channel (loan-level data from the LendingClub platform), data on loans that were originated from traditional banking channels (loan-level data from the Y-14M stress test data), consumer credit panel data (FRBNY Equifax Consumer Credit panel), banking market concentration data and bank branch information (based on the FDIC Summary of Deposits database), and economic factors (from the Haver Analytics database).

III.1 Online Alternative Lending Channel

Our research on fintech consumer lending focuses on the LendingClub for two reasons. First, the company is one of the few lenders that has made its data publicly available. Second, it is one of the larger, more established alternative lenders in this space, and, 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 the LendingClub's consumer loans that were originated in 2007 to 2016. The loan-level database contains loan-specific information (i.e., loan rate, maturity, origination date, etc.), risk characteristics of the borrowers (i.e., FICO scores, employment, DTI ratio, age, homeownership), other risk characteristics, and monthly payment and performance of the loans. Our analysis is based on data from the LendingClub consumer loan platform. We focus on loans that were specified for two purposes: credit cards and debt consolidation purposes. As shown in Figure 1, these loans account for more than 80 percent of LendingClub consumer loans overall.

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 the LendingClub to more precisely identify the location of the loans. To evaluate the differences in credit access and pricing between traditional versus alternative lending channels, we compare these loans (for credit cards and debt consolidation) with account-level credit card data from banks, as in the following description. We observe the differences between these two lending channels in terms of lending in underserved areas, price of credit, and loan performance.



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

III.2 Traditional Lending Channels

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 CCAR banks (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 period.[15] 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

[15] We note that the CCAR stress testing data is 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.

report that they borrow from the LendingClub to pay off their credit cards, we compare the average price and performance of LendingClub loans with Y-14M consumer cards, using card credit limits and LendingClub origination amounts as control factors (along with other relevant risk factors).

This loan-level data contains mostly similar information on the borrowers, and their risk characteristics as are reported on the LendingClub website (i.e., origination date, origination amount, location of the borrowers, borrowers' credit scores). However, we use a few variables for LendingClub analysis that are not reported by banks in Y-14M data, such as homeownership and DTI ratio at origination. It is important to note that while the credit card loans from Y-14M and LendingClub consumer loans that are used to pay off credit card loans (or for debt consolidation) are the most comparable products, some credit cards have rewards (cash back or points) and/or some period of low-rate promotion period (e.g., in the first six months) to encourage balance transfers from other cards. We control for the Promotion period and the rewards in our analysis that use Y-14M data.

III.3 FRBNY Equifax Consumer Credit Panel

Who are LendingClub's borrowers? To provide an overview of where LendingClub borrowers (our sample) are positioned among the overall population of U.S. consumers and how the trends may have changed over the years, we use the Federal Reserve Bank of New York (FRBNY) Equifax Consumer Credit Panel (CCP) database. The 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 the consumers.[16] Our FRBNY Equifax CCP sample includes only the primary consumers (with assigned consumer identification) who have at least three continuous years of credit records (to avoid the possibility of fake accounts) and have assigned some type of credit scores.

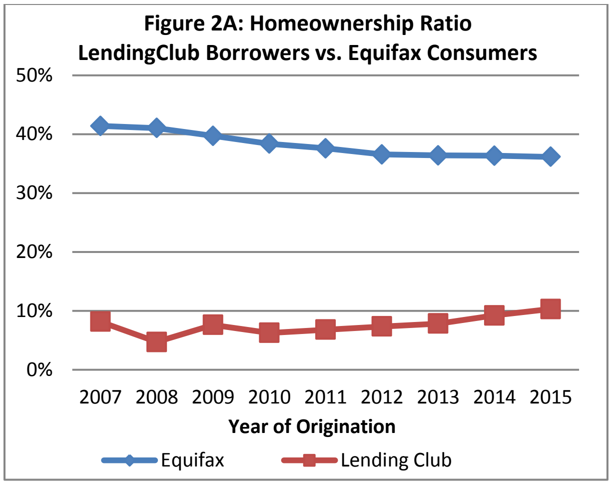
[16] Primary consumers are followed through time on the FRBNY Equifax Consumer Credit Panel, allowing us to examine their behavior over the years. Those who are part of the primary consumer's households would also be included in the database as long as they continue to belong to a primary consumer's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

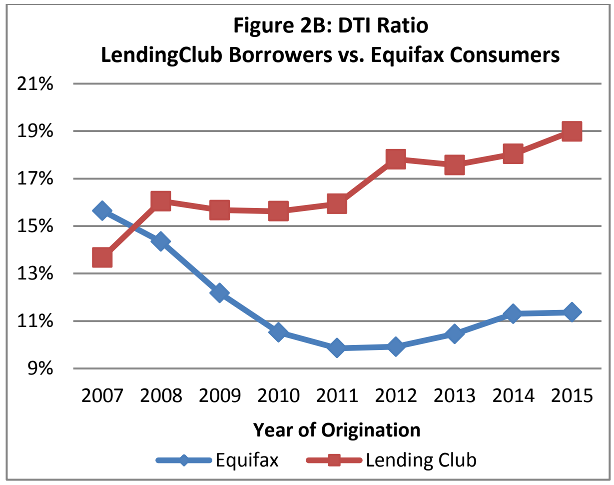
In this paper, we focus on three important characteristics: homeownership, DTI ratio at origination, and average credit scores. We compare the trends for LendingClub borrowers with those from the overall U.S. consumer population. The summary of these differences for homeownership and DTI are presented in Figures 2A and 2B, respectively. LendingClub borrowers are less likely to own a home and are more leveraged (having a significantly higher DTI) than the average U.S. population on the consumer credit panel. In addition, the distribution of credit scores for LendingClub borrowers and the overall U.S. borrowers is presented in Figures 3A and 3B, respectively.

From the FRBNY Equifax CCP, we define homeownership as having at least one mortgage and at least a $100 balance in at least one outstanding mortgage loan. Figure 2A shows that LendingClub borrowers are less likely to be homeowners compared with the general U.S. consumer population in the FRBNY Equifax CCP sample (people with credit records).[17] Our data indicate that as of 2012-2016, about 40 percent of LendingClub borrowers did not own a home. LendingClub could be filling a credit gap for borrowers who do not have a home to serve as collateral.

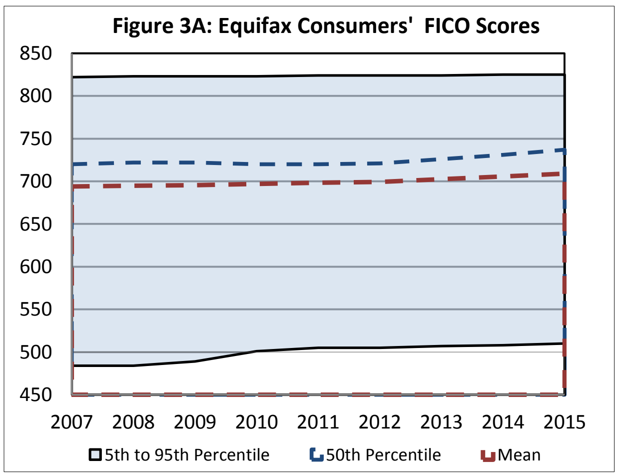
Figure 2B shows that LendingClub borrowers are more leveraged than general U.S. consumers from the FRBNY Equifax CCP population. In addition, it is important to note the rising trend of DTI for LendingClub borrowers over the years. LendingClub borrowers became more leveraged starting in 2012 and appeared to have a greater risk appetite with respect to debt burden while consumers in the FRBNY Equifax CCP population de-leveraged over this time period.[18] The DTI ratio calculated from the FRBNY Equifax CCP data is the median total debt (excluding mortgages) divided by median household income.[19] The DTI for average U.S. population is significantly lower than for LendingClub borrowers.

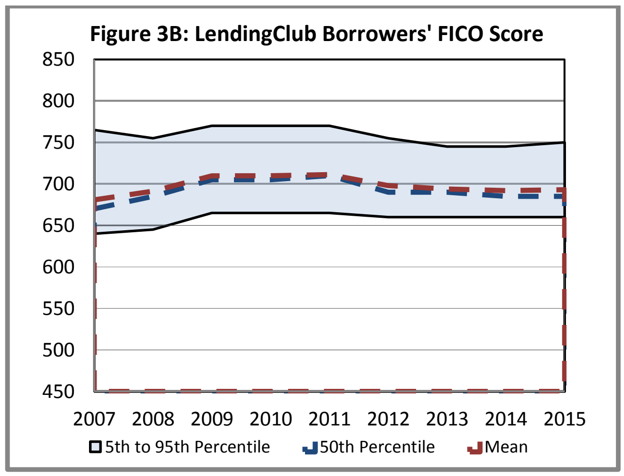
[17] Homeowners who have already paid off all their mortgage loans are not captured in this analysis. This could potentially result in an underestimation of the ratio of homeowners from the general Equifax CCP population -- with no impact on ratio of homeownership for LendingClub borrowers.
[18] LendingClub borrowers' reported DTI ratio is defined as the borrowers' 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.
[19] For total debt calculation, we exclude severely delinquent balances (at least 120 days past due).





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

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 has been only very slightly below the average of overall Equifax consumers. The data indicate (not shown here) that as of 2009-2011, about 60 percent of LendingClub borrowers have at least a 700 FICO score, but that number dropped to about 40 percent in 2012-2016.

III.4 FDIC Summary of Deposits Database:

We obtain data on market concentration based on the FDIC Summary of Deposits data, which reports deposits that each banking organization accepted from each bank branch every year. 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 level, 3-digit zip level, and county level) based on the market share of deposits and number of banks in the market.[20] The calculated HHI approximates the degree of market concentration (or degree of competition) in the banking market. The U.S. Department of Justice defines a concentrated market as one that has an HHI above 2,500. 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 highly concentrated banking market. The HHI measure is useful in exploring the role of the LendingClub in highly concentrated markets.

We also obtain branching information from the FDIC Summary of Deposits database. We count number of branches that each bank has in each of the 5-digit zip codes, and in each of the 3-digit zip codes. We then calculate the changes in number of bank branches in each of these markets (each zip code area) over the years.[21] This information is useful in exploring the role of the LendingClub in areas that face a decline in the number of bank branches, which is another indicator of declining banking competition.

III.5 Economic Factors:

We collect various economic factors from the Haver Analytics database. For example, we use data on economic factors including local unemployment, local average household income, local home price index. We use the most granular level (5-digit zip code level) of economic factors when possible. When data are not available at the zip code level, we use county level or state level.

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

[21] 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).

IV. The Impact of Fintech on Consumer Access to Credit

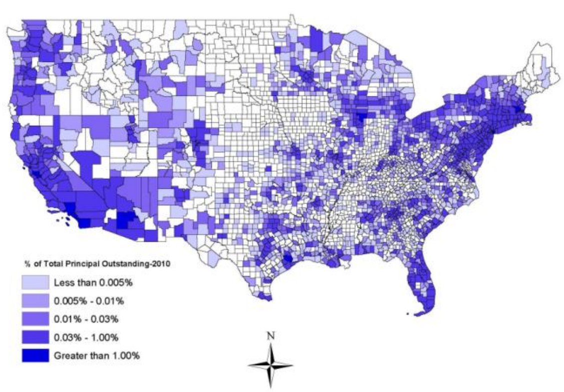
In this section, we examine whether online alternative lenders have expanded overall credit availability so consumers who were previously underserved can get credit through the fintech lenders. We investigate whether the LendingClub made loans in areas where demand for consumer credit was not met by asking certain questions. Specifically, we explore the geographic distribution of LendingClub loans – focusing on: 1) where the banking market is highly concentrated; 2) where number of bank branches decreased significantly; and 3) where average income per capital is low (to proxy LMI neighborhoods).

IV.1 Geographic Distribution of LendingClub Loans

Using LendingClub data on consumer lending, we find that initially its lending practices were concentrated in the Northeast and on the West Coast. Today, the LendingClub has loans in every state. Figure 4 presents the LendingClub (as a representative of fintech lenders) 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) – in which darker colors represent a larger share of LendingClub's loan portfolio.

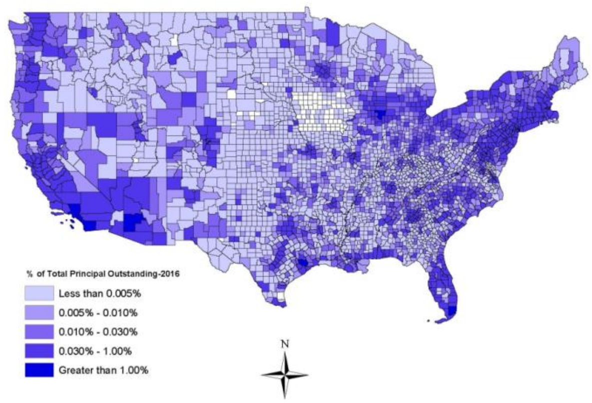
Figure 4: Geographic Distribution of LendingClub Portfolio (Percent of Total Principal Outstanding by 5-Digit Zip)

As of December 31, 2010



Source: LendingClub data

As of June 30, 2016



Source: LendingClub data

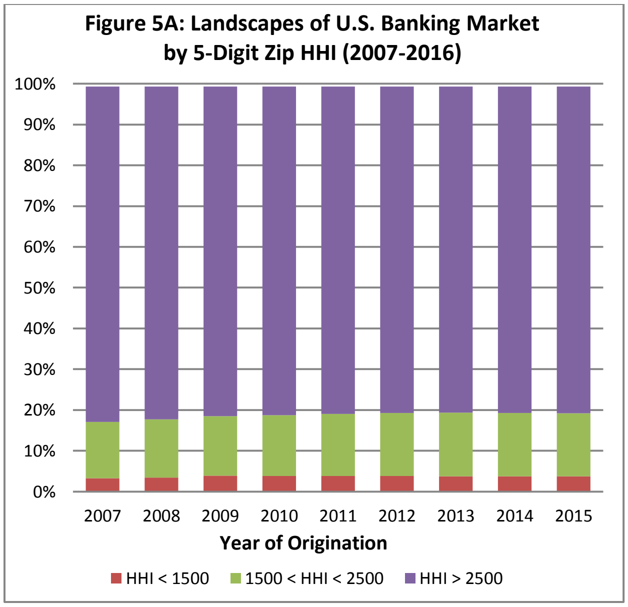
It is evident that, while LendingClub loans were concentrated along the West and East coasts in 2010 (about three years after its inception), the LendingClub has covered an increasing number of counties over the years. Its lending activities expanded to cover roughly the entire country by 2016, with the exception of a small pocket (in white) in the Midwest. 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.

We then examine the portfolio distribution in terms of banking market concentration, as measured by the HHI. We define the market in two ways – in terms of 3-digit zip codes and 5-digit zip codes. As mentioned earlier, there are about 43,000 5-digit zip codes and 900 3-digit zip codes in the U.S. A 5-digit zip code area is approximately the size of a town. The 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 Summary of Deposits data. A smaller HHI means a greater degree of competition.[22]

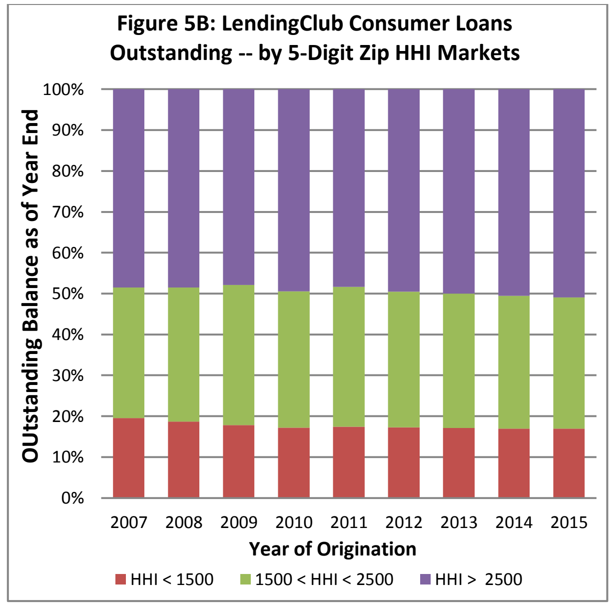
The overall landscape of the U.S. banking market (5-digit zip code market) based on banking (deposit-taking) activities is presented in Figure 5A, where approximately 80 percent of the markets are considered highly concentrated (purple). Figure 5B shows that about 50 percent of all LendingClub consumer loans are made to consumers in the highly concentrated markets with the HHI>2,500 (purple). We find that consistently half of LendingClub's new consumer loans are in areas where a few banks dominate the market; there is less banking competition.

In addition, our regression results find a positive relationship between the share of LendingClub loans and the degree of banking market concentration (more loans in more concentrated markets), when loans are measured either by number of loans or by dollar amount of loans, even after controlling for other relevant factors.

[22] The Department of Justice defines a *concentrated market* as one that has an HHI above 2,500. An HHI below 1,000 indicates a highly competitive market; otherwise, an HHI up to 1,500 indicates an unconcentrated market. An HHI between 1,500 and 2,500 indicates moderate concentration.

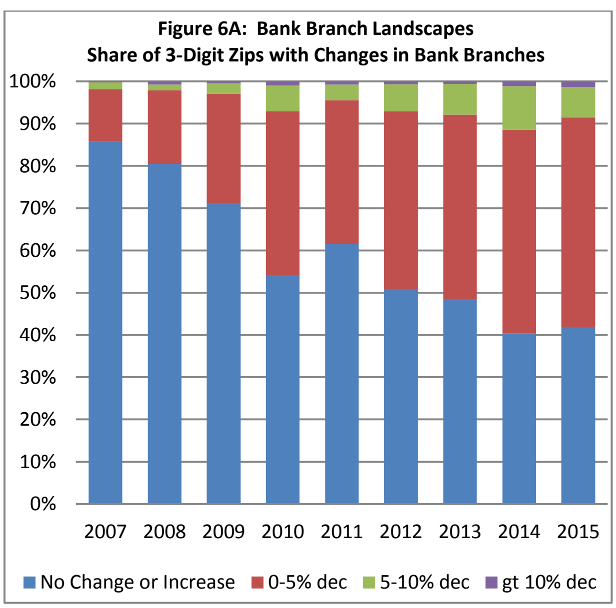


Source: FDIC Summary of Deposits Database

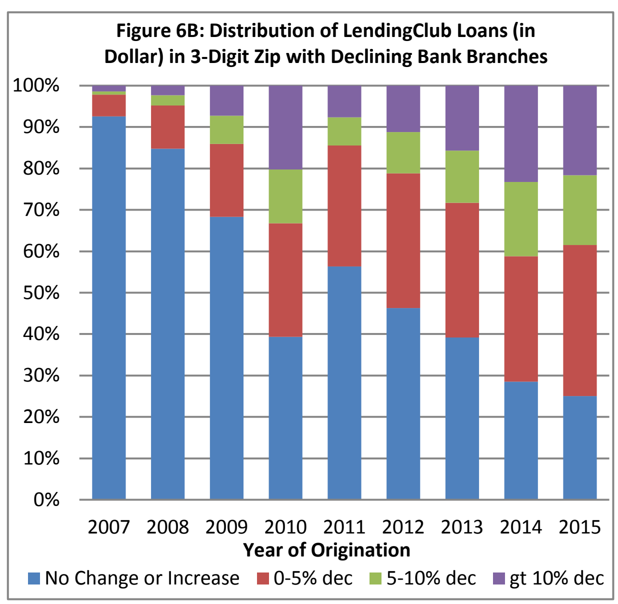


Source: LendingClub data

We then explore the distribution of consumer loans made by the LendingClub (in terms of number of accounts and total outstanding amount) across counties with varying degrees of bank branching activities (by traditional banking firms). We divide the U.S. market into 929 zip codes (3-digit zip codes) and group them into four segments based on the percentage change in number of bank branches in a 3-digit zip code in each year. The four segments are: no decline in bank branches, up to 5 percent decline, 5-10 percent decline, and more than a 10 percent decline.



Source: FDIC Summary of Deposits (for branch data)



Sources: LendingClub Data

The branching landscapes: Figure 6A shows the landscape of the banking markets in the period from 2007 to 2015 based on the percentage changes in bank branches in the zip codes. About 10 percent of all the banking markets experience at least a 5 percent decline (green and purple) in bank branches each year during 2014-2015.

LendingClub loan portfolio: Over the years, an increasing percentage of LendingClub loans are originated in markets that had a declining number of bank branches. Specifically, Figure 6B shows that during the same period (2014-2015), about 40 percent of LendingClub consumer loans were made in the markets that experienced at least 5 percent decline (green and purple) in bank branches. The empirical evidence presented so far is consistent with an argument that fintech lenders such as the LendingClub have played a role in filling the credit gap. LendingClub activities have been mainly in the areas in which there has been a decline in bank branches except for the first few years of its inception. More than 75 percent of newly originated loans in 2014 and 2015 were in the areas where bank branches declined in the local market.

We explore this further with regression analysis, using 3-digit zip code level data derived from loan-level data from the LendingClub. The dependent variables are defined as: 1) the ratio of loan accounts originated in a specific zip code (3-digit zip) in a specific year relative to all loan accounts originated in the year, and 2) the ratio of the loan amount originated in a specific zip code (3-digit zip) in a specific year relative to all loan amounts originated in the year.[23] The analysis focuses on key factors such as the HHI concentration index at the zip code level and the percent change in the number of bank branches in the zip code in the year. In the regression we attempt to control for factors that would influence the excess demand for credit in the local market. Control factors include some measure of

[23] Note that the most granular information about customer location is reported at 3-digit zip code level on the LendingClub website. Thus, we define the market based on the 3-digit zips – total about 9,000 unique markets.

average personal income, HPI, unemployment, number of bank branches (zip code level), and year dummies.[24] The results are reported in Table 1.

Regression results suggest that the LendingClub penetrated areas that are underserved. The activities both in terms of loan accounts and loan amounts are positively related to the market concentration indicators. The coefficients of the *D_HHI_1500 to 2500* and *D_HHI_2500+* indicators are significantly positive and with larger positive coefficient for the *D_HHI_2500+* indicator, after controlling for all other relevant factors that impact the lending activities. The LendingClub made more loans in those areas (zip codes) with high banking market concentration (with HHI>2,500).

We further explore the impact of the decline in bank branching. Recall that the plots shown in Figures 6B and 7B show an increasing ratio of LendingClub loans in areas with declining bank branches. Statistically, however, the impact is weakly significant after controlling for the other relevant factors in the regressions. We explore the variable *Pct Change in Branch* which is defined as the difference in number of bank branches in the 3-digit zip from the previous year.[25] Additionally, we explore the variable *Pct Decline in Branch;* this variable assigns the value zero to all the areas with the increasing number of bank branches.[26] We find weak significance in the loan amount regression (Table 1, column 3) and insignificance in all other cases. Both *Pct Change in Branch* and *Pct Decline in Branch* are not significant in Table 1, columns 1 and 2, indicating that the declining number of bank branches are not a significant factor in the loan account regressions.

Separately, we find that the coefficient of the variable *Number of Branches* (total number of bank branches in the zip code) is consistently positive and significant for both loan accounts and loan

[24] Most of the economic factors are at the state level. LendingClub report location by 3-digit zip code, which could not be accurately merged into 5-digit zip level data or county-level data, we had to settle for a less granular -- state-level data – for HPI, unemployment rates, and per capital income. Bank branching information is available at the 3-digit zip code level to merge with LendingClub data.

[25] The value of this variable is positive (or negative) for markets that face increasing (or decreasing) number of bank branches, respectively.

[26] The value is the same as that of the variable *Pct Change in Branch* for areas with declining bank branches.

amount regressions. The results are consistent with the finding that declining bank branches may not be significant in determining lending activities after controlling for other economic and risk factors. 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.

Our results provide evidence that support an argument that lending activities by fintech lenders seem to have filled the credit gap. Specifically, the LendingClub data shows that about 50 percent of consumer loans are made to borrowers in highly concentrated banking markets with an HHI>2,500. The positive relationship between high market concentration and lending activities remains significant in the regressions even after controlling for other risk and economic factors. In addition, the plot of homeownership shows that the LendingClub has also made loans more accessible to consumers who do not own a home (Figure 2A), although they tend to be charged a higher credit spread (see Section VI). The heat maps also show that LendingClub has rapidly expanded geographically to cover almost all counties in the U.S. by mid-2016.

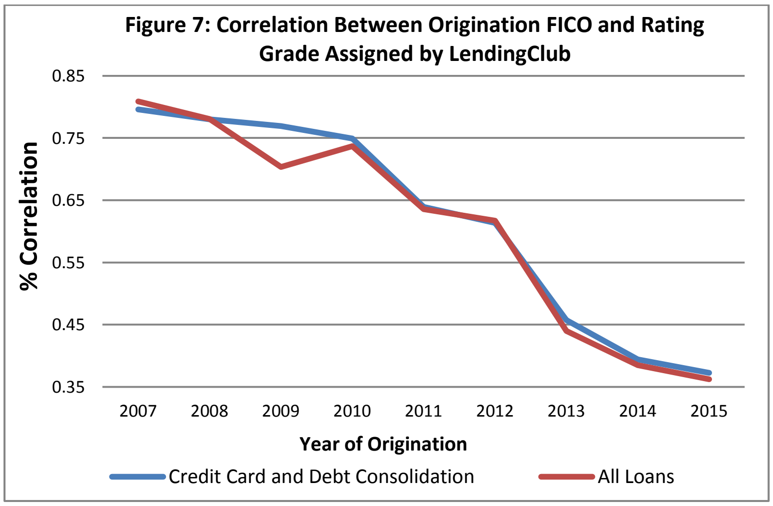
In exploring fintech activities in areas where traditional banks are pulling out, our plots in Figures 6A and 6B show a rising trend of LendingClub loans in areas where bank branches are declining, but the regression results do not show a significant relationship between changes in bank branching and LendingClub activities after controlling for all the other relevant risk and economic factors associated with the areas, such as the local unemployment rate. We find a statistically significant relationship between LendingClub activities and local unemployment rate, consistent with the argument that some unemployed borrowers might not be considered as risky as their FICO score indicates when incorporating other alternative nontraditional sources of information (the topic of Section V).

V. The Role of Alternative Information Sources and Impact on Financial Inclusion

One of the attractive features of getting credit from an alternative lenders is how quickly lending decisions are made. An important advantage to fintech lenders is that they have access to non-traditional data sources that are not used (or not available) to traditional bank lenders, such as FICO scores and DTI ratios. The additional sources of information include consumers' payment history (utility, phone, PayPal, Amazon), their medical and insurance claims, their social network, and so forth. These are not factors that are reflected fully in the traditional credit scores.

In the case of the LendingClub, consumers are assigned a rating grade from A to G based on the full set of information (after the loan has been approved). The loan application process is as follows: (1) the application is submitted online; (2) LendingClub's Credit Model immediately grades and prices the loans at application; (3) the applicant receives immediate feedback about the loan's terms they are qualified for. Additionally, before funding, the verification process takes place. For example, if the Credit Model data sources indicate the application is fraudulent, the application may be declined. If not, after an offer is presented, further income or employment verification may be requested. The LendingClub has its own proprietary models that identify whether each of the loan applications should be verified or not. As of 2015, about 70 percent of all loans made through the LendingClub platform were verified.

We explore the correlation between LendingClub rating grades and the FICO scores as of loan origination. We convert LendingClub's rating grades to numerical values, where A is 7, B is 6,… and G is 1. It is interesting to note that while the rating grades and the FICO scores were highly correlated at about 80 percent correlation as of origination date for loans originated in 2007, the correlation has weakened over the years. The plot in Figure 7 shows the correlation over time between FICO scores and loan grades. While we do not know how the LendingClub defines their credit grades, it is obvious that these credit grades are increasingly defined using additional metrics beyond FICO scores. The correlation has declined from over 80 percent in 2007 to approximately 35 percent for loans that were originated in 2015.[27] It is similar for the DTI ratio (not shown in this paper). This seems to indicate that the LendingClub is relying more on additional information.



Source: LendingClub data

The rating grades are assigned based on LendingClub's Credit Model which looks beyond FICO scores to estimate the likelihood of default. The model attempts to identify applicants with FICO scores that do not reflect their true credit quality, and thus the risk could have been mispriced based on FICO scores alone.[28] What are the implications for consumers? Some consumers with low FICO scores (below 680) could end up being rated A by the LendingClub's Credit Model, especially in later years (2014-2015 origination). Figures 8A, 8B, and 8C present the composition of loans for each rating grade and how the composition has evolved over the years for loans originated in 2007, 2011, and 2015, respectively. There are some consumers that would be considered subprime that are slotted into the "better" loan grades.

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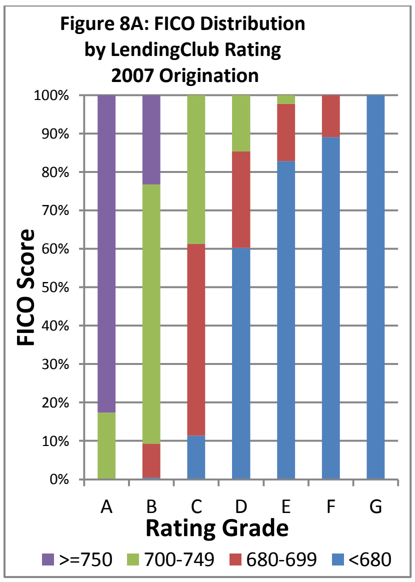
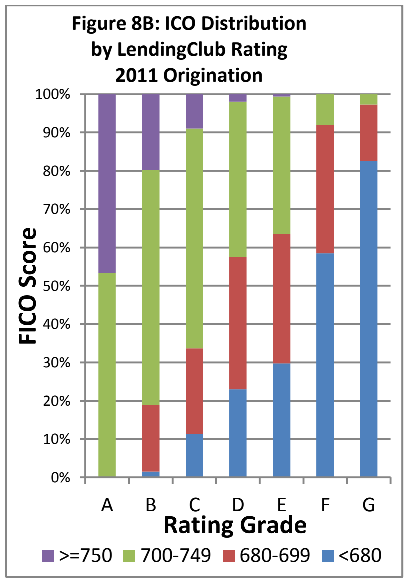
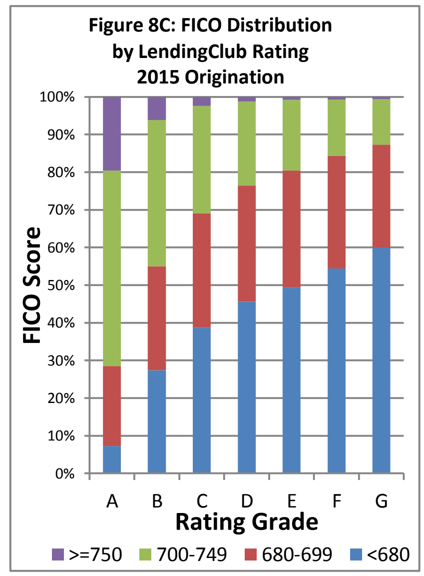
[27] We also tried calculating the correlation when both the rating grades and the FICO scores are grouped into segments – FICO is 1 if FICO<680; FICO is 2, 3, and 4 if it is between 680 and 700, 700 and 750, and more than 750, respectively. This way, the correlation between rating grades and FICO fell from xxxx for loans that were originated in 2007 to xxxx for loans that were originated in 2015.

[28] LendingClub has documented that its credit models have KS scores that outperform generic scores by identifying strong borrowers with lower FICOs and vice versa. See the link from the LendingClub site for more details -- at https://www.lendingclub.com/public/income-verification.action.

For loans originated in 2015 (see Figure 8C), over 25 percent of the B-rated borrowers have FICO scores in the subprime range. And, about 8 percent of loans that were assigned A-rated grade had FICO scores below 680. This provides evidence that the use of additional information sources and other soft information could allow some borrowers with low FICO scores to get access to credit -- and potentially get a lower price than if FICO scores were the only criteria.





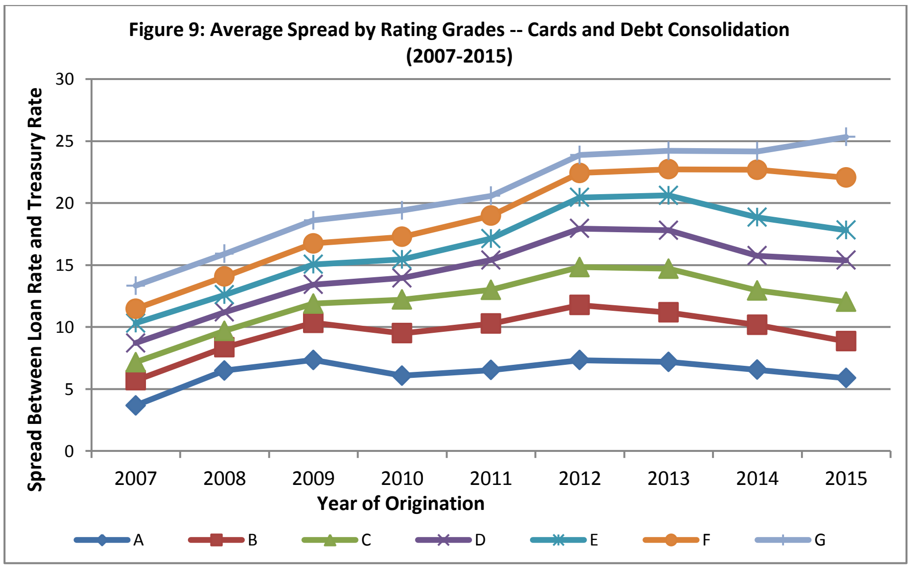


Source: LendingClub data

VI. Fintech Lending and Pricing of Credit

In this section, we explore the pricing of LendingClub loans versus similar loans from traditional lenders. To compare similar bank loans with LendingClub consumer loans, we focus on loans with the purposes identified as credit cards or debt consolidation. This allows us to compare the LendingClub rating grade against credit card loans made by large banks based on Y-14M loan-level data that large CCAR banks report to the Federal Reserve monthly. The data include pricing information and other details about the account and the borrower.

Pricing is measured in terms of the credit spread between the reported interest rate and the matching Treasury rates for the same time to maturity. The LendingClub's own rating (from A to G), based on its internal proprietary rating system (which is used to price loans) seems to demonstrate the risk-price rank ordering consistently throughout the sample period, where better rated borrowers receive lower prices (smaller credit spreads) as shown in Figure 9A. The LendingClub uses loan grades to differentiate interest rates offered to borrowers. We observe a tight relationship between the loan grades and the interest rate spreads on the loans in the regression analysis, even after controlling for other relevant risk and economic factors.



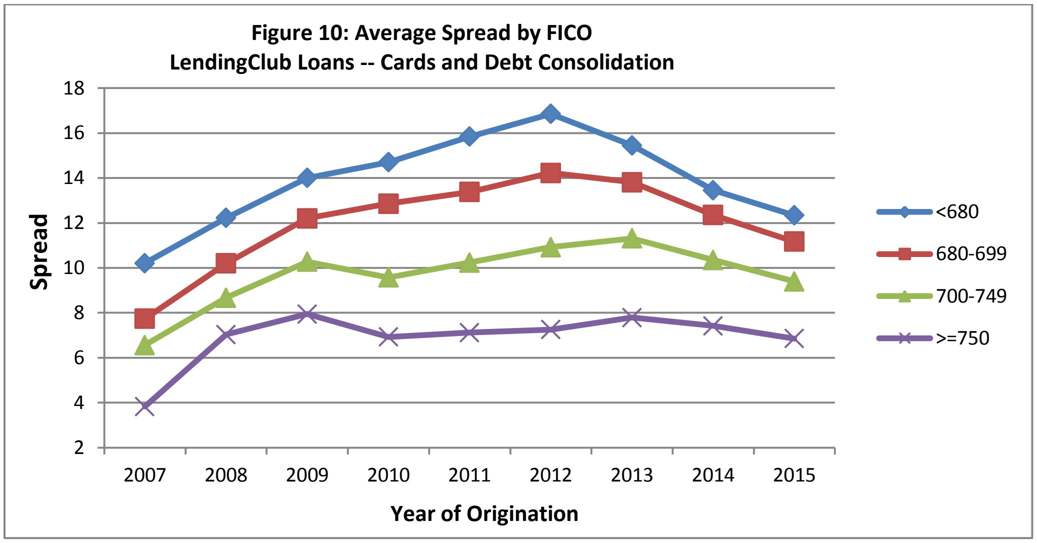
Source: LendingClub data; Treasury rates from the Bloomberg database.

We observe from Figure 9 that while the rating grade and spreads are consistently in rank order over the years, the spread differential between the A-rated and G-rated borrowers widened significantly to approximately 20 percent for loans originated in 2015. If we go back to that subprime borrower who was slotted into a B-rated loan grade (because of the additional information), he will be paying approximately 9 percent over Treasuries instead of 25 percent over Treasuries if he had been slotted into the G-rated loan grade, which is a meaningful difference.[29]

In contrast, the spread differentials between the highest and the lowest FICO score brackets did not widen as much – see Figure 10. This, again, is consistent with the different information contained in the proprietary rating grade (using alternative information sources) and the conventional FICO scores.

[29] It is shown in the next section that higher probability of default is observed for loans that were appropriately subject to larger credit spreads (higher price). The interest rate spreads appear to have a strong relationship with the likelihood of becoming delinquent.

To conclude, the use of additional information allows some borrowers who would be classified as subprime by traditional criteria to be slotted into "better" loan grades and therefore obtain lower priced credit. And, it does not appear that this credit is "mispriced" in terms of default risk.



Source: LendingClub data; Treasury rates from the Bloomberg database.

We further explore the relationship between loan grades, loan rates (spreads), and loan performance using regression analysis, controlling for other factors that are likely to impact loan price and/or credit performance. The results are presented in Table 2A for the pricing of LendingClub loans and Table 2B for pricing of credit card loans at CCAR banks. This allows us to examine the difference in the pricing algorithms used by LendingClub compared with traditional CCAR banks.

In Table 2A, we explore important factors that determine credit spreads. The dependent variable is the interest rate spread, which is calculated as the difference between the interest rate charged on the loans and the equivalent risk-free loans (Treasury rate of securities with the same time to maturity). We control for risk characteristics such as DTI ratio at origination, FICO scores or rating grades at origination, loan maturity, whether the loans required a verification, the banking market concentration (HHI), whether the consumer owns a home, consumer's employment, income at origination, loan amount, and economic factors (such as local unemployment rate, average income per capita, and year dummies). The independent variable for loan grades are measured in two ways – the

LendingClub proprietary rating in columns (1) and (2), and the traditional FICO scores in columns (3) and (4). We find that spreads are significantly correlated with both the FICO scores and the LendingClub's own rating. That is, larger spreads are required for less creditworthy borrowers, with everything else fixed (controlling for other risk and economic factors).[30] As expected, the adjusted R-squares are more than double (at over 90 percent) in columns (1) and (2) when the rating grades are included, compared with less than 50 percent when FICO scores are used as credit risk measures in columns (3) and (4).

The results in Table 2A indicate that the LendingClub charges significantly higher spreads in regions of higher banking market concentration – with (1,500<HHI<2,500) and (HHI>2,500). The coefficients are positive and significant for areas with 1,500<HHI<2,500 and HHI>2,500 in columns (1) and (3). It appears that the LendingClub has more monopolistic power in these markets and is able to charge higher prices. We also explore the factors that are important in determining credit spreads for traditional loans to compare with LendingClub loans, using Y-14M account-level data on credit cards that banks issued to consumers (business cards are excluded) during 2014-2015.[31] For this analysis of traditional banks, credit ratings are measured in terms of FICO scores only. Some of the cards were issued with a promotional rates at the beginning and we control for that along with other risk and economic factors. The results, reported in Table 2B, indicate that banks also charge higher credit spreads in areas with greater degree of market concentration, with an HHI>2,500. More market power has allowed both banks and fintech lenders to charge consumers higher prices.

VII. Price of Credit and Credit Performance – Compare Fintech Loans versus Traditional Channels

So far, we have observed a tight relationship between the LendingClub's own credit spreads and the proprietary rating grades. We have also observed that the relationship between the rating grades

[30] Controlling for other risk and economic factors -- including year of origination, years of employment, local unemployment rate, local average income, homeownership, DTI at origination.
[31] Banks started reporting Y-14M data for CCAR stress testing purposes in 2012 but the data became much more complete and reliable in 2014.

and FICO scores have declined dramatically, suggesting the increasing role of alternative information sources used by the LendingClub. In this section, we explore the relationship between these credit risk measures and consumer credit performance, focusing on the delinquency within 12 months after origination. Since some borrowers with low FICO scores have been able to access credit and at a lower rate (as shown in Figure 9C, some of the A-rated borrowers actually had FICO scores below 680), we explore here how well the rating grades could predict delinquency within 12 months after origination.

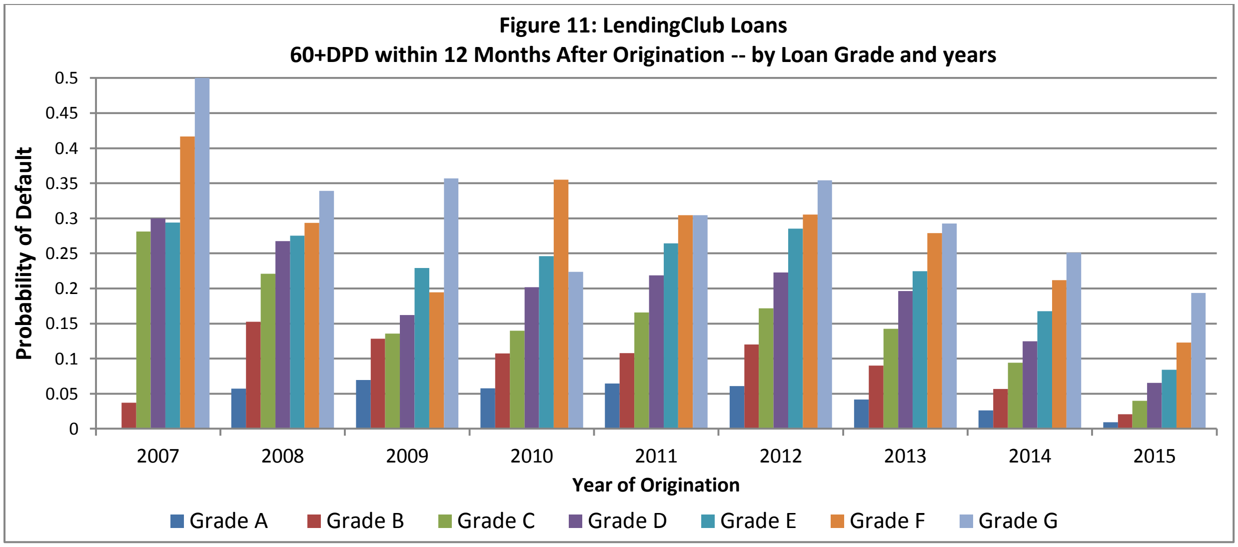
Data indicate a tight relationship between credit spreads and loan grades.[32] Recall from Table 2A how well the rating grades determined spread, with R-Square more than 90 percent compared to under 50 percent in the regressions that use FICO scores. The correlation coefficient between credit spreads and rating grades is 93.51 percent (significant at the 1% level) compared with 47.01 percent (significant at the 1% level) between spreads and FICO scores.[33] Data also indicates a tight relationship between loan grades and delinquency rates. Figure 11 shows that the delinquency rate and rating grades are well aligned and rank ordering for all origination years, including 2015 when some borrowers with FICO scores <680 received A-rating based on LendingClub rating grades.

Overall, we find that LendingClub's rating grades have served as a good predictor for the borrowers' probability of becoming at least 60 days past due within the 12-months period following loan origination date.[34] This is true despite the fact that the rating grades have a low correlation with the FICO scores especially for loans originated after 2013.

[32] Note that LendingClub interest rates (as reported on the LendingClub website) do not include origination fees, which range from 1 percent to 5 percent of origination amount, depending on the rating grades of the borrowers. The origination fee is usually deducted from the total loan amount. The interest rate from Y-14M data is an APR.

[33] The correlation coefficient between rating grades and FICO scores is 43.69 percent (significant at the 1% level) over the entire sample period. The coefficients declined steadily from about 80 percent for loans originated in 2007 to about 35 percent for loans originated in 2015.

[34] Loans that became at least 60 days past due (DPD) and self-cured (became current again) would also be included in these statistics.

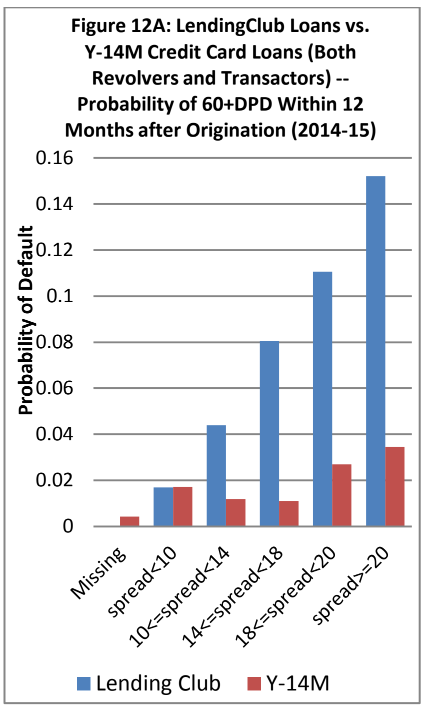


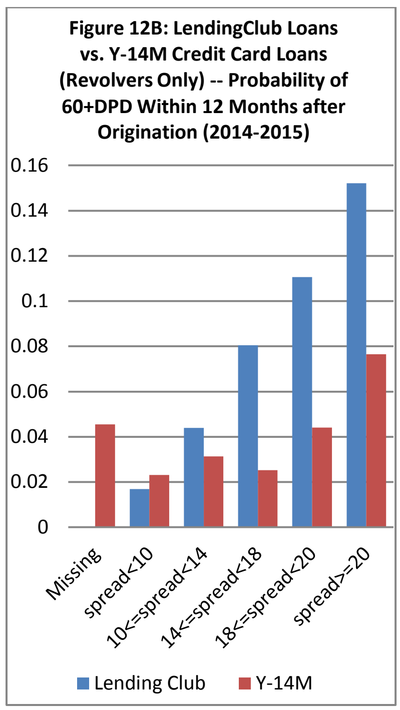
Source: LendingClub loans (cards and debt consolidation purposes only)

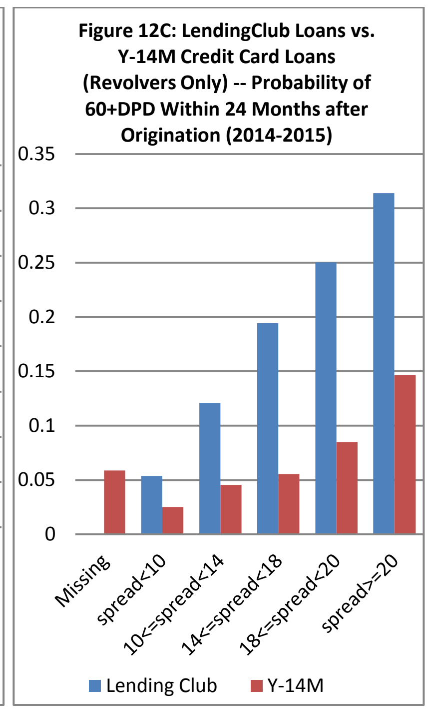
Now, we focus on LendingClub loans that were originated during the period from January 2014 to December 2015 (with the 12-month performance period ending in December 2016). These origination dates are during the period when the rating grades (assigned by the LendingClub) and FICO scores are not highly correlated (e.g., when rating grades contain different information than what is contained in the FICO scores). Figures 12A, 12B, and 12C compare delinquency rates across the credit spread brackets for LendingClub consumer loans (loans for credit cards and debt consolidation purposes) versus traditional credit cards (issued by large U.S. banks). Only loans originated between January 2014 and December 2015 are included in the analysis for both LendingClub and Y-14M bank data.[35] In Figures 12A and 12B, we measure delinquency during the initial 12 months after loan origination. Figure 12C expands the performance window from 12 months to 24 months after origination. For credit card delinquency (from Y-14M data), we only cards that carry a balance (Revolvers) in the sample in Figures 12B and 12C, while all credit card holders (including both Revolvers and Transactors) are included in Figure 12A. Note that all cards that involved the initial promotion low interest rates are excluded from the sample.

[35] We do not include credit card accounts from the Y-14M database that were originated prior to 2014 -- to avoid the sample survival bias, because cards that defaulted and were closed before 2014 would not be included in the Y-14M reports (as of 2014).

Delinquency rates and credit spreads line up very well for LendingClub loans, where higher credit spreads correspond to higher delinquency rates – for all three measures of delinquencies in Figures 12A, 12B, and 12C.[36] All the three plots below show that the delinquency rates are higher for LendingClub loans than for bank loans with the same credit spreads. The results indicate that given the same credit risk (i.e., for borrowers with the same expected delinquency rate), consumers would be able to obtain credit at a lower rate through the LendingClub than through traditional credit card loans offered by banks.





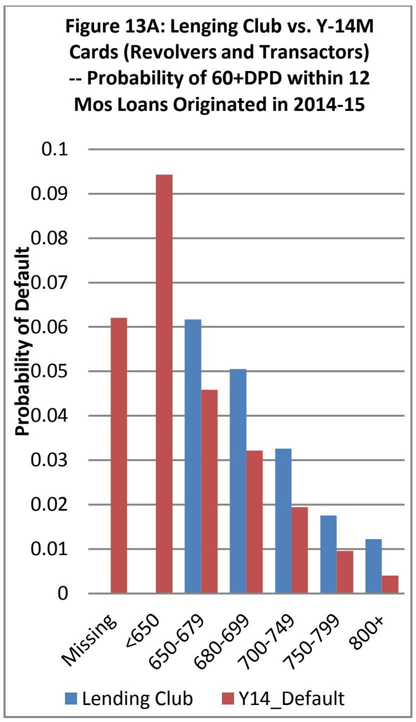


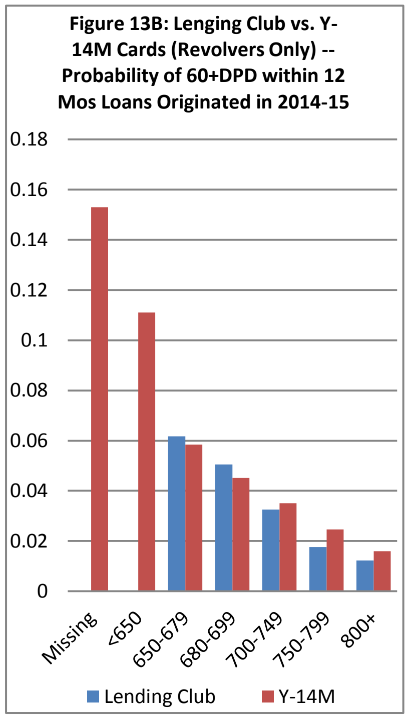
Sources: LendingClub loans (cards and debt consolidation purposes only) and Y-14M data on credit cards.
Note: All loans were originated during the period from January 2014 to December 2015.

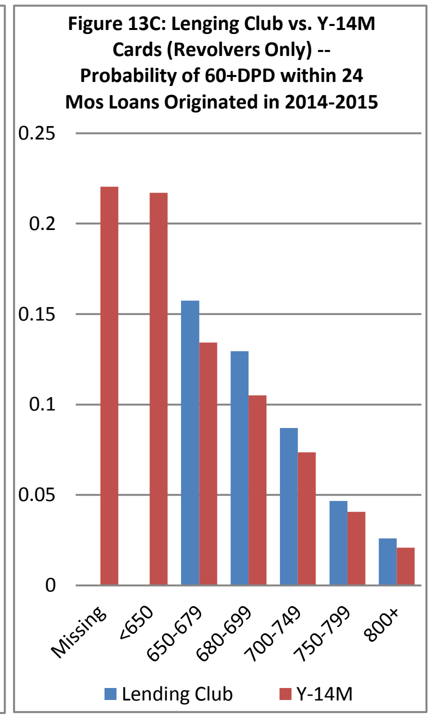
In addition, Figures 13A, 13B, and 13C show that for loans that were originated in the same period (2014-2015) and in the same FICO score brackets, the delinquency rate is slightly higher for LendingClub loans than for Y-14M credit card loans – using three different measures of delinquency in

[36] Note that some (small number) of the credit card loans reported on Y-14M have missing interest rates – in the missing category in Figures 12A, 12B, and 12C. In addition, Y-14M credit card accounts with promotional APR flag are excluded from this plot (to accurately assign the correct credit spread for the loans).

Figures 13A, 13B, and 13C.[37] In Figures 13A and 13B, we measure delinquency during the initial 12 months after loan origination. Figure 13C expands the performance window from 12 months to 24 months after origination. For credit card delinquency (from Y-14M data), we only include accounts that carry a balance (Revolvers) in the sample in Figures 13B and 13C, while all credit card holders (including both Revolvers and Transactors) are included in Figure 13A. Note that all cards that involved the initial promotion low interest rates are excluded from the sample.







Sources: LendingClub loans (cards and debt consolidation purposes only) that were originated in 2014 and 2015 only; Y-14M data on credit card accounts were issued to consumers during 2014-2015.

These results imply that for consumers with the same FICO scores, those who borrow from the LendingClub have a higher risk of becoming delinquent. As shown earlier (Figure 8C), for loans that were originated in 2015, some of the borrowers with FICO scores above 700 were assigned the lowest rating grades (F-rated and G-rated) by the LendingClub. Borrowers of the same FICO brackets at the

[37] Note that some of the credit card loans reported on Y-14M have missing FICO scores at origination – in the missing FICO category in Figures 13A, 13B, and 13C. LendingClub consumers have at least 650 FICO.

LendingClub tend to be more risky, on average, than those who stick with credit card loans through traditional lending channels.

Overall, data support an argument that rating grades (assigned based on information not included in the FICO scores) seem to do a good job of identifying riskier borrowers. We explore this further using Logistic regression analysis to control for a number of additional factors (e.g., credit spreads, borrower's risk characteristics, and economic factors). The dependent variable is the probability that the loan becomes delinquent within 12-months following the origination date. The results reported in Table 3 confirm the earlier findings that rating grades do a good job of predicting future loan defaults.

VIII. Conclusions

Fintech has been playing an increasing role in shaping the financial and banking landscapes. Technology has allowed both banks and fintech lenders to serve small businesses and consumers without brick and mortar investments. Banks have been concerned about the uneven playing field since fintech lenders are not subject to the same rigorous oversight. The FDIC and the CFPB have also expressed concerns about impacts on consumer credit access and privacy around credit provided by fintech lenders.

In this paper, we explored the impact of fintech lending on consumers' ability to access credit and the price of credit. In addition, we explored the role of alternative information sources potentially used by fintech lenders. Since our results are derived based on loans originated on the LendingClub platform, one should be cautious in extrapolating the interpretation of our findings to all loans originated through other online alternative platforms. We would note that the Y-14M data are constrained by the limited number of reporters and does not include credit card lending by banks under $50 billion in total assets.

In terms of credit access, we investigated whether LendingClub loans penetrated previously underserved areas, where there is less competition in banking services, lower income borrowers, and areas where bank branches have decreased proportionately more than others. We found that LendingClub's consumer lending activities have penetrated into areas that could benefit from additional credit supply, such as in areas that lose bank branches and in highly concentrated banking markets.

To investigate the impact on the price of credit, we explored credit spreads of similar loans (consumer loans made for the same purposes) made by the LendingClub versus traditional bank lenders. Given that credit spreads are priced accurately based on the expected delinquency of the loans, we found that for the same risk of default, consumers pay smaller spreads on loans from the LendingClub than from traditional lending channels, implying that fintech lending has provided credit access to consumers at a lower cost.

We also found that the use of alternative information sources allowed consumers with few or inaccurate credit records (based on FICO scores) to access credit. We find that some consumers with poor FICO scores have been highly rated as low-risk borrowers. The correlation between rating grades and FICO scores declined steadily from over 80 percent in 2007 to about 35 percent for loans originated in 2015, but the rating grades continued to serve as a good predictor for future loan delinquency. The declining correlation between traditional risk scores and LendingClub's rating grades suggests that the traditional credit scores may have been discriminatory since the models were built based on experience from those consumers who already had access to credit. There is additional (soft) information in the LendingClub's own internal rating grades that are not already incorporated in the obvious traditional risk factors. This has enhanced financial inclusion and allowed some borrowers to be assigned better loan ratings and receive lower priced credit.

Banks are increasingly viewing these alternative lenders as potential partners rather than disrupters. Banks are associating with fintech lenders in a number of ways. They range from providing origination services and funding to customer referrals. In some cases, these associations are seamless to customers so that the relationship with the bank is maintained. For examples, fintech firms such as the LendingClub and Prosper are turning to commercial banks and industrial banks to originate their loans. Banks are also making equity investments in fintech firms avoiding the cost of in-house development: Fifth Third's investment in ApplePie Capital (online lender specializing in franchise loans) is one example. Bank Alliance, a network of over 200 banks, partners with the LendingClub and Fundation to allow members to offer small dollar consumer and business loans. Members may also purchase loans from these fintech firms to add to their balance sheets. In addition, JPMorgan Chase has licensed technology from OnDeck to offer Chase customers small business loans in an entirely digital process. The loans are Chase-branded and held on the bank's balance sheet, where JPMorgan sets the underwriting criteria for the loans.

We have presented evidence that fintech lenders fill credit gaps in areas where bank offices may be less available and provide credit to credit worthy borrowers that banks may not be serving. And this credit seems to be "appropriately" risk-priced. Banks are responding to these innovations by partnering with fintech firms. This relationship is evolving quickly. We have also presented some positive evidence of what impacts these firms have on credit access, but more remains to be done to fully answer the question about risks to borrowers presented by these new innovations.

Our results provide policy implications related to the consumer protection. While consumers' information and privacy should be protected by laws and regulations, certain private information could play a key role in allowing lenders to fully understand credit quality of the potential borrowers and allowing certain consumers access to credit that would not have been granted otherwise. Banks could potentially benefit from the alternative data sources and "big data" through partnership with online fintech lenders.

Table 1: Regression Results — Credit Access
Lending Activities in Specific Zip Codes (relative to the rest of the country)

Dependent variables measure the lending activities in the specific zip code in a specific year, measured in terms of number of accounts (columns 1 and 2) and total loan amount (columns 3 and 4). Loans were originated in 2007–2016. Data — panel data set of loans in a 3-digit zip code and originated in specific year. Data are from the LendingClub. Sample loans only those specified as for "Credit Cards" or "Debt Consolidation"purposes. The ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Independent Variables	***Dependent Var. = % of Accounts Originated in Zip (Relative to All Zip Codes)***		***Dependent Var. = % of $ Loan Amount Originated in Zip (Relative to All Zip Codes)***	
	(1)	(2)	(3)	(4)
Intercept	-0.0044***	-0.0044***	-0.00463***	-0.0046***
	(0.0006)	(0.0006)	(0.00057)	(0.00057)
Number of Branches	0.00002***	0.00001***	0.00002***	0.00002***
	(0.0000)	(0.0000)	(0.0000)	(0.00000)
Unemployment Rate	0.00007***	0.00007***	0.00006***	0.00006***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
HPI	0.000002***	0.000002***	0.000002***	0.000003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Log_Income/Capita	0.00072***	0.00071***	0.00076***	0.00075***
	(0.00016)	(0.00016)	(0.00017)	(0.00017)
Pct Change in Branch	0.00057	--	0.00074*	--
	(0.00040)		(0.00042)	
Pct_Num_Decline	--	-0.00010	--	-0.00006
		(0.00052)		(0.00054)
D_2008	-0.00007	-0.00007	-0.00006	-0.00006
	(0.00007)	(0.00007)	(0.00007)	(0.00007)
D_2009	-0.00019**	-0.00019**	-0.00014*	-0.00015*
	(0.00008)	(0.00008)	(0.00008)	(0.00008)
D_2010	-0.00019**	-0.00020**	-0.00014	-0.00015*
	(0.00008)	(0.00008)	(0.0001)	(0.00009)
D_2011	-0.00013*	-0.00014*	-0.00009	-0.0001
	(0.00008)	(0.00008)	(0.0001)	(0.00008)
D_2012	-0.00008	-0.00009	-0.00004	-0.00006
	(0.00008)	(0.000077)	(0.00008)	(0.00008)
D_2013	-0.00004	-0.00006	-0.000007	-0.00003
	(0.00007)	(0.00007)	(0.00008)	(0.00008)
D_2014	0.000004	-0.000017	0.00003	-0.000001
	(0.00007)	(0.00007)	(0.00007)	(0.00007)
D_2015	0.00002	-0.000005	0.00003	0.000001
	(0.00007)	(0.00007)	(0.00007)	(0.00007)
D_HHI_1500 to 2500	0.00029***	0.00029***	0.00029***	0.00029***
	(0.00004)	(0.00004)	(0.00004)	(0.00004)
D_HHI_2500+	0.00041***	0.00041***	0.00042***	0.00042***
	(0.00005)	(0.00005)	(0.00005)	(0.00005)
Adjusted R-Square	55.89%	55.88%	55.32%	55.31%
Observation Number	7,887	7,887	7,887	7,887

Table 2A: Regression Results — LendingClub Loans
Price of Credit (Credit Spreads for LendingClub Loans)

Data are at loan level from LendingClub consumer loans (with specified purposes as credit cards or debt consolidation) for all loans originated in 2007–2015. Dependent variables are interest rate spreads, which are calculated as the difference between the interest rates charged on the loans and the equivalent risk-free loans (i.e.; the U.S. Treasury rate of securities with the same time to maturity). Local economic factors during the origination month are measured at the most granular (zip code) level whenever possible. The ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Independent Variables	(1)	(2)	(3)	(4)
Intercept	4.1975*** (0.0159)	-0.7401*** (0.0659)	11.3040*** (0.1130)	11.502*** (0.2135)
DTI at Origination	--	--	0.04476*** (0.0005)	0.05014*** (0.0005)
Dummy_B_Grade	3.5302*** (0.0049)	3.4282*** (0.0041)	--	--
Dummy_C_Grade	6.67305*** (0.0051)	6.5901*** (0.0043)	--	--
Dummy_D_Grade	9.7893*** (0.0060)	9.7173*** (0.0050)	--	--
Dummy_E_Grade	12.487*** (0.0076)	12.461*** (0.0063)	--	--
Dummy_F_Grade	16.114*** (0.0118)	15.996*** (0.0098)	--	--
Dummy_G_Grade	18.0846*** (0.02335)	18.1087*** (0.01945)	--	--
D_FICO_LT650	--	--	7.2099*** (0.2675)	7.5743*** (0.2744)
D_FICO_650 to 679	--	--	6.5409*** (0.0507)	6.5365*** (0.0493)
D_FICO_680 to 699	--	--	5.2022*** (0.0508)	5.1409*** (0.04941)
D_FICO_700 to 749	--	--	3.1257*** (0.0507)	3.0901*** (0.0493)
D_FICO_750 to 799	--	--	0.67274*** (0.0530)	0.7274*** (0.0515)
D_Maturity_5 Years	-0.4242*** (0.0039)	-0.3658*** (0.0033)	3.2831*** (0.0091)	3.3825*** (0.0089)
D_Purpose_Credit Card	-0.1089*** (0.0036)	-0.1181*** (0.0030)	-1.3969*** (0.0085)	-1.3948*** (0.0082)
D_Verified	--	--	1.5558*** (0.0103)	1.4403*** (0.01003)
D_Source Verified	--	--	0.4124*** (0.0095)	0.5208*** (0.0093)

D_HHI_1500 to 2500	0.03495*** (0.0041)	0.00183 (0.0034)	0.0484*** (0.0098)	0.0177* (0.0095)
D_HHI_ZIP_2500+	0.1277*** (0.0064)	0.00099 (0.0054)	0.18764*** (0.0152)	0.00933 (0.0148)
D_Homeowner	--	--	0.0979*** (0.0133)	0.1441*** (0.0129)
Years of Employment	--	--	-0.00385*** (0.0011)	-0.00915*** (0.0011)
Local (State) HPI	-0.00206*** (0.00002)	-0.00003 (0.00002)	-0.00218*** (0.00005)	0.00006 (0.00005)
Log(Borrower Income)	--	--	-1.18647*** (0.0092)	-1.094*** (0.0089)
Log(Origination Amt.)	--	--	0.3957*** (0.0082)	0.3371*** (0.0080)
Local Unemp Rate	0.35566*** (0.00113)	0.0013 (0.0014)	0.48587*** (0.0027)	0.0380*** (0.0040)
Local Income per Capita	0.01783*** (0.0004)	-0.00079** (0.0004)	0.02373*** (0.0009)	0.0048*** (0.0009)
Dummy_2008	--	3.3303*** (0.0713)	--	1.9353*** (0.1995)
Dummy_2009	--	6.4528*** (0.0684)	--	3.25172*** (0.1953)
Dummy_2010	--	6.14398*** (0.0666)	--	2.06956*** (0.1903)
Dummy_2011	--	7.0619*** (0.0659)	--	2.3342*** (0.1886)
Dummy_2012	--	8.914*** (0.0653)	--	4.0256*** (0.1869)
Dummy_2013	--	8.7292*** (0.0650)	--	3.54071*** (0.1862)
Dummy_2014	--	7.4054*** (0.0649)	--	2.2906*** (0.18579)
Dummy_2015	--	6.54029*** (0.0648)	--	1.11588*** (0.1856)
Adjusted R-Square	90.06%	93.12%	44.25%	47.32%
Observation Number (N)	694,234	694,234	694,234	694,234

Table 2B: Regression Results — Bank Loans
Price of Credit (Credit Spread of Credit Cards Issued by Banks)

Data are account-level consumer credit cards samples from Y-14M stress testing data that CCAR banks report monthly to the Federal Reserve. The sample includes only credit card accounts that were originated in 2014–2015. Dependent variables are interest rate spreads, which are calculated as the difference between the interest rate charged on the loans and the equivalent risk-free loans (i.e.; the U.S. Treasury rate of securities with the same time to maturity). Local economic factors during the origination month are measured at the most granular (zip code) level whenever possible. Charge cards are excluded. The ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Independent Variables	(1)	(2)	(3)	(4)
Intercept	23.4980***	22.1564***	24.4156***	22.3499***
	(0.4078)	(0.5283)	(0.3889)	(0.5039)
D_FICO_Missing	-0.8914***	1.0116***	-0.9017***	1.0018***
	(0.0585)	(0.0787)	(0.0585)	(0.0787)
D_FICO_LT 650	2.2069**	3.9086***	2.2012***	3.9063***
	(0.0373	(0.0503)	(0.0373)	(0.0503)
D_FICO_650_679	2.4734**	4.0541***	2.4685***	4.0529***
	(0.0317)	(0.0432)	(0.0317)	(0.0432)
D_FICO_680_699	2.3303***	3.8826***	2.3282***	3.8842***
	(0.0331)	(0.0454)	(0.0331)	(0.0454)
D_FICO_700_749	1.5224***	2.9828***	1.5223***	2.9852***
	(0.0228)	(0.0307)	(0.0228)	(0.0306)
D_FICO_750_799	0.4197***	1.8322***	0.4213***	1.8357***
	(0.0213)	(0.0287)	(0.0213)	(0.0287)
D_FICO_Missing_Promo	--	-14.2453***	--	-14.2095***
		(0.2658)		(0.2658)
D_FICO_LT 650_Promo	--	-21.1559***	--	-21.1489***
		(0.1161)		(0.1161)
D_FICO_650 to 679_Promo	--	-19.4942***	--	-19.4803***
		(0.0949)		(0.0949)
D_FICO_680 to 699_Promo	--	-19.0732***	--	-19.0615***
		(0.1086)		(0.1086)
D_FICO_700 to 749_Promo	--	-18.0545***	--	-18.0421***
		(0.0680)		(0.0679)
D_FICO_750 to 799_Promo	--	-17.2831***	--	-17.2816***
		(0.0654)		(0.0654)
D_HHI_2500+	-0.1041***	0.3632***	-0.1075***	0.3648***
	(0.0262)	(0.0356)	(0.0262)	(0.0356)
D_HHI_2500+_Promo	--	-4.3033***	--	-4.2956***
		(0.1140)		(0.114)

D_Reward	-6.2833***	-6.2289***	-6.2821***	-6.2269***
	(0.0162)	(0.0209)	(0.0162)	(0.0209)
Log_Borrower Income	0.0679***	0.1802***	0.0649***	0.1784***
	(0.0051)	(0.0066)	(0.0051)	(0.0066)
Log_Credit Limit	-0.3975***	-0.5186***	-0.3977***	-0.5198***
	(0.0102)	(0.0132)	(0.0102)	(0.0132)
Local HPI	-0.0020***	-0.0005	-0.0387***	-0.0374***
	(0.00025)	(0.0003)	(0.0028)	(0.0036)
Local_Unemploy Rate_State	0.0075	-0.0168*	0.0468***	0.0246**
	(0.0067)	(0.0087)	(0.0074)	(0.0096)
Log(Income per Capita_Zip3)	0.1523***	0.1033**	0.0414	0.0784*
	(0.0379)	(0.0492)	(0.0351)	(0.0455)
Number of Observations	200,191	200,191	200,191	200,191
R-Square (Adjusted)	78.47%	63.88%	78.48%	63.90%

Table 3: Logistic Regressions Results
Performance of LendingClub Loans

Data include all LendingClub consumer loans (cards and debt consolidation) that were originated in 2007–April 2015 (to allow a 12-month performance window; Lending Card performance data ends in May 2016). Dependent variables are the probability of becoming 60+DPD anytime within 12 months since the origination (including those that cured within a year). Economic factors (unemployment and average income per capital) are at the state level. The ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Independent Variables	(1)	(2)	(3)	(4)
Intercept	-1.3162***	-0.5995	-1.8475***	-0.6753
	(0.4748)	(0.5104)	(0.5447)	(0.58)
SPREAD	0.0500***	0.1177***	0.1242***	0.1312***
	(0.0071)	(0.00894)	(0.0028)	(0.00284)
DTI at Origination	0.0118***	0.0118***	0.0134***	0.0129***
	(0.0014)	(0.00137)	(0.00137)	(0.00137)
D_Grade B	0.5397***	0.307***	--	--
	(0.059)	(0.0615)		
D_Grade C	0.9478***	0.5101***	--	--
	(0.0691)	(0.0773)		
D_Grade D	1.1795***	0.5355***	--	--
	(0.0848)	(0.099)		
D_Grade E	1.3960***	0.5469***	--	--
	(0.1026)	(0.1229)		
D_Grade F	1.5266***	0.4659***	--	--
	(0.1268)	(0.1525)		
D_Grade G	1.7597***	0.5549***	--	--
	(0.1497)	(0.1772)		
FICO <650	--	--	1.8725***	0.2984
			(0.3918)	(0.4092)
FICO 650-679	--	--	0.4653*	0.4206
			(0.2700)	(0.2700)
FICO 680-699	--	--	0.3777	0.3482
			(0.2698)	(0.2699)
FICIO 700-749	--	--	0.2468	0.2176
			(0.2697)	(0.2698)
FICO 750-800	--	--	0.0982	0.0551
			(0.2788)	(0.2789)
Dummy_CreditCard	-0.134***	-0.1235***	-0.1647***	-0.1422***
	(0.0253)	(0.0253)	(0.0253)	(0.0254)
Log_Borrower Income	-0.2353***	-0.2348***	-0.2518***	-0.2518***
	(0.0263)	(0.0262)	(0.0264)	(0.0263)
Log_Origination Amt.	-0.0652***	-0.0434**	-0.0177	-0.0147
	(0.0215)	(0.0216)	(0.0220)	(0.0220)

D_Verify	0.0617**	0.0886***	0.0681**	0.1027***
	(0.0294)	(0.0296)	(0.0293)	(0.0296)
D_Source Verified	0.0922***	0.1124***	0.1229***	0.1244***
	(0.0278)	(0.0282)	(0.0277)	(0.0281)
D_Homeowner	-0.0372	-0.0375	-0.0373	-0.0367
	(0.037)	(0.037)	(0.037)	(0.037)
Years of Employment	-0.0216***	-0.0196***	-0.0218***	-0.0191***
	(0.00295)	(0.00296)	(0.00295)	(0.00296)
HPI	0.000949***	0.000751***	0.00108***	0.000741***
	(0.000148)	(0.000152)	(0.000148)	(0.000152)
Unemployment Rate	0.00289	0.0223**	-0.0115	0.0224**
	(0.00728)	(0.0101)	(0.00725)	(0.0101)
Log_Income per Capita	-0.3105***	-0.2243*	-0.3697***	-0.2177*
	(0.1176)	(0.1192)	(0.1177)	(0.1192)
D_2008	--	-0.4826**	--	-0.5315**
		(0.2431)		(0.2452)
D_2009	--	-1.3431***	--	-1.422***
		(0.2528)		(0.2562)
D_2010	--	-1.474***	--	-1.5605***
		(0.2394)		(0.2437)
D_2011	--	-1.7959***	--	-1.9144***
		(0.2378)		(0.2397)
D_2012	--	-1.8857***	--	-2.063***
		(0.2371)		(0.2325)
D_2013	--	-2.0087***	--	-2.1757***
		(0.2336)		(0.2293)
D_2014	--	-1.8012***	--	-1.9533***
		(0.2273)		(0.2271)
D_2015	--	-1.6416***	--	-1.791***
		(0.2256)		(0.2269)
Observation (N)	393,926	393,926	393,926	393,926
Percent Concordant	68.6%	69.0%	68.3%	68.9%
Percent Discordant	31.4%	31.0%	31.7%	31.1%

Note: The results are robust for using alternative economic factors at the (estimated) county level, based on the 3-digit zip codes of the loans.

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